Livestock network characterisation in data-scarce settings: the structure of the live pig trade network in Cambodia and implications for influenza transmission dynamics

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Declaration of own work

I, William Leung, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

Across Southeast Asia, expanding and intensifying swine production sectors face major disease threats, yet data on livestock trade networks remains limited. This thesis aimed to characterise the live pig trade network in Cambodia to identify key points of vulnerability to pathogen introduction and dissemination, with a focus on swine Influenza A viruses (IAV).

In Chapter 2, I systematically reviewed the literature on models applied to simulate contact networks among livestock. I identified seven model frameworks broadly classified as being mechanistic, statistical, or machine learning-based. Large variation in model applications, calibration to data, and validation approaches were observed. This chapter guided methodological choices made in subsequent chapters.

In Chapters 3 and 4, I analysed data from a questionnaire-based, cross-sectional, network survey I co-conducted within four provinces in south-central Cambodia. In Chapter 3, the personal 'egocentric' networks of value chain actors (n=377) and their immediate swine trading partners (n=1,101) are described. Network analysis identified smallholder boar service providers, middlemen, and breeding farms as 'brokers' at a high risk of disease introduction and dissemination – having many inward and outward connections with producers. Breeding farms supplied pigs to all producer types, increasing opportunities for disease dissemination along the value chain.

In Chapter 4, I employed a subclass of exponential random graph models (ERGMs), estimable from egocentric data, to dissect the factors relevant for network formation. Complete, sociocentric, networks were simulated from fitted ERGMs, and IAV transmission was modelled on them. Simulations revealed that epidemic probabilities were highest when seeding in breeding farms, which, in addition to boar-lenders became infected soonest. Breeding farms also had the highest node-level prevalence at epidemic stationarity highlighting them as potential targets for IAV virological surveillance.

Collectively, this thesis sheds light on vulnerabilities in the Cambodian swine sector, presents opportunities for targeted disease control and surveillance, and demonstrates the utility of egocentric sampling methods paired with ERGMs for network characterisation in data-constrained settings.

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Acronyms and abbreviations

ABM	Agent-based model
ABNM	Agent-based network model
AI	Artificial insemination
ASEAN	Association of Southeast Asian Nations
ASF	African swine fever
ASFV	African swine fever virus
BSE	Bovine spongiform encephalopathy
BSP	Boar service provider
Bu	Butcher
EA	Eurasian avian-like
EID	Emerging infectious disease
ERGM	Exponential random graph model
(T)ERGM	(Temporal) exponential random graph model
FAMD	Factor analysis for mixed data
FB	Farm - breeding
FG	Farm - growing
FMDV	Foot and mouth disease virus
GDP	Gross domestic product
GM	Gravity model
HA	Haemagglutinin
HCA	Hierarchical clustering analysis
HP-PRRS	Highly pathogenic porcine reproductive and respiratory syndrome
IAV	Influenza A virus
JEV	Japanese encephalitis virus
Lao PDR	Lao people's democratic republic
LITS	Livestock identification and traceability systems
Mi	Middleman
NA	Neuraminidase
NAHPRI	National Animal Health and Production Research Institute
ODK	Open Data Kit
OLS	Ordinary least squares
PED	Porcine epidemic diarrhoea
PEDV	Porcine epidemic diarrhoea virus
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
PRRSV	Porcine reproductive and respiratory syndrome virus
RF	Random forests
SB	Smallholder - breeding orientated
SCC	Strongly connected component
SEA	Southeast Asia
SG	Smallholder - growing orientated
Sl	Slaughterhouse
Sm	Smallholder (breeding or growing orientated)
Tr	Trader
USAMM	United States animal movement model
WCC	Weakly connected component

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1 General Introduction

1.1 Southeast Asia as a hotspot for emerging infectious disease

Southeast Asia (SEA) – defined here as the countries within the Association of Southeast Asian Nations (ASEAN): Brunei, Cambodia, Indonesia, Lao People's Democratic Republic (Lao PDR), Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam, and one observer state to ASEAN: Timor-Leste – is highly diverse from a political, cultural, socioeconomic, and ecological stand-point (Chongsuvivatwong et al., 2011; Saba Villarroel et al., 2023; Schipper et al., 2008). The region is recognised as a hotspot for emerging infectious diseases (EIDs) including zoonoses (Coker et al., 2011; Grace et al., 2011; Saba Villarroel et al., 2023); EIDs being defined as "infections that have newly appeared in a population or have existed but are rapidly increasing in incidence or geographic range" (Morse, 1995). The process by which infectious agents emerge has been described as a two-stage process whereby an infectious agent first invades a new host, and then disseminates within the new host population (Morse, 2004). In recent decades SEA has experienced major socioeconomic transformations including population and economic growth. These transformations are associated with a range of interacting factors which can facilitate disease emergence such as increased human and livestock population densities, rapid urbanisation, greater mobility of populations, and environmental and land-use changes (Gortazar et al., 2014; Grace et al., 2011; Jones et al., 2008).

1.2 Livestock expansion and intensification

With larger and increasing wealthy populations, demand for meat and livestock products has inevitably grown. Expansion and intensification of livestock and poultry production, while offering advantages, such as enhanced productivity and food security, is recognised as an important driver for infectious disease emergence and amplification across SEA (Coker et al., 2011; Hassan, 2014; Liverani et al., 2013; Saba Villarroel et al., 2023) and globally (Jones et al., 2013). Livestock intensification can impact pathogen ecology and evolution through several mechanisms: increased livestock population sizes and densities, heightened use of antimicrobials, greater waste production with potential for environmental accumulation, and decreased livestock genetic diversity. Additionally, specialisation of production and increasingly globalised markets can lead to more frequent movements of animals at greater distances (Hassan, 2014; Jones et al., 2013; Liverani et al., 2013). The expansion and encroachment of agricultural systems on natural ecosystems further increases opportunities for pathogen exchange between wild animals and livestock. Livestock systems at these boundaries can therefore facilitate the amplification, adaption, and invasion of novel pathogens into new host species, including humans (Grace et al., 2011; Hassan, 2014; Jones et al., 2013; Liverani et al., 2013).

Infectious diseases of livestock pose a threat to productivity, food security, livelihoods, health, and the economies of countries in SEA. Agriculture serves a major role in the economies of all ASEAN countries except Brunei and Singapore. In 2022, the sector contributed between 9% of GDP in Thailand to 22-23% in Myanmar and Cambodia, and employed over a quarter of the workforce except in Brunei, Singapore, and Malaysia (ASEAN, 2023). Alongside increasingly intensive livestock production, smallholder production remains common in many countries in the region (Mason-D'Croz et al., 2022; Samkol et al., 2006). Livestock are therefore important for livelihoods as they serve as an important source of household income and nutrition, as well as providing organic waste to improve soil nutrient management, and serving important cultural roles (Leslie et al., 2015; Mason-D'Croz et al., 2022; Samkol et al., 2006; Tiemann and Douxchamps, 2023).

In recent years, the swine production sector in many countries in SEA have grown and intensified. Pig production has seen growth in the region in the past 30 years (Figure 1.1). Moreover, while smallholder pig production has traditionally predominated (Samkol et al., 2006), there are recent shifts towards large-scale, industrialised production (Deka et al., 2014; Mason-D'Croz et al., 2022; Thai, 2018; Thanapongtharm et al., 2016). In 2021, pigs constituted the largest share of total meat production by mass in Vietnam, Cambodia, Lao PDR, and Timor-Leste (FAO, 2021; Ritchie et al., 2019). Globally, demand for pork is projected to grow by 17% by 2031, with rising demand particularly pronounced in Asia (OECD and Nations, 2022; Yu and Jensen, 2022).

Against this backdrop, multiple high-profile, swine-associated EIDs and zoonoses have emerged or caused impacts in SEA in recent decades. This includes important epizootic production pathogens such as foot and mouth disease virus (FMDV), porcine reproductive and respiratory syndrome virus (PRRSV), porcine epidemic diarrhea virus (PEDV), and African swine fever virus (ASFV); pathogens with pandemic potential such as influenza A virus (IAV); and neglected zoonoses such as Japanese encephalitis virus (JEV) (Hassan, 2014; Henriksson et al., 2021; Kedkovid et al., 2020; Saba Villarroel et al., 2023; VanderWaal and Deen, 2018). In the following sections, I focus on ASFV and IAVs due to the considerable and ongoing impacts of the former and the high pandemic risk posed by the latter.

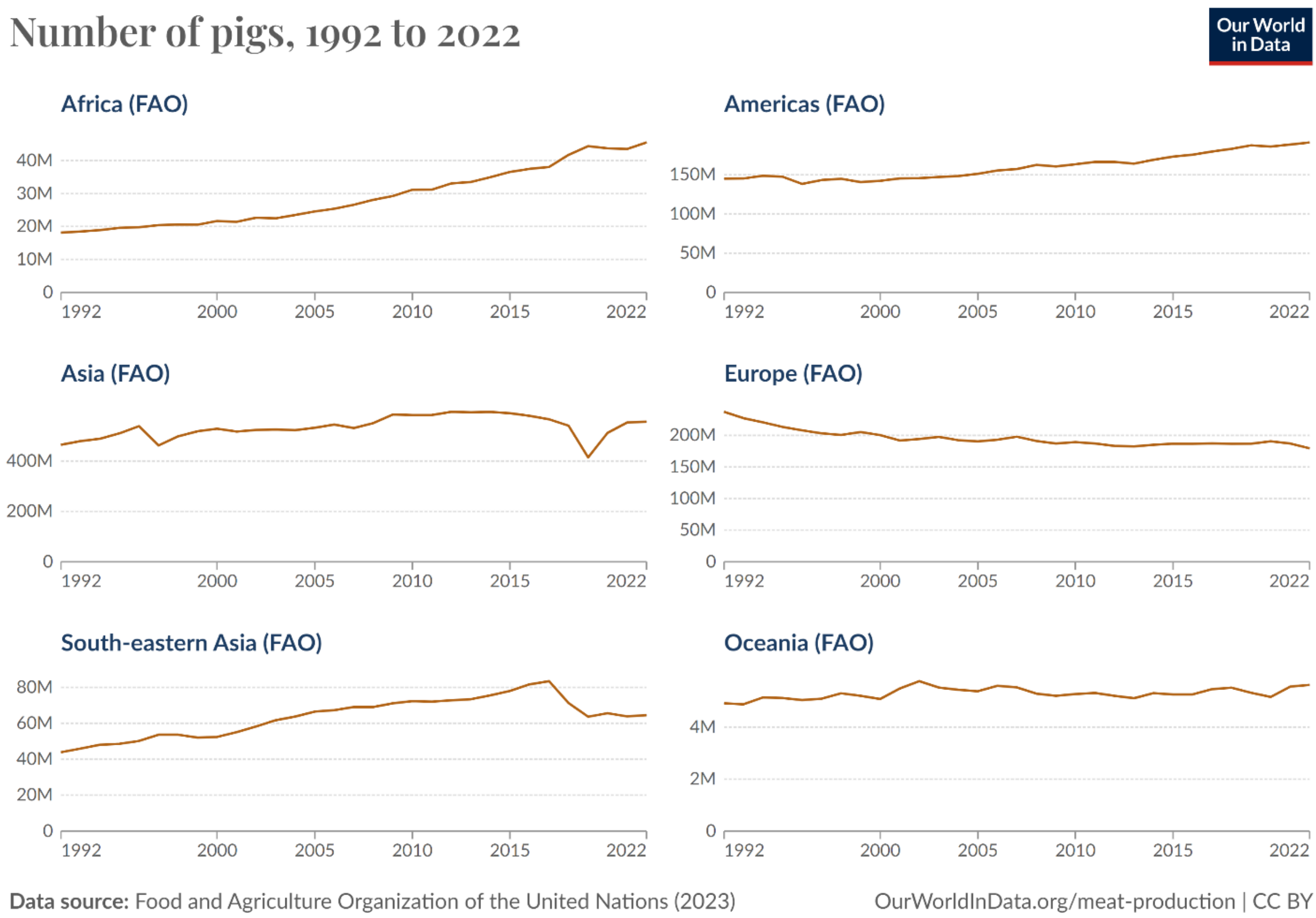

Figure 1.1 ***Global pig sector growth from 1992 to 2022****. Number of pigs produced by continent and the SEA region. Data source: Food and Agriculture Organization of the United Nations (2023). Image reproduced from Our World in Data: "Data Page: Number of pigs", part of the following publication: Hannah Ritchie and Pablo Rosado (2023) - "Agricultural Production". Data adapted from Food and Agriculture Organization of the United Nations. Retrieved from https://ourworldindata.org/grapher/pig-livestock-count-heads [online resource]. Used under CC BY, no modifications made.*

1.3 African swine fever

The incursion of African swine fever (ASF) into Asia was first documented in China in 2018. In 2019, within a year of its introduction, an estimated 500 million pigs, a third of the national herd, had died or been culled as a result of the disease (Binns and Low, 2019). ASF has subsequently been reported across all countries in SEA except Brunei (FAO, 2024) resulting in estimated direct losses of between US$55-130 billion across China, Vietnam, Myanmar, Lao PDR, and Cambodia, and generating considerable disruption to trade and worldwide effects on global meat and animal feed markets (Berthe, 2020; Weaver and Habib, 2020). Compared to commercial farms, the low biosecurity characteristic of smallholders, along with their limited resilience to production losses from disease outbreaks, is further accelerating the transition from smallholder to large-scale commercial pig producers within the region (Mason-D'Croz et al., 2022).

In its ancestral geographic range in sub-Saharan Africa, ASFV exists in a sylvatic cycle which involves warthogs and soft ticks of the genus *Ornithodoros*. Outside of this range, ticks do not appear to play an important role in the epidemiology of ASFV, with major transmission routes being direct contact between pigs, indirect contact via fomites, and contaminated food products e.g. via swill feeding (Blome et al., 2020). Across Europe, wild boar also play an epidemiological role in viral maintenance and transmission to farmed pigs (Blome et al., 2020). Carcasses of infected boar also facilitate environmental persistence and maintenance in wild boar populations (Chenais et al., 2018). In SEA, based on passive reporting, ASFV has been confirmed in wild boar carcasses in Laos, Vietnam, but not yet in Cambodia (Denstedt et al., 2020). The discovery of carcasses several months after mass mortality events in farmed pigs nearby, suggests transmission from domestic to wild pigs. The epidemiological role of wild boar in maintaining and transmitting the virus back to domestic pigs in SEA is currently unknown due to a lack of research in this area (Denstedt et al., 2020).

Globally, smallholder swine producers are considered to play an important role in ASFV epidemiology due to a number of high-risk practices including swill feeding and allowing pigs to scavenge freely (Chenais et al., 2022; Solenne Costard et al., 2009; Costard et al., 2013). Moreover, these farming systems often operate on small profit margins, providing little economic incentive to invest in enhanced biosecurity measures (Chenais et al., 2017; S. Costard et al., 2009). Given these practices, and their ubiquity in SEA, smallholder producers are suspected to play an important role in the epidemiology of ASFV in the region (Dixon et al., 2020; Kedkovid et al., 2020; Normile, 2019). An improved understanding of pig value chains in SEA, including of drivers influencing the movements of pigs and pig products along these value chains, has been highlighted as a research gap and a key area of long-term ASF control in the Asia-Pacific region by the World Organisation of Animal Health (Kalpravidh & Holley, 2019).

1.4 Influenza A viruses

IAVs are another important EID in the region (Hassan, 2014). IAVs are a species of RNA virus and broadly classified into subtypes according to their surface glyoproteins: haemagglutinin (HA) and neuraminidase (NA), with 18 HA and 11 NA subtypes having been identified in mammals and birds (Sautto et al., 2018). Aquatic birds are the natural reservoir for all IAVs but there have been repeated interspecies transmission events, resulting in establishment in other species (Joseph et al., 2017; Webster et al., 1992) (Figure 1.2). High genetic and antigenic evolution and diversity is facilitated by reassortment of the segmented genome, and frequent point mutations due to lack of proof-reading activity of the viral RNA-polymerase. Point mutations result in gradual antigenic changes, termed ‘antigenic drift’, while genetic reassortment can generate large antigenic changes, termed ‘antigenic shift’ (Joseph et al., 2017; Webster et al., 1992). The high rate of genetic and antigenic evolution presents a major challenge to control in affected species with IAV outbreaks in domesticated pigs and poultry causing major economic impacts in SEA and globally (Choi et al., 2013; Rushton et al., 2005). For example, highly pathogenic avian influenza subtype H5N1 emerged in China in 2003, and rapidly spread across Asia, Europe and Africa (Hassan, 2014; Kilpatrick et al., 2006). By late 2003, H5N1 was reported in Vietnam, and by 2004, it had spread to Thailand, Indonesia, Lao PDR, Malaysia, Myanmar, and Cambodia (Hassan, 2014; Kilpatrick et al., 2006). By May 2005, over 150 million domestic poultry had died or been culled in SEA (Food and Agriculture Organization of the United Nations, 2005). Economic losses to the Asian poultry sector were estimated at US$10 billion in 2005 (Food and Agriculture Organization of the United Nations, 2005).

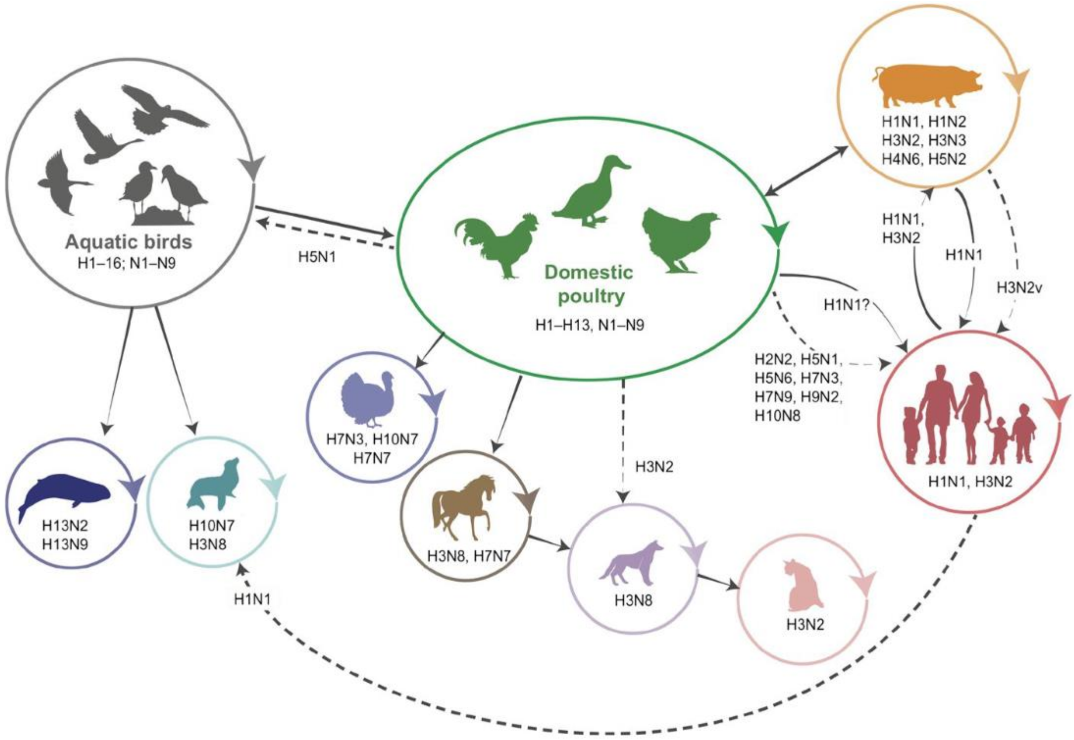

Figure 1.2 ***Significant interspecies transmission of influenza A viruses.*** *Solid arrows = direct transmission events that have since been established in the host species. Dashed arrows = sporadic or limited infection of subtypes where sustained transmission in the new host has not been detected. Image reproduced from Joseph et al. (2017) without changes and used under CC BY 4.0.*

1.4.1 Host specificity and interspecies transmission

IAVs are primarily adapted towards infection and transmission within a given host group. For example, in mammals, avian-origin IAVs face molecular barriers to cell entry, and replication, however, interspecies and zoonotic transmission events do occur (Mänz et al., 2013; Suzuki et al., 2000). Taking H5N1 for example, as of 28th January 2024, 884 human cases and 461 deaths had been reported globally (WHO, 2024). Around half of cases (47%) have been reported in SEA (CDC, 2024), where cases peaked in 2005 (Saba Villarroel et al., 2023) but are still being reported at the time of writing – most recently in Cambodia which has experienced 9 cases since 2023 (CDC, 2024; WHO, 2024). The vast majority of human cases have been associated with direct contacts with poultry, with no strong evidence for sustained transmission in humans (Nelson and Worobey, 2018). Coinfections with IAVs of multiple species origins are a major concern as this can result in the reassortment of novel viruses with pandemic potential (Ma et al., 2008). Indeed, four pandemics of the 20th and 21st centuries (1918 H1N1, 1957 H2N2, 1968 H3N2 and H1N1pdm09) are believed to have been caused by reassortant IAV subtypes adapted to humans from an animal source (Smith et al., 2009a).

1.4.2 Swine IAVs

Pigs have been proposed as mixing vessels for IAVs as they can become co-infected with IAVs of avian, human, and swine origin and therefore provide a vehicle for such reassortment events to occur (Scholtissek, 1990). The most recent pandemic in 2009 gave support to this hypothesis as it was caused by an H1N1 subtype originating in pigs (H1N1pdm09) and exhibited a constellation of gene segments of swine, human, and avian origin (Gatherer, 2009; Sullivan et al., 2010). However humans and some bird species, such as turkeys and quails, can also fulfil the role of a mixing-vessel on the basis of recent molecular evidence (Hennig et al., 2022).

Nonetheless, pigs and their production systems function as important reservoirs for IAV genetic diversity, providing an environment conducive to genetic reassortment and adaption of avian- or mammalian- origin subtypes to humans (Hennig et al., 2022; Nelson and Worobey, 2018; Smith et al., 2009a; Vijaykrishna et al., 2011). For instance, reverse zoonotic transmission, from humans to swine, has been documented for all human pandemic IAVs in the past century except for the 1957 H2N2 pandemic (Choi et al., 2013; Hennig et al., 2022). The H1N1 subtype from the 1918 pandemic was detected in pig populations shortly after its detection in humans across, Europe, Asia, and America, and is termed "classical" H1N1 in swine (Choi et al., 2013). The recent 2009 pandemic strain (H1N1pdm09) has also been sampled in swine populations globally (Choi et al., 2013; Hennig et al., 2022) and continues to be detected in newly sampled populations such as in Cambodia (Zeller et al., 2023). Reverse zoonotic transmission events of human seasonal IAVs, in addition to other swine and avian origin gene segments, has further increased the genetic diversity of IAVs in swine and consequently, the potential for zoonoses and pandemic emergence (Q. Liu et al., 2012; Nelson and Worobey, 2018; Zeller et al., 2023).

1.4.3 Swine sector intensification and IAVs

Pig production systems play an important role in the maintenance and dissemination of IAVs via locally and globally connected value chains (Cheung et al., 2022; Nelson et al., 2015). Industrialised production systems, characterised by farms with large population sizes and rapid restocking of pigs, have a high capacity for viral persistence, as evidenced by modelling studies (Pitzer et al., 2016) and field observations (Allerson et al., 2014; Diaz et al., 2017; Ryt-Hansen et al., 2019). Such viral persistence further increases opportunities for virus reassortment and adaptation (Diaz et al., 2017; Hennig et al., 2022). Industrial farms may further be epidemiologically connected, via the movements of pigs or personnel for example, to smallholders, which are characterised by high rates of interspecies contact (Chea et al., 2020; Osbjer et al., 2017; Vincent et al., 2014). Therefore, as pig sectors transform, there is a need to characterise swine production systems in order to understand the potential transmission dynamics within these systems, and to inform disease control and surveillance activities.

Globally, there is a need for IAV surveillance in swine populations for pandemic preparedness (Nelson et al., 2015; Smith et al., 2009b; Van Reeth et al., 2008). However, these activities are limited, due in part to low pig-level virological prevalence necessitating large sample sizes which presents logistical and financial barriers (Corzo et al., 2013; Decorte et al., 2015). SEA is considered a priority area for IAV surveillance due large and dense populations of swine, poultry, and humans, and the close interaction between them (Wei et al., 2015). There is a well-established need for cost-effective, setting-specific, and risk-based strategies of IAV surveillance in swine that are tailored to a country's capacities across SEA (Trevennec et al., 2011; Wei et al., 2015), including Cambodia (Goutard et al., 2015; Netrabukkana et al., 2015; Zeller et al., 2023).

1.5 Livestock contact networks

Against a backdrop of intensifying livestock production and evolving disease transmission risks, there is a need to strengthen livestock health systems across SEA. Key to this is an understanding of the contact patterns among livestock populations generated by livestock movements. The movement of livestock between livestock holdings and locations is an important transmission route for many infectious diseases (Fèvre et al., 2006) including IAVs in swine (Cheung et al., 2022; Nelson et al., 2015), and ASFV (Costard et al., 2013; Kedkovid et al., 2020). Reflecting the value of such data, routine, centralised, and sometimes digitised recording of livestock movements via livestock identification and traceability systems (LITS) has been adopted in some settings. In Europe, major disease impacts such as those caused by bovine spongiform encephalopathy (BSE) and FMDV prompted the establishment of LITS which are now written into legislation (Ammendrup and Füssel, 2001; European Parliament, Council of the European Union, 2000; Webb, 2005). Principles of livestock traceability are also incorporated into international standards of trade via the World Trade Organization and World Organization for Animal Health (Edwards, 2004). The structure of these networks plays a crucial role in shaping the transmission patterns of infectious diseases in livestock populations (Danon et al., 2011; Dube et al., 2011; Keeling and Eames, 2005; Martinez-Lopez et al., 2009). Identifying high-risk farms or nodes on the basis of network metrics can inform the design of targeted surveillance strategies, disease control interventions, including via the use of disease transmission models which explicitly account for contact network structure (Bajardi et al., 2012; Dube et al., 2011; Fournié et al., 2013; Hardstaff et al., 2015; Kao, 2002; Kiss et al., 2006; Marquetoux et al., 2016; Maurella et al., 2019; Napp et al., 2013; Natale et al., 2009; S. Rautureau et al., 2012).

Unfortunately, LITS are often restricted to high income settings with sufficient resources and capacity to establish them (Brooks-Pollock et al., 2015; Chaters et al., 2019; Edwards, 2004). In SEA, there are few examples of such systems. In Thailand, an electronic system is in place which aims to capture all livestock movements between subdistricts and provinces. The analysis of pig movements using this data has recently been published (Wiratsudakul and Sekiguchi, 2018). In Indonesia, a mobile-based national animal health surveillance system, 'iSIKHNAS', includes a module for electronically recording livestock movement certificates required for livestock movements but its implementation has so far been limited (Chapot et al., 2023). Indeed, trade networks remain under-characterised in many countries in SEA (ACIAR, 2012; Kalpravidh and Holley, 2019), due to various challenges which are discussed in later chapters. Within this context, this thesis uses targeted network surveys to characterise the swine trade network in Cambodia while exploring methods of livestock trade network characterisation, and network simulation modelling methods relevant to resource or data-constrained settings.

1.6 Study setting

Above, I have highlighted two key research gaps: (1) the need to understand evolving disease transmission risks under intensifying livestock production, including that presented by IAVs; and, (2) a need for broadly applicable methods for characterising livestock networks in resource- or data-constrained settings. In Cambodia, under-characterised livestock trade networks, and an intensifying swine sector make it a relevant setting in which to conduct research addressing these gaps.

Located in mainland SEA, Cambodia has a population of 16.5 million people, approximately 61% of which live in rural settings (National Institute of Statistics, 2021). Raising livestock and poultry plays an important role in supporting livelihoods and contributing to household income, with 51% of all households engaged in such activities (National Institute of Statistics, 2021). Agriculture is a priority in Cambodia's national development agenda, aimed at reducing poverty, increasing food security, and boosting household incomes (Ministry of Agriculture, Forestry and Fisheries, 2015). Enhancing animal health and production, including disease reduction, is a key component of this agenda.

The swine sector in Cambodia was comprised of approximately 3.2 million pigs in 2019 (MAFF, 2019) and has traditionally been dominated by smallholder backyard production (Huynh et al., 2006; Tornimbene and Drew, 2012). Smallholders primarily keep pigs for sale, with pig production providing an important source of supplementary household income and functioning as an economic reserve (National Institute of Statistics, 2021; Osbjer et al., 2015; Ström et al., 2017; Tornimbene and Drew, 2012). Smallholders commonly represent mixed-farming systems, keeping multiple species of domesticated animal species and integrating both livestock and crop production (Borin and Henrichs, 2012; Chea et al., 2020; Ly, 2016; Samkol et al., 2006). Pig raising can therefore further promote sustainable resource management by enabling the utilization of agricultural by-products (Strom et al., 2017).

Reflecting the pattern of intensifying livestock production across SEA, the swine production sector in Cambodia is currently under a period of transformation, with rapid shifts towards large-scale intensive commercial production (Asian Development Bank, 2022; Hin et al., 2022; Mason-D’Croz et al., 2022; Thai, 2018). Compared to commercial farm settings, the percentage of pigs raised in smallholder settings reduced from 80% in 2016, to 41% by 2021. Over these six years, the annual reduction of pigs kept in smallholder settings averaged 7.9%, while commercial farms expanded at an average rate of 32% per annum (Asian Development Bank, 2022, p. 6). Along with the socioeconomic factors driving livestock sector intensification across SEA, other specific factors are driving the pig sector transformation in Cambodia. This includes unstable market prices resulting from large volumes of unregulated imports from neighbouring Vietnam and Thailand which has reduced pig prices and disproportionately affected local producers (International Livestock Research Institute, 2006; Ly, 2016; Ström et al., 2017). As mentioned above for SEA more generally, disease outbreaks have accelerated this trend, most recently as a result of ASF (Mason-D’Croz et al., 2022).

Former value chain mapping exercises have qualitatively characterised the value chain actors in Cambodia and the flows of pigs among them (Borin and Henrichs, 2012; Gross, 2019; Ly, 2016; Tornimbene and Drew, 2012). For example, building on the work of Borin and Henrichs (2012) and Ly (2016), Gross (2019) generated an updated value chain map based on key informant interviews (n=18; Figure 1.3). While these exercises have qualitatively mapped the flows of pigs among actors, a quantitative characterisation of the pig trade network and its structure remains lacking. This limits the potential to assess the risk of disease transmission within the heterogeneous swine production sector, including via the use of data-driven epidemiological models accounting for the structure of the pig trade network.

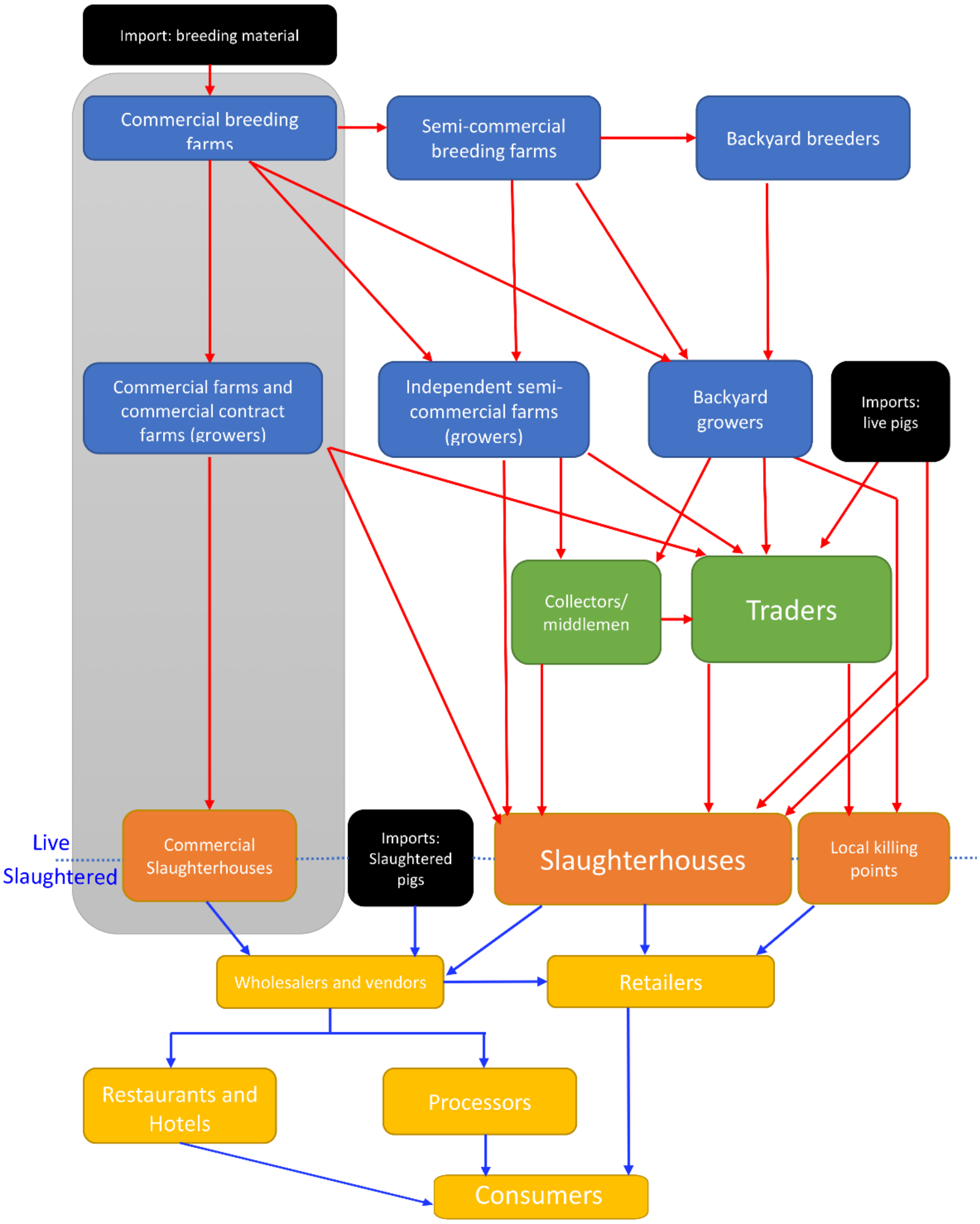

Figure 1.3. ***Value chain map of the swine production sector in Cambodia****. Movement pathways of live pigs (red arrows) and pig products (blue arrows) are shown among value chain actors which include producers (blue boxes), pig exchangers (green boxes) and slaughter points (orange boxes), and meat retailers, processors, and end consumers (yellow boxes). The grey box represents vertical integration which is taking place in the commercial pig sector. Image adapted from Gross (2019).*

1.7 Aims and objectives

The overarching aim of this thesis is to quantitatively characterise the live pig trade network in Cambodia to identify key points of vulnerability for pathogen introduction and dissemination, with a particular focus on swine IAVs. In so doing, I also aim to explore and demonstrate how model-based approaches can be applied to simulate epidemiologically-relevant livestock contact networks in data-scarce settings.

The objectives are to:

1. Identify the types of modelling approaches that have been applied to simulate livestock contact networks, along with their applications, data requirements, and methods of validation (Chapter 2).
2. Generate an updated, data-driven typology of swine value chain actors in Cambodia according to their trading and management practices (Chapter 3).
3. Characterise the swine trade network in Cambodia including the key drivers shaping its organisation (Chapter 3 and Chapter 4).
4. Quantify value chain actors' potential for IAV epidemic generation and susceptibility to infection (Chapter 4).

1.8 Thesis structure

The thesis is organised around five chapters which include this introductory chapter (chapter 1), chapters 2-4 which are presented as self-contained but complementary research articles, and a general discussion (chapter 5):

Chapter 2 is a systematic review published in the Journal of the Royal Society Interface in April 2023 titled: 'Simulating contact networks for livestock disease epidemiology: a systematic review'. In this chapter, I review empirically-informed, model-based approaches of network simulation, (re)-construction, or inference, i.e. 'network simulation models', which have been applied to simulate epidemiologically-relevant (i.e. potentially infectious) contacts among livestock populations. I identify the main modelling frameworks that have been applied towards this objective and compare their methodological characteristics, applications, utilisation of data, and methods of validation. This review serves to guide the analytical approaches used in later chapters of this thesis (chapters 3 and 4) along with future analyses seeking to simulate livestock contact networks from available, often limited or incomplete, data.

Chapter 3 presents a descriptive egocentric network analysis of live pig movements and trade within four provinces in south-central Cambodia. Data were collected via a questionnaire-based, cross-sectional survey conducted from May 2020 to April 2022 in collaboration with local project partners. Pig farms (n=90), smallholders (n=176), pig-exchangers (n=84) and slaughterhouses (n=18) were selected via a multi-stage cluster sampling design enabling the integration of this study within an epidemiological survey of IAVs in swine and humans. A data-driven typology of swine value chain actors is presented, their network roles and positions characterised, and implications for disease surveillance and control in swine populations are discussed, particularly in the context of ASF and IAVs

Chapter 4 is guided by the systematic review presented in chapter 2, and the data collected in chapter 3. In this chapter, I employ a subclass of exponential random graph models (ERGMs), estimable from egocentric data (Krivitsky and Morris, 2017), to dissect the factors influencing the organisation of the Cambodian pig trade network and to simulate sociocentric networks for the entire study area. Epizootic IAV transmission is then modelled on the simulated contact networks using an agent-based network modelling (ABNM) framework in which nodes represent swine farms or smallholders - the epidemiological units - and edges represent potentially infectious contacts. This ABNM accounts for the contact network structure inferred by the ERGMs, and infectious disease modelling parameters drawn from the available literature, or the herd management practices described in chapter 3, to explore the potential dynamics of IAV within the swine production sector in Cambodia. More broadly, this chapter serves to evaluate the utility of the presented methods for improved understanding of disease dynamics in relation to the heterogenous landscape of actors involved in pig production and trade.

Chapter 5: is an integrated discussion of the findings presented in chapters 2-4. Here, I summarise the key findings from this thesis. I then synthesise the evidence and findings across these chapters to discuss opportunities for targeted disease-control interventions within the Cambodian swine sector. I then address the limitations of this thesis and discuss potential avenues for future research, focusing on the application of network simulation models to simulate livestock contact networks in data-scarce settings

2 Simulating contact networks for livestock disease epidemiology: a systematic review

RESEARCH PAPER COVER SHEET

Please note that a cover sheet must be completed <u>for each</u> research paper included within a thesis.

SECTION A – Student Details

Student ID Number	1805783	**Title**	Mr
First Name(s)	William		
Surname/Family Name	Leung		
Thesis Title	Livestock network characterisation in data-scarce settings: the structure of the live pig trade network in Cambodia and implications for influenza transmission dynamics		
Primary Supervisor	James Rudge		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

<u>SECTION B – Paper already published</u>

Where was the work published?	Journal of the Royal Society Interface		
When was the work published?	24/04/2023		
If the work was published prior to registration for your research degree, give a brief rationale for its inclusion	N/A		
Have you retained the copyright for the work?*	**Yes**	Was the work subject to academic peer review?	**Yes**

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SECTION C – Prepared for publication, but not yet published

Where is the work intended to be published?	
Please list the paper's authors in the intended authorship order:	
Stage of publication	Choose an item.

SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	All authors were involved in conceptualising the review and defining the search strategy. I performed the search and screened records through consultation with Guillaume Fournie (GF) and James Rudge (JR). I analysed the data. I prepared the article with guidance, input, and feedback from GF and JR. All authors read and approved the final manuscript.

SECTION E

Student Signature	William Leung
Date	21/04/2024

Supervisor Signature	James Rudge
Date	21/04/2024

Simulating contact networks for livestock disease epidemiology: a systematic review

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2.1 Abstract

Contact structure among livestock populations influences the transmission of infectious agents among them. Models simulating realistic contact networks therefore have important applications for generating insights relevant to livestock diseases. This systematic review identifies and compares such models, their applications, data sources, and how their validity was assessed. From 54 publications, 37 models were identified comprising seven model frameworks. These included mathematical models (n=8; including generalised random graphs, scale-free, Watts-Strogatz, and spatial models), agent-based models (n=8), radiation models (n=1) (collectively, considered 'mechanistic'), gravity models (n=4), exponential random graph models (n=9), other forms of statistical model (n=6) ('statistical'), and random forests (n=1) ('machine learning'). Overall, nearly half of models were used as inputs for network-based epidemiological models. In all models, edges represented livestock movements, sometimes alongside other forms of contact. Statistical models were often applied to infer factors associated with network formation (n=12). Mechanistic models were commonly applied to assess the interaction between network structure and disease dissemination (n=6). Mechanistic, statistical, and machine learning models were all applied to generate networks given limited data (n=13). There was considerable variation in the approaches used for model validation. Finally, we discuss the relative strengths and weaknesses of model frameworks in different use-cases.

Key words: livestock production; network model; epidemiology; network simulation model; livestock trade; infectious disease

2.2 Introduction

Livestock holdings may be epidemiologically connected through both direct and indirect contacts. Direct contact typically pertains to the movement of livestock between holdings, while mechanisms for indirect contact include the transfer of biological material, equipment or personnel (Fèvre et al., 2006). These contact patterns can be conceptualised as networks in which nodes may represent livestock populations (given that livestock are often managed in groups or are otherwise spatially clustered) and edges represent the contact(s) of interest between those populations. It is well recognised that the structure of livestock contact networks have important implications for infectious disease transmission dynamics (Craft, 2015; Dubé et al., 2011; Meyers et al., 2006; Newman, 2002; Shirley and Rushton, 2005). Characterising the structure of these networks therefore plays a crucial role in understanding transmission patterns of infectious diseases in livestock and, consequently, for informing disease risk assessments and control strategies. This may involve the use of disease transmission models which explicitly account for contact network structure (Dubé et al., 2011; Fournié et al., 2013; Hardstaff et al., 2015; Marquetoux et al., 2016; Maurella et al., 2019; Napp et al., 2013).

Insights about the epidemiological importance of livestock contact networks, especially livestock movement (e.g. trade) networks (Fèvre et al., 2006; Gibbens et al., 2001; Olugasa and Ijagbone, 2007; Ortiz-Pelaez et al., 2006; Qiqi Yang et al., 2020), have been generated by the analysis of routinely recorded livestock movement data collected via livestock identification and traceability systems (LITS) (Aznar et al., 2011; Bigras-Poulin et al., 2007; Guinat et al., 2020; Natale et al., 2011; Ortiz-Pelaez et al., 2006). Where such routine data are unavailable (or insufficient), targeted network surveys can also be conducted (Apolloni et al., 2018; Baudon et al., 2017a; Fournié et al., 2013; Moyen et al., 2021; Noopataya et al., 2015; O'Hara et al., 2020).

Such empirical approaches are, however, associated with major challenges. In certain settings, LITS may not be implemented as data collection and sharing may be restricted by commercial interests and related data privacy concerns (Dubé et al., 2011; Lindstrom et al., 2013; Moon et al., 2019; Wiltshire et al., 2019). The costs and infrastructure required to implement and sustain routine systems also constrains their feasibility, especially in low- and middle-income countries (Chaters et al., 2019). The analysis and utility of such data may be constrained by its vastness (Chaters et al., 2019). Moreover, a lack of updated or complete data may also limit its use for supporting decision making during disease outbreaks (Chaters et al., 2019; Relun et al., 2017; Valdano et al., 2015). While network surveys have been used when such data are unavailable, these are usually targeted towards specific geographic locations and time-periods. Indeed, both routine and non-routine network-data capture activities are highly resource intensive and are therefore likely to be targeted towards livestock species or production types of particular interest from a national livestock disease-management perspective (Chaters et al., 2019; Dawson et al., 2015; Kukielka et al., 2017; Nickbakhsh et al., 2011).

Model-based approaches are increasingly being used to help address some of these challenges. We therefore conducted a systematic review to provide an overview of the state-of-the-art in modelling livestock contact networks. Our objectives were to identify the main types of models and methods used, compare their applications and data requirements, and examine the extent to which such models have been validated. Based on the findings, we also discuss key challenges and opportunities for future research in this area. In this review, we focus on studies which have employed empirically-informed, model-based approaches of network (re)-construction or inference, with a primary interest in epidemiologically-relevant (i.e. potentially infectious) contacts between livestock populations.

2.3 Methods

2.3.1 Systematic search strategy

This systematic review followed the PRISMA 2020 guidelines for the reporting of systematic reviews (Page et al., 2021). Search terms were developed around four key topics: 1) livestock and poultry, 2) networks, 3) models, 4) disease. Four databases – Medline, Embase, Web of Science, and Scopus – were queried using title, abstract, and keyword searches on 22nd January 2021 and no date limits. Database searches were repeated on 27th Jan 2023 to cover all records published up to this date. Relevant subject headings were applied to databases using subject heading indexing (i.e. Medline and Embase; Table S 8.1). Search terms within the 'networks' topic were informed by previous reviews of the use of network simulation models in different contexts (Bellerose et al., 2019; Goldenberg et al., 2009; Keeling and Eames, 2005; Kolaczyk, 2009; Welch et al., 2011). However, broad terms were also included to ensure identified records were not restricted to known model types. Within each search topic, Boolean "OR" operators were used to combine search terms and subject headings, while different topics were combined using "AND" operators (Table S 8.1). Wildcards, truncations, and adjacency searches were applied using the relevant syntax for each database. Peer reviewed papers and conference proceedings were all eligible for inclusion. The screening process was expanded to include the reference lists of the included publications, as well as any papers that cited them. For full search terms see Table S 8.1.

2.3.2 Inclusion and exclusion criteria

Inclusion and exclusion criteria were agreed by all authors. A single reviewer screened records but discussed any records for which inclusion was uncertain with the other authors. Screening was split into two stages:

Stage 1: Titles, abstracts, and keywords were screened; records were rejected if any of the following statements were true: 1) there was no reference to livestock; 2) there was no reference to contacts between livestock, contact networks, or infectious disease dynamics on networks; 3) the record was not peer-reviewed; 4) the record was not written in English.

Stage 2: Full texts were screened; records were retained if all following statements were true: 1) a model was used to simulate a network of epidemiologically-relevant contacts between livestock subpopulations; 2) the model attempted to reproduce structural properties of an empirical network and/or its underlying generating mechanisms; and 3) these properties or mechanisms were informed empirically.

Hence, we did not review records which simulated theoretical networks (e.g. to be used as reference or null models) and/or which randomised some aspects of a network to make comparisons to empirical networks (e.g. Croft et al., 2011; Hobson et al., 2021). We also excluded studies that solely reconstructed transmission networks, since these are subsets of the contact networks which are the focus of this review. Where multiple models were used in papers, each model was screened individually for inclusion.

2.3.3 Data extraction

Information from each study was systematically recorded in a data extraction table. This was designed to record information about: 1) the type of model used; 2) the applications of models; 3) characteristics of the empirical network under study (livestock type, geographical location, disease focus); 4) definition of network nodes and edges; 5) data types and variables used for model fitting; and 6) how the performance of models was assessed (Table 2.1). Descriptive analyses and visualisations of the frequency of key study characteristics were conducted using R version 4.2.0 (R Core Team, 2020).

2.3.4 Model classifications

Following exploratory scoping of the literature, particularly previous reviews on network simulation models in other disciplines (Goldenberg et al., 2009; Keeling and Eames, 2005; Kolaczyk, 2009;

Welch et al., 2011), we classified models into three groups: mechanistic, statistical, and machine learning. Though these categories are not mutually exclusive (e.g. mechanistic model parameters may be estimated using statistical methods), they are useful for describing the general characteristics of the reviewed models, as described below.

Mechanistic models are here defined as mathematical equations *or* an algorithmic set of rules, a 'mechanism', used to generate a set of edges between nodes i.e. a network. We include in this grouping mechanistic models that span from (i) abstracted and intentionally simplified 'mathematical models' (Kolaczyk, 2009), such as scale-free and small-world models (and which include the 'probabilistic' and 'idealised' models/networks described by others) (Keeling and Eames, 2005; Welch et al., 2011), to (ii) complex agent-based models (ABMs) explicitly modelling individual-level contact processes. Notably, across both of these sub-groups, the generating mechanisms may simply serve as an arbitrary algorithmic tool used to generate networks exhibiting a certain topology, or else they may be configured to reproduce the emergent processes (assumed or otherwise) that generated the observed network, that is, based on 'first-principles' (Barabasi, 2016; Gates and Woolhouse, 2015).

Statistical models describe a network as a function of factors hypothesised to be associated with edge formation. They start with observations of an empirical network and fit the parameters of a selected model-framework to the data through formal statistical inference (Goldenberg et al., 2009; Kolaczyk, 2009; Welch et al., 2011). Within this group, we include standard statistical models (e.g. generalised linear models) which may be used to estimate the probability or strength of an edge between nodes given a set of covariates, in addition to network-specific statistical models which explicitly account for the dependencies inherent to network data (Goldenberg et al., 2009; Kolaczyk, 2009; Welch et al., 2011).

Machine learning models learn patterns in the data without the model being specified by the user and commonly place an emphasis on predictive accuracy rather than causal inference (Bi et al., 2019; Samuel, 1959). These can be broadly categorised according to whether the model fitting is ‘supervised’, where the value of the dependent variable is known (i.e. data are ‘labelled’ in ML-terminology), or ‘unsupervised’, which use ‘unlabelled’ data and commonly include clustering algorithms (Bi et al., 2019). In the context of network simulation, they may be used to solve classification and regression problems.

Table 2.1 ***Summary of key characteristics and applications of 37 identified models****. ABM = agent based model; GM = gravity model; (T)ERGM = (temporal) exponential random graph model; LITS = livestock identification and traceability system; Limited data = simulating a network from the available data, when empirical networks are incompletely characterised; Network generating processes = inference of factors associated with network (or edge) generation; Structure & transmission = analytical exploration of the relationship between network structure and diffusion of phenomena (e.g. disease) on networks; SA disease control = scenario analysis related to assessing the impact of disease control strategies; SA altering network = comparing the impact of alternative network configuration scenarios on simulated disease transmission patterns; SA surveillance = exploring disease surveillance scenarios; Behavioural response = modelling adaptive behaviour e.g. farmers' response to disease on a network.*

Model ID		**Model classification**			**Model purpose**		**Network characteristics**						**Data**
#	**Model [model name];** Other papers using the model	**Year**	**Model category**	**Model framework**	**Model applications**	**ID model**	**Livestock focus**	**Setting**	**Disease focus**	**Nodes**	**Edges**	**Static / dynamic**	**Data used for calibration**
1	**(Ferdousi et al., 2019)**	2019	Mechanistic	Generalised random graph	Structure & transmission, Limited data, SA: disease control	1	Pigs	USA	African swine fever	Livestock holdings, Markets	Livestock movement	Static	Network survey
2	**(Gates and Woolhouse, 2015)**	2015	Mechanistic	Generalised random graph	SA: altering network	1	Cattle	Britain	Hypothetical	Livestock holdings	Livestock movement	Static	LITS
3	**(Thakur et al., 2015) (A)**	2015	Mechanistic	Watts-Strogatz	Structure & transmission, Limited data	1	Pigs	Canada	Porcine reproductive and respiratory syndrome	Livestock holdings	Livestock movement, Vehicle	Static	Network survey
4	**(Thakur et al., 2015) (B)**	2015	Mechanistic	Scale-free	Structure & transmission, Limited data	1	Pigs	Canada	Porcine reproductive and respiratory syndrome	Livestock holdings	Livestock movement, Vehicle	Static	Network survey
5	**(Tago et al., 2016)**	2016	Mechanistic	Scale-free	SA: disease control, Behavioural response	1	Cattle	France	Hypothetical	Livestock holdings, Markets, Exchangers	Livestock movement	Static	LITS
6	**(Lennartsson et al., 2012; [SpecNet])**	2012	Mechanistic	Other mathematical	Presents model	0	Pigs	Sweden	Non-specific	Livestock holdings, Slaughter-point	Livestock movement	Static	LITS
7	**(Rossi et al., 2017)**	2017	Mechanistic	Spatial	Structure & transmission, Limited data	1	Cattle	Italy	Hypothetical highly contagious	Livestock holdings	Livestock movement, Personnel	Static	LITS
8	**(Hu et al., 2021)**	2021	Mechanistic	Spatial	Limited data	1	Pigs	China	African swine fever	Livestock holdings, Slaughter-point	Livestock movement	Static	LITS
9	**(Wiltshire, 2018; RUSHPNBM)** (Bucini et al., 2019; Koliba et al., 2022; Wiltshire et al., 2019)	2018	Mechanistic	ABM	SA: altering network, Structure & transmission, Behavioural response	1	Pigs	USA	Porcine epidemic diarrhea	Livestock holdings, Slaughter-points, Feed-mills	Livestock movement, Feed, Vehicle	Dynamic	Emergent

Model ID			Model classification		Model purpose		Network characteristics						Data
#	**Model [model name];** Other papers using the model	**Year**	**Model category**	**Model framework**	**Model applications**	**ID model**	**Livestock focus**	**Setting**	**Disease focus**	**Nodes**	**Edges**	**Static / dynamic**	**Data used for calibration**
10	**(Yang et al., 2019**) (Yang et al., 2021, 2020)	2019	Mechanistic	ABM	SA: disease control, Limited data, Behavioural response	1	Cattle	USA	Foot and mouth disease	Livestock holdings, Exchangers, Markets	Livestock movement, Vehicle	Dynamic	Emergent
11	**(Ross et al., 2011)**	2011	Mechanistic	ABM	Presents model	0	Cattle	USA	Bovine Tuberculosis	Livestock holdings, Markets	Livestock movement	Dynamic	Emergent
12	**(Liu et al., 2012; Epirur_Cattle)**	2012	Mechanistic	ABM	Limited data	1	Cattle	USA	Hypothetical direct contact	Livestock holdings	Livestock movement	Dynamic	Emergent
13	**(Ansari et al., 2021)**	2021	Mechanistic	ABM	Presents model	0	Pigs	Germany	Non-specific	Livestock holdings, Exchangers	Livestock movement	Dynamic	LITS
14	**(Brock et al. 2021)**	2021	Mechanistic	ABM	SA: disease control	1	Cattle	Ireland	Bovine herpesvirus type 1	Livestock holdings	Livestock movement	Dynamic	Emergent
15	**(Knight et al., 2021)** (Knight et al., 2022)	2021	Mechanistic	ABM	Structure & transmission, Behavioural response	1	Cattle	Scotland	Hypothetical slowly spreading	Livestock holdings	Livestock movement	Dynamic	LITS
16	**(Kim et al., 2016)** Pomeroy et al., 2019	2016	Mechanistic	ABM	Structure & transmission	1	Cattle	Cameroon	Foot and mouth disease	Geo-locations	Livestock movement	Dynamic	Network survey
17	**(Kong et al., 2022)**	2022	Mechanistic	Radiation model	Limited data	0	Poultry	China	Non-specific	Geo-locations	Livestock movement	Static	Emergent
18	**(Valdes-Donoso et al., 2017)**	2017	Machine learning	Random Forest	Limited data, Network generating processes	0	Pigs	USA	Porcine reproductive and respiratory syndrome	Livestock holdings, Markets	Livestock movement	Static	Network survey
19	**(Nicolas et al., 2018)**	2018	Statistical	Gravity model	Network generating processes, Limited data	0	Cattle, Sheep/goats, Camels	Mauritania	Non-specific	Geo-locations	Livestock movement	Static	Network survey
20	**(Chaters et al., 2019)**	2019	Statistical	Gravity model	Limited data, Network generating processes	1	Cattle	Tanzania	Non-specific	Geo-locations	Livestock movement	Static	Movement permits
21	**(Qiqi Yang et al., 2020**	2020	Statistical	Gravity model	Limited data	0	Poultry	China	Avian influenza	Geo-locations	Livestock movement	Static	Network survey, Emergent
22	**(Blair and Lowe, 2022)**	2022	Statistical	Gravity model	SA: disease control	0	Pigs	USA	Non-specific	Geo-locations, Slaughter-point	Livestock movement	Static	Network survey
23	**(Ortiz-Pelaez et al., 2012)**	2012	Statistical	ERGM	Network generating processes	0	Sheep/goats	Ethiopia	Non-specific	Geo-locations	Livestock movement	Static	Network survey
24	**(Relun et al., 2017) (A)**	2017	Statistical	ERGM	Network generating processes	0	Pigs	Bulgaria	Non-specific	Livestock holdings, Exchangers	Livestock movement	Static	LITS
25	**(Relun et al., 2017) (B)**	2017	Statistical	ERGM	Network generating processes	0	Pigs	Spain	Non-specific	Livestock holdings, Exchangers	Livestock movement	Static	LITS

Model ID		Model classification			Model purpose		Network characteristics						Data
#	**Model [model name];** Other papers using the model	**Year**	**Model category**	**Model framework**	**Model applications**	**ID model**	**Livestock focus**	**Setting**	**Disease focus**	**Nodes**	**Edges**	**Static / dynamic**	**Data used for calibration**
26	**(Relun et al., 2017) (C)**	2017	Statistical	ERGM	Network generating processes	0	Pigs	France	Non-specific	Livestock holdings, Exchangers	Livestock movement	Static	LITS
27	**(Kukielka et al., 2017)**	2017	Statistical	ERGM	Network generating processes	0	Pigs	Georgia	African swine fever	Geo-locations	Livestock movement	Static	Network survey
28	**(Poolkhet et al., 2018)**	2018	Statistical	ERGM	Network generating processes	0	Poultry	Thailand	Avian influenza	Livestock holdings, Exchangers, Markets, Slaughter-point, Other	Livestock movement, Other	Static	Network survey
29	**(Belkhiria et al., 2019)**	2019	Statistical	ERGM	Network generating processes	0	Cattle, Sheep/goats, Donkeys	Senegal	Rift valley fever	Geo-locations	Livestock movement	Static	Network survey
30	**(Hammami et al., 2022)**	2022	Statistical	ERGM	Network generating processes	0	Pigs	France	Non-specific	Livestock holdings, Slaughter-point	Livestock movement	Static	LITS
31	**(Lee et al., 2021)**	2021	Statistical	TERGM	Structure & transmission, SA: disease control	1	Pigs	Vietnam	African swine fever	Livestock holdings	Livestock movement, Indirect	Dynamic	Network survey
32	**(Lindstrom et al., 2013; USAMM)** (Brommesson et al., 2021; Buhnerkempe et al., 2014, 2013; Gilbertson et al., 2022; Gorsich et al., 2018, 2016; Kao et al., 2018; Sellman et al., 2022a; Tsao et al., 2020)	2013	Statistical	Statistical other	SA: disease control, Limited data, SA: surveillance	1	Cattle	USA	Non-specific, Foot and mouth disease, Bovine Tuberculosis	Geo-locations	Livestock movement	Static	Movement permits, Census
33	**(Sellman et al., 2022b)**	2022	Statistical	Statistical other	Limited data	0	Pigs	USA	Porcine epidemic diarrhea	Livestock holdings	Livestock movement	Static	Movement permits, Census
34	**(Lindström et al., 2009)** (Brommesson et al., 2016; Lindström et al., 2012, 2011, 2010)	2009	Statistical	Statistical other	Network generating processes, Structure & transmission	1	Cattle, Pigs	Sweden	Non-specific, Hypothetical	Livestock holdings	Livestock movement	Static	LITS
35	**(Xiao et al., 2015)** (Pomeroy et al., 2019)	2015	Statistical	Statistical other	Network generating processes	1	Cattle	Cameroon	Foot and mouth disease	Geo-locations	Livestock movement	Dynamic	Network survey
36	**(Moon et al., 2019)**	2019	Statistical	Statistical other	Limited data	0	Pigs	USA	Non-specific	Livestock holdings	Livestock movement	Static	Census
37	**(Schumm et al., 2015)**	2015	Statistical	Statistical other	Limited data	0	Cattle	USA	Non-specific	Geo-locations	Livestock movement	Static	Census

2.4 Results

2.4.1 Screening process

Database searches retrieved 12,226 publications of which 7,981 (65%) were unique. Title, abstract, and keyword screening excluded 7,518 (94%) unique records (Figure 2.1). A further 416 (5%) were excluded after screening full texts, mostly because they did not simulate a livestock contact network but presented descriptive analyses of empirical networks, or simulated infectious disease transmission on empirical networks (Figure 2.1). Six additional publications were identified from the citations of included papers. A single additional publication citing these publications was then identified. Therefore, a total of 54 publications published between 2009 and 2022 were eligible for inclusion.

To identify the number of different models used across all included studies, we considered a model to be “distinct” from others when a specific framework was applied to a particular dataset. Hence, analyses in 22 publications were based on previously published models (Table 2.1), while two publications presented multiple models, applying different model types to a single setting (Thakur et al., 2015), or the same model type to different settings (Relun et al., 2017). Consequently, 37 distinct models (Table 2.1 and Table 2.2) were identified and reviewed across the 54 included publications. We refer to unique models using the first published instance.

Following the PRISMA checklist, we highlight nine studies that might appear to meet the inclusion criteria, but were excluded. Three studies re-wired empirically observed networks without also attempting to simulate the empirical network (Ezanno et al., 2022; Hidano et al., 2016; Mohr et al., 2018). Three studies simulated the timing or volume of livestock movements on a pre-defined (non-modelled) network (Hoscheit et al., 2017; Sottile et al., 2021; Tennant et al., 2021). Two used mechanistic models with entirely hypothetical parameter values (Scoglio et al., 2016; Sekamatte et al., 2019). One study applied random forests to predict the timings of trading events, without using this information to simulate a network (Marsot et al., 2022).

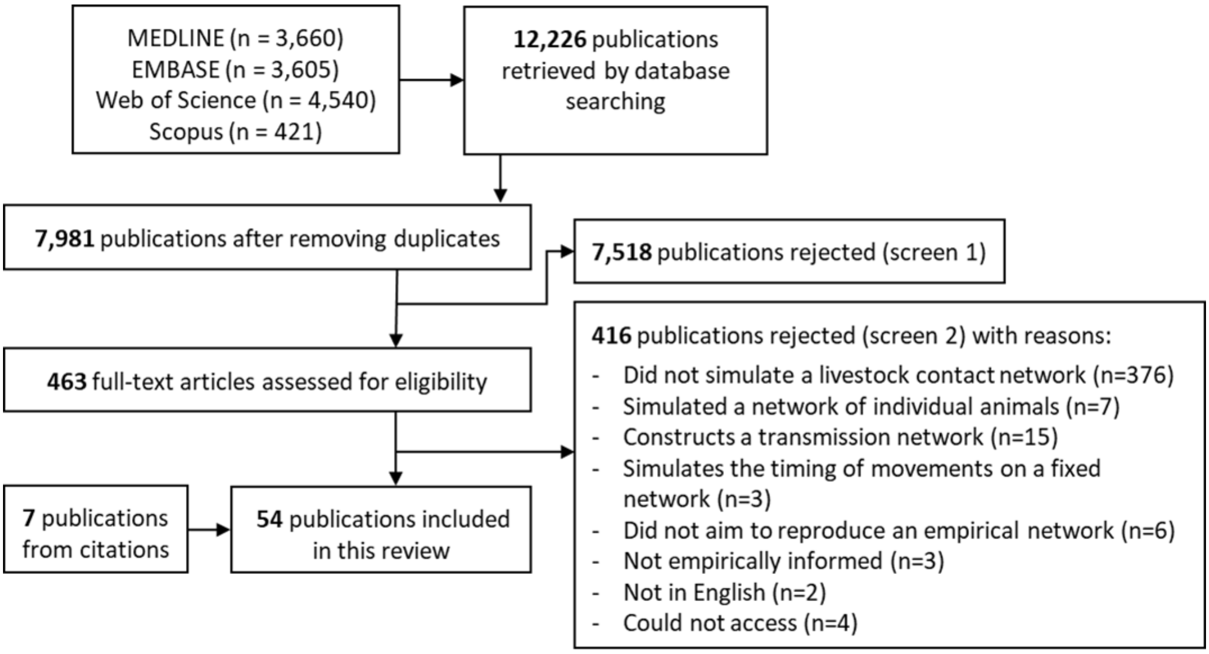

Figure 2.1. ***PRISMA flow diagram***

2.4.2 General model characteristics

The identified models were applied to 20 countries in four continents; no eligible models were applied to Australia or South America. The USA was the most well represented country, with eleven distinct models applied (Figure 2.2a). Most models were applied to a single livestock type, including pigs (n=17), cattle (n=13), and poultry (n=3). Three models were applied to multiple livestock types (Figure 2.2d). All models were applied in a disease context, related to specific (n=18), non-specific (n=13), or hypothetical diseases with specific characteristics (n=6). Infectious disease transmission was simulated on the networks generated by 18 models (13 mechanistic; 5 statistical).

In 25 models, nodes represented farms or herds, with 14 of these also accounting for other units such as markets, slaughterhouses and/or livestock traders. Nodes were livestock populations in given administrative areas (e.g. villages, provinces, counties) in the other 12 models. Edges represented livestock movements in all models: either movements of animals among populations (n=24), or transhumant movements of whole livestock populations between geographical areas (n=3). Seven models simulated multi-layer networks with additional sets of edges representing epidemiologically-relevant contacts via vehicles, personnel, or feed providers. A single model broadly defined an edge as any type of potentially infectious contact in the context of avian influenza without defining transmission routes specifically (Poolkhet et al., 2018). Most models (n=27) generated static networks. However, the timing of trades on the simulated static network was sometimes time-varying e.g. based on a probability of trading (Tago et al., 2016a). Alternatively, nodes or edges were sometimes added or removed by copying empirical records exactly (i.e. without modelling these) (Gates and Woolhouse, 2015; Hu et al., 2021). Contrastingly, eight ABMs and two statistical models generated dynamically evolving networks.

Most models were statistical (n=19), with the most common frameworks being exponential random graph models (ERGMs; n=9), gravity models (n=4), and other statistical models (n=6). Only one machine learning model, based on random forests, was identified. The mechanistic models (n=17) included mathematical models (n=8), agent-based models (ABMs; n=8), and a radiation model (n=1) (Table 2.2). The first model was published in 2009, but most (n=31; 84%) were published between 2015-2022 (Figure 2.2 a-b).

In the following sections, we first review the objectives addressed by the different model frameworks and the data sources utilised. We then introduce the key methodological characteristics of each modelling framework, including how they have been calibrated to data, and review the degree to which their performance was assessed.

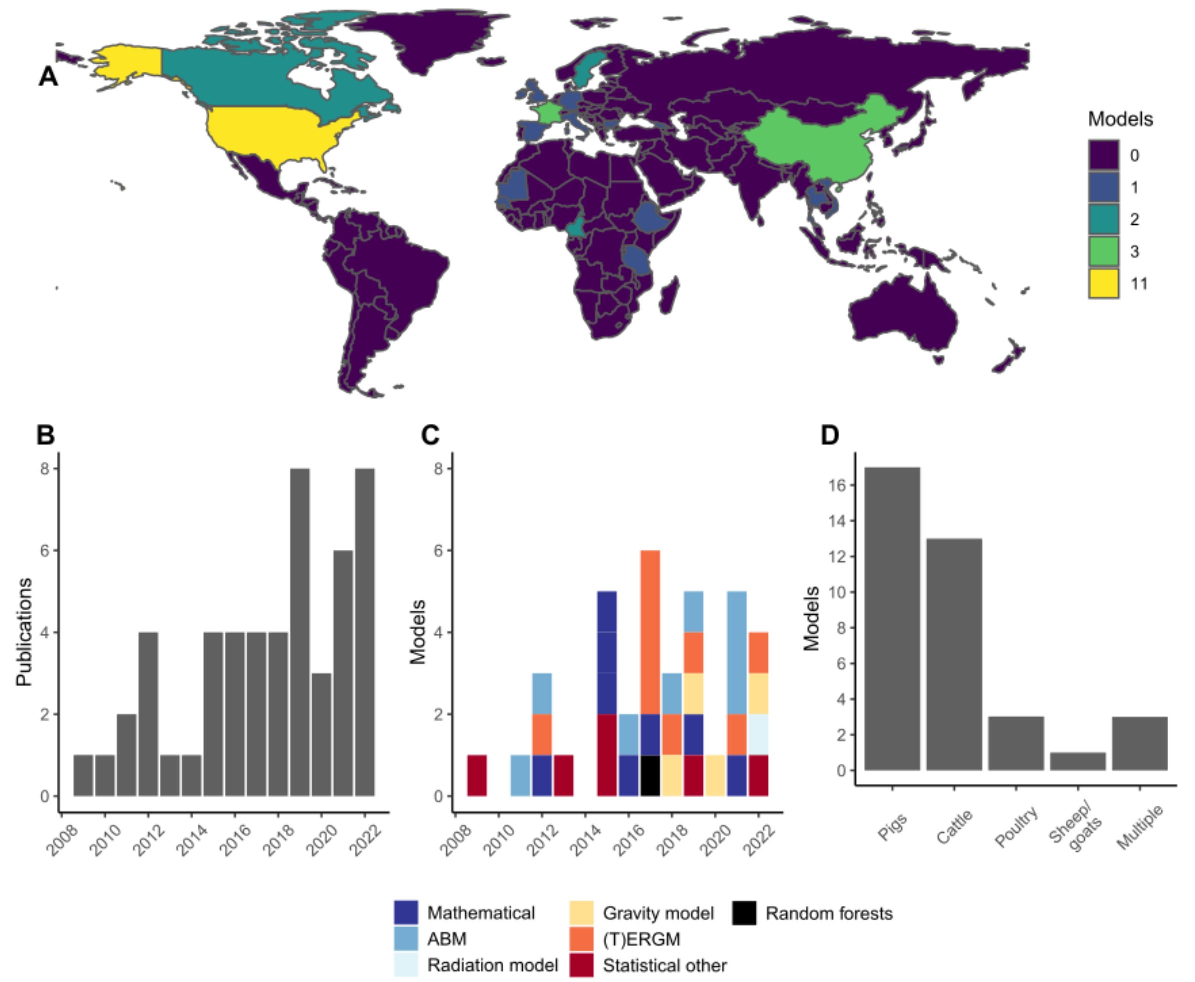

Figure 2.2. ***Scope of included papers and models. (A)*** *Map of countries models were applied to;* ***(B)*** *Papers published by year;* ***(C)*** *Models published by year according to model group (blue = mechanistic, red/orange = statistical, black = machine learning);* ***(D)*** *Livestock types models were applied to.*

Table 2.2. Model frameworks applied to simulate livestock contact networks across 52 included studies

Category	**Model framework**	**Number of models**	**Number of publications**
Mechanistic	Mathematical models	8	7
	Agent based models	8	15
	Radiation models	1	1
Statistical	(T)ERGMs	9	7
	Gravity models	4	4
	Other statistical models	6	19
Machine learning	Random forest	1	1
Total	**-**	**37**	**54**

2.4.3 Model applications

Network simulation models were used for a range of applications which varied according to the model type utilised (Figure 2.3a; Table 2.1). For 13 models, multiple applications were identified.

Approximately half of models (16/37) were used to generate networks based on limited data, for example where total network data was not available but descriptive statistics of that network were, or where models based on complete networks were used for prediction in other settings. These included all model frameworks described above, except ERGMs. A single study used artificially constrained data on indirect contacts among farms to explore how inferring these contacts using different levels of information and assumptions influenced the outputs of disease transmission models (Rossi et al., 2017).

A third of models (n=13), mostly statistical (n=12), were applied to explore network generating processes, specifically, the inference of factors associated with network (or edge) generation. For the random forest model, the relative importance of predictors was assessed by comparing prediction accuracies of models with, and without a given predictor. Nine models, mostly mechanistic (n=7), were applied to analytically explore the relationship between network structure and diffusion of phenomena (e.g. disease) on networks.

Models were also applied to test scenarios related to a) assessing the impact of disease control strategies (n=7) such as targeted livestock-movement restrictions, culling, or vaccination; b) using simulated livestock movement patterns to inform optimal sites for directing disease surveillance activities (n=1; Gorsich et al., 2018); and c) comparing the impact of alternative network configuration scenarios on simulated disease transmission patterns (n=2; all mechanistic). These scenarios involved, for example, re-wiring nodes (Gates and Woolhouse, 2015) and changing the composition of the farm population (Wiltshire, 2018). Mechanistic models were applied to explore the interaction between agents' adaptive behaviour, and network formation or disease spread. Examples of such applications included modelling of farmers' decisions to implement biosecurity measures in response to disease risk (Bucini, 2019) or trigger sales in anticipation of movement restrictions (Tago et al., 2016). In Knight et al. (2022), farmers' adaptive behaviour (i.e. anticipatory response to disease control interventions) influenced the formation of the network itself.

Three models were presented as a proof of principle to demonstrate their ability to reproduce structural features of an empirical livestock contact network, without further application (Ansari et al., 2021; Lennartsson et al., 2012; Ross et al., 2011); these models were therefore omitted from Figure 2.3a.

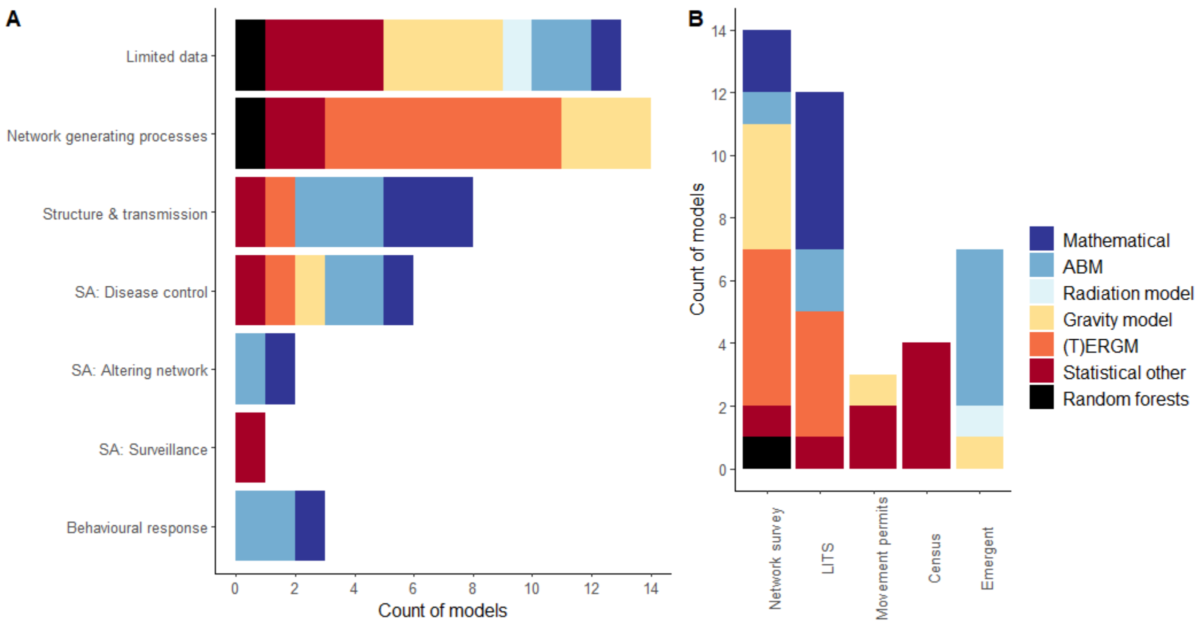

Figure 2.3. ***Model applications and data sources by model framework. (A)*** *Model applications (multiple permitted): Limited data = simulating a network from the available data, when empirical networks are incompletely characterised; Network generating processes = inference of factors associated with network (or edge) generation; Structure & transmission = analytical exploration of the relationship between network structure and diffusion of phenomena (e.g. disease) on networks; SA disease control = scenario analysis related to assessing the impact of disease control strategies; SA altering network = comparing the impact of alternative network configuration scenarios on simulated disease transmission patterns; SA surveillance = exploring disease surveillance scenarios; Behavioural response = modelling adaptive behaviour e.g. farmers' response to disease on a network.* ***(B)*** *Data sources utilised for model calibration. Blue = mechanistic; red/orange = statistical; black = machine learning. LITS = livestock identification and traceability systems; Emergent = did not utilise network data but instead used data to parameterise model processes influencing edge formation.*

2.4.4 Data sources utilised

Different data sources were exploited for calibrating models, with some variation seen between model types (Figure 2.3b). Most models (n=30) were informed by empirical network data, including data from network surveys (n=13), LITS (n=12), censuses with some data on livestock trade i.e. capturing total number of animals “sold or moved” by actors in a given year (n=2), and livestock movement permits which are used in some countries for recording and regulating movements e.g. across administrative borders (n=1; Figure 2.3b). Contrastingly, mechanistic models sometimes did not utilise network data, but instead used data to parameterise model processes influencing edge formation (e.g. herd demographic processes [n=6; Table 2.1]).

While models sometimes exploited similar data types, the way that these data were used to calibrate models varied substantially according to model type as detailed in next section (section 2.4.5).

2.4.5 Model frameworks

2.4.5.1 Mechanistic

2.4.5.1.1 Mathematical models (n=8)

2.4.5.1.1.1 Generalised random graphs

Random graphs generate edges between sets of nodes at random, either by assigning a fixed number of edges (Erdős and Rényi, 1960, 1959) or by assigning edges with a fixed uniform probability (Gilbert, 1959). These models therefore control for network density alone, and the resulting networks fail to capture some important structural features of empirical networks, especially high clustering and a right-skewed degree distribution (Albert and Barabasi, 2002; Kolaczyk, 2009; Newman, 2003).

Generalisations may however be applied to control for other network structural features beyond density thus permitting the generation of more 'realistic' networks (Kolaczyk, 2009; Newman, 2003). The configuration model, or matching algorithm (Bollobás, 1980; Britton et al., 2006), allows for degree distribution to be fixed by algorithmically assigning a number of incoming and outgoing connections ('stubs') to nodes, while randomly matching in- and out- stubs between different nodes. Other structural features can be controlled for: For example, in the pig movement network generated in Ferdousi et al. (2019), connections were only permitted between certain stub combinations, thus additionally controlling for selective mixing among nodes (assortativity). Gates and Woolhouse (2015) also adopted a modified configuration algorithm to generate cattle trade networks, preserving farms' empirical daily amounts of purchases and sales, while selectively matching those reported to have exchanged cattle of the same type (dairy/beef) in the same market, on the same day.

2.4.5.1.1.2 Scale-free models

Other types of mathematical model seek to reproduce stylised topologies that are common in empirical networks. A key example is the scale-free property which results from the network degree distribution following a power law: $p_k \sim k^{-\gamma}$; where k denotes degree and γ the scaling parameter. The Barabasi and Albert (1999) preferential-attachment model generates scale-free networks by progressively adding nodes to a network, with new nodes preferentially forming edges with high-degree nodes. This generates hub-like structures observed in many empirical networks, including those of livestock, where most nodes are poorly connected and a small number of nodes (e.g. markets, breeding farms) have a very high number of connections (Albert and Barabasi, 2002; Fielding et al., 2019).

Thakur et al. (2015) used the Barabasi-Albert model to simulate scale-free pig trade networks, fitting the model with a scaling-parameter derived from empirical studies. The resulting network was altered in a second step by randomly re-wiring edges connecting node types that were not connected in the empirical network, while preserving clustering coefficient and mean degree of the Barabasi-Albert model simulation. Tago et al. (2016) generated a scale-free cattle trade network using an empirically derived scaling parameter, and mimicked the real network by classifying nodes as markets, dealers, or farms, based on the degree of these nodes determined empirically.

2.4.5.1.1.3 Watts-Strogatz model

The Watts-Strogatz model is another example of a model which reproduces particular features of empirical networks - in this case, 'small-world' properties. The latter refers to networks with short average path lengths, as observed in random graphs, but with higher clustering than is found in random graphs of equivalent size and the same mean degree (Watts and Strogatz, 1998).

This is achieved by taking a ring lattice network, which exhibits high clustering, and randomly re-wiring a proportion of its edges such that average path length is reduced. The edge re-wiring probability (*p*) is the single parameter by which the network can be interpolated between the highly clustered lattice and random graph (Albert and Barabasi, 2002; Goldenberg et al., 2009). Thakur et al. (2015) used this model to generate pig trade networks, choosing a value for *p* to reproduce clustering coefficients observed in empirical networks.

2.4.5.1.1.4 Other mathematical models

Other network simulation model frameworks have been devised within different fields of study. Lennartsson et al. (2012) describe an algorithm which generates spatially explicit networks of a defined number of nodes and mean degree which can then be tuned to target specified levels of degree-assortativity (selective mixing between nodes of similar degree), clustering coefficient, fragmentation index, and spatial aggregation of nodes (random to aggregated). As a proof of principle, the authors generated networks matching values of these statistics as observed in an empirical swine transportation network.

2.4.5.1.1.5 Spatial models

With the models described above, the influence of nodes' spatial locations is irrelevant for edge formation. In reality however, the probability of a connection between livestock populations is likely to be influenced by the geographical distance between them (Boender et al., 2007; Lindström et al., 2009; Rossi et al., 2017). While distance may be a variable in other types of model, some of the simplest spatial models express the probability of an edge between nodes as a function of distance alone. For example, in Hu et al. (2021) edges between nodes were simply assigned if the Euclidean distance was lower than an empirically-informed threshold. In Rossi et al. (2017), the probability of contacts between farms via veterinary staff visits was estimated by fitting a logistic regression with distance as the predictor variable.

2.4.5.1.2 Agent based models (n=8)

In agent-based modelling (ABM), a set of autonomous agents interact with one another and their environment according to defined rules and processes (Grimm et al., 2006; Lanzas and Chen, 2015). A key feature of ABMs is that they allow complex phenomena to emerge from such processes (Lanzas and Chen, 2015). Indeed, a livestock contact network can be considered to emerge from the multitude of economic, demographic, husbandry, or other behavioural processes occurring at the level of individual agents operating in the system. This may be explicitly modelled within an ABM framework.

In six identified ABMs, network evolution was driven by herd demographic processes (e.g. livestock births, ageing/growth, and deaths), and agent trade or partnership generation processes (e.g. selection of trade partners according to geographical distance, and compatibility in terms of industry role and current need to buy or sell) (Ansari et al., 2021; Brock et al., 2021; H. Liu et al., 2012; Ross et al., 2011; Wiltshire, 2018; Yang et al., 2021, 2019). In these models, agents could be defined with distinct industry roles, holding capacities, and geographical locations. In an additional model layer in Liu et al. (2012), individual animal contacts during grazing were modelled using random walks. In

Knight et al. (2022, 2021), a dynamic trade network was generated from defined partnership rules – with the rate at which trade partnerships formed and dissolved, dependent on farms' in and out flow of animals (i.e. supply and demand). In the most recent paper, farm level demand, and consequently farmers' edge forming and dissolving behaviours, were adaptive to market shocks such that farms with high demand sought partnerships at a higher rate. Kim et al. (2016) simulated a population of mobile pastoralist agents based on seasonal movement rules informed by field surveys. Edges (contact between herds via grazing) were then considered between agents setting up camp within a given distance from one another.

2.4.5.1.3 Radiation models (n=1)

Radiation models, which were initially developed in the human mobility literature as an alternative to gravity models (Simini et al., 2012; see next section), represent a mechanistic approach to predict human movements based on population distributions alone (i.e. distance is not used directly). This method takes analogy from radiation emission and absorption processes in physical sciences and was initially used to describe human commuting patterns, with commuters being 'emitted' from an origin and 'absorbed' by employment opportunities (Simini et al., 2012). The model stipulates that the commuting flow (T_{ij}) between an origin (*i*) and destination (*j*) is a function of the size of their respective populations (m_i and n_j) and, notably, the 'intervening opportunities' between *i* and *j* (alternative employment sinks). The latter are represented by the population (s_{ij}) in the area of the circle with radius r_{ij}, centred at *i* (excluding m_i and n_j) (Equation 1). The variable, T_i represents the overall count of individuals starting their journey at location *i* ($T_i \equiv \sum_{j \neq i} T_{ij}$), which is taken as a proportion of m_i.

$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})} \qquad \text{Equation 1}$$

Kong et al. (2022) adapted the radiation model to predict country-scale poultry flows in China, with poultry population representing supply (m_i), and human populations representing demand (n_j) and 'intervening' demand (s_{ij}).

2.4.5.2 Statistical

2.4.5.2.1 Gravity models (n=4)

Gravity models (GMs) were initially developed to model the flow of commodities between pairs of discrete geographical areas (C_{ij}, from origin i to destination j) as a function of their distance (d_{ij}) and Gross National Products representing supply (push) at origin and demand (pull) at destination (p_i and p_j), with normalising constant k and coefficients α, β, and γ (Equation 2) (Broekel et al., 2014; Tinbergen, 1962). The standard formulation of the flow of commodities from node i to j (C_{ij}) is:

$$C_{ij} = k\frac{p_i^{\alpha} p_j^{\beta}}{d_{ij}^{\gamma}} \qquad \textit{Equation 2}$$

This concept has been applied to model livestock trade as a function of livestock population at an origin (supply) and human population at a destination (demand) (Blair and Lowe, 2022; Chaters et al., 2019; Nicolas et al., 2018; Qiqi Yang et al., 2020), with different functional relationships (e.g. exponential, power law) between distance and flows having been investigated (Qiqi Yang et al., 2020). Beyond the basic principles of mass and distance, the actual specification of GMs has been loosely defined (Conlan et al., 2021). GMs may be parameterised in Equation 2 by fixing the coefficients α, β, and γ; an approach which essentially represents a mechanistic parameterisation. More often, however, these coefficients are estimated by statistical inference. For example, Qiqi Yang et al. (2020) used both mechanistic and statistical GM-parameterisations to model poultry movements. Equation 2 is commonly linearised by logarithmic transformation allowing additional covariates, hypothesised to be relevant for edge formation, to be included in the model (Equation 3).

$$og(C_{ij}) = k + \alpha \log(p_i) + \beta \log(p_j) + \gamma \log(d_{ij}) + \cdots \qquad \textit{Equation 3}$$

The coefficients of such models may then be estimated e.g. by Ordinary Least Squares (OLS) or maximum likelihood estimation (MLE) (Blair and Lowe, 2022; Chaters et al., 2019; Nicolas et al., 2018).

2.4.5.2.2 Exponential random graph models (n=9)

Under an ERGM formulation, the observed network is considered as just one realisation of possible networks (configurations of edges given a set of nodes) with certain characteristics, that results from an unknown stochastic process (Robins et al., 2007b). The ERGM defines a model of this network generation process and a probability distribution over all possible networks. Parameters are selected and estimated, such that the probability of the observed network being generated under the defined model is maximised. It may take a general form as in Equation 4. Here, the dependent variable is the whole network (the probability of drawing the observed network y from the distribution Y), which is modelled as a function of covariates $z_k(y)$ hypothesised to be relevant for network formation. The covariates are weighted by coefficients θ_k, with *c* being a normalising constant (Lusher, 2013; Robins et al., 2007b).

$$P_\theta(Y = y | n\ nodes) = ce^{\theta_1 z_1(y) + \cdots + \theta_k z_k(y)} \qquad \text{Equation 4}$$

A model with a covariate for network density alone is equivalent to a random graph model (Robins et al., 2007b). However, additional covariates may describe attributes of edges, nodes, or notably, local structural features, such as the tendency for reciprocated edges, or the tendency for triangles to form (i.e. where three nodes are completely connected) (Hunter et al., 2008a). Network simulation is achieved by drawing from the probability distribution of possible network configurations given a set of nodes and their attributes. This is the basis for model fitting and assessment of goodness-of-fit: coefficients are fit and the model goodness-of-fit checked based on comparison between characteristics of the simulated and empirical networks (Hunter et al., 2008b). ERGM output is analogous to a logistic regression making their interpretation straight forward (Ortiz-Pelaez et al., 2012; Relun et al., 2017).

ERGMs have been fitted to networks of livestock movements between aggregated spatial units (Belkhiria et al., 2019; Kukielka et al., 2017; Ortiz-Pelaez et al., 2012), or actors such as livestock holdings (Hammami et al., 2022a; Poolkhet et al., 2018; Relun et al., 2017). These models have sometimes been applied to livestock networks of entire countries (e.g. Hammami et al., 2022; Relun et al., 2017). The use of ERGMs in this context has allowed livestock contact networks to be modelled and simulated as a function of the tendency of farms to form (dis-)assortative trade partnerships with respect to farm size, type, management practices, company affiliation, or location (Hammami et al., 2022a; Relun et al., 2017), in addition to local structural factors (Belkhiria et al., 2019; Kukielka et al., 2017; Ortiz-Pelaez et al., 2012; Relun et al., 2017).

An extension of ERGMs, Temporal Exponential-family Random Graph Models (TERGMS), enables the statistical modelling of tie dynamics (Krivitsky and Handcock, 2014). Here, ERGMs are used to model both tie formation and dissolution, with potentially distinct models for each process. Separable-TERGMs (STERGMS) are used in the latter case. While these models were developed for the statistical modelling of empirical dynamic networks, model parameters may alternatively be defined without being inferred statistically i.e. similar to mechanistic modelling. Lee et al. (2021) applied TERGMs in this way to simulate dynamic contact networks among pig farms according to a defined mean degree (overall, and by node type) and the frequency of contacts.

2.4.5.2.3 Other statistical models (n=6)

In a series of developments, (Brommesson et al., 2016; Lindström et al., 2012, 2011, 2010, 2009) applied a hierarchical Bayesian model to Swedish pig and cattle movement networks incorporating data on between-holding distances, origin and destination production types, and the number of animals in each holding.

Building on these, the USAMM model (Lindstrom et al., 2013), which has been applied and modified extensively (Brommesson et al., 2021; Buhnerkempe et al., 2014, 2013; Gilbertson et al., 2022; Gorsich et al., 2018, 2016; Kao et al., 2018; Sellman et al., 2022a; Tsao et al., 2020), uses a Bayesian kernel approach to reconstruct the U.S. cattle trade network. Similarly to gravity models, movement probabilities were modelled as a function of the number of cattle premises at the origin and destination and the distance between them, while also incorporating data on historical state-level cattle inflows. Sellman et al. (2022b) adapted these methods to reconstruct the national U.S. pig movement network.

Xiao et al. (2015) modelled pastoralists' movements by fitting statistical models to detailed movement survey data. Distinct seasonal movement trajectories were modelled according to different movement models. For example, origin-destination movements were modelled using a Brownian bridge motion model. This movement model was used to generate dynamic daily contact networks among mobile herds in a separate study (Pomeroy et al., 2019), with 'contacts' between herds being considered when pastoralists set up camp within a given distance from one another on a given day – corresponding to grazing distances observed in field surveys.

Moon et al. (2019) and Schumm et al. (2015) utilised a statistical inferential method of maximum entropy (which is designed to estimate probability distributions from highly dimensional data) to estimate the movement probabilities of pigs within and between geographic units from census data. Based on the size and number of farms within each county, these movement probabilities were then used to simulate a farm-to-farm pig movement network.

2.4.5.3 Machine Learning

2.4.5.3.1 Random Forest (n=1)

The probability or strength of an edge between two nodes can be treated, respectively, as a classification or regression problem which may be addressed using machine learning models such as classification or regression tree-based approaches. These models perform repeated partitions of the data based on the values of predictor variables, such that the observations in each partition are increasingly homogeneous with respect to the outcome of interest (Kuhn and Johnson, 2013). The values of observations in the resulting terminal tree-nodes are used as the basis of prediction. Random forest (RF) models combine multiple trees to reduce the variance of predictions and increase predictive performance (Kuhn and Johnson, 2013; Lichtenwalter et al., 2010). Predictors may take the form of node or edge attributes. Valdes-Donoso et al. (2017) used a RF to classify whether livestock movement occurred between pairs of nodes (farms or markets) as a function of geographical distance, node type mixing patterns (i.e. farm, market), and whether or not nodes were under shared ownership. This fitted model was then used to predict edges among nodes in the larger region, for which relevant node attributes were available.

2.4.6 Model validation

Adopting definitions by Porgo et al., 2019, model validation (i.e. "how well a model performs and how applicable the results are to a particular situation") was performed for around two thirds (23/37) of models. We do not consider model calibration here (see section 3.6). There was considerable variation in the methods by which model performance was assessed. This extended from the types of network properties considered, the methods of validation used, and the rigour to which this was carried out.

In terms of the types of validation used, 17 models were internally validated, while 9 were externally validated. Approaches for external validation included splitting the data into training and validation sets (e.g. Valdes-Donoso et al., 2017), or through comparison to different datasets (Kim et al., 2016; Kong et al., 2022; Qiqi Yang et al., 2020; Yang et al., 2019), such as for different time points (Brommesson et al., 2016; Hammami et al., 2022; Sellman et al., 2022b). A single gravity model was externally validated by assessing whether observed changes in livestock movements resulting from demand changes (i.e. closure of a terminal swine-processing facility) could be reproduced in the model (Blair and Lowe, 2022). Lastly, for two models, cross-validation was performed by comparing networks simulated by different models (Kim et al., 2016; Xiao et al., 2015).

Regarding the types of network statistic considered, a third of models were validated by comparing structural network statistics of simulated and empirical networks (n=14). For example, model goodness-of-fit for ERGMs (n=9) was assessed by comparing distributions of structural metrics not used for calibration such as in- and out-degree, geodesic distances, edgewise shared partnership, and triad census.

Other models were internally-validated at the level of the dyad (n=6). Examples of approaches here included computing the predictive accuracy of binary or weighted edges based on, respectively, the area under the receiver operating characteristic (ROC) curve, or correlation coefficients (Nicolas et al., 2018 [GM]; Lindström et al., 2013 [Other statistical]; Valdes-Donoso et al. 2017 [RF]; Kong et al. (2022) [radiation model]). Distributions of observed and predicted geographical distances between connected dyads were also sometimes compared (Lindström et al., 2009 [Other statistical]; Valdes-Donoso et al. 2017 [RF]; Yang et al., 2019 [ABM]).

Alternatively, the outcomes of epidemics modelled on simulated networks were compared (n=4) to either a) epidemics modelled on empirical networks (Rossi et al., 2017 [Spatial]), or b) empirical disease-incidence. For example, the outputs of epidemics simulated on the pastoralist ABM by Kim et al. (2016) were compared to annual disease incidence data. Meanwhile, Qiqi Yang et al. (2020)

assessed the statistical association between a GM-inferred poultry trade network and the geographic distribution of different avian influenza virus subtypes.

2.5 Discussion

In this systematic review, we present an overview of empirically informed, model-based approaches of network generation and inference that have been applied to simulate networks of contacts between livestock populations. We found 54 publications presenting 37 distinct models and 7 model frameworks being utilised in this context. The increasing number of publications identified over the past decade illustrates the growing interest in this area. This reflects the considerable interest in applying network science to study the contact networks of livestock more broadly (Craft, 2015; Dubé et al., 2011)

All models were applied to generate insights relevant to livestock diseases, with nearly half being used as inputs of infectious disease transmission models. However, the reviewed models varied greatly in their formulation, complexity and realism, use of data, and in the methods by which their performance was assessed. Consequently, we now turn to a comparison of model frameworks and discuss how their particular features can present opportunities and challenges in different use-cases. Finally, we discuss issues and possible solutions around model assessment and validation.

A major application of reviewed mathematical models was to explore the relationship between network structure and disease transmission dynamics. Indeed, the relative simplicity of some of these models and, in particular, their ability to yield analytical solutions, lends them towards such applications. These types of model have consequently been applied extensively to explore the diffusion of phenomena on networks in the network literature (Albert and Barabasi, 2002; Kolaczyk, 2009; Newman, 2003). This simplicity – in particular the ability of these models to be calibrated using few parameters – has also resulted in their application towards generating networks when empirical data are limited (Ferdousi et al., 2019; Rossi et al., 2017b; Thakur et al., 2015), or else totally absent, through the adoption of hypothesised parameter values (e.g. Scoglio et al., 2016; Sekamatte et al., 2019). Mechanistic approaches, such as ABMs and radiation models, can also be used in cases where network data are unavailable but the processes underlying the formation of the network are understood and can be parameterised, i.e. based on first principles.

Notably, mechanistic models based on first principles may be more suitable for extrapolating beyond the data to which they were calibrated (Bolker, 2008). Hence, by altering their generative rules, such models can be applied to explore, for example, how counterfactual network configuration scenarios influence disease transmission dynamics (Wiltshire, 2018). Explicit modelling of the assumed generative mechanisms of the network further allows for an examination of its emergent properties. This makes it possible to explore realistic farm (or node) level disease control interventions that act to modify network structure (Gates and Woolhouse, 2015). Importantly, such approaches also allow complex adaptive properties of the system to be explored (Grimm et al., 2006). This includes agents' behavioural adaptations as a response to disease (Bucini et al., 2019; Tago et al., 2016a), or as an unintended consequence following regulatory changes or top down interventions (e.g. Knight et al., 2022), as has been observed empirically (Christley et al., 2011; Gates et al., 2013; Robinson et al., 2007; Vernon and Keeling, 2012).

Despite these important functions, purely mechanistic approaches commonly rely on calibration to select structural features (e.g. degree distribution, clustering coefficients) with no attempt to assess whether these features are necessary, or adequate, for representing an empirical network (Goldenberg et al., 2009; Welch et al., 2011). A comparative strength of statistical network models lies in their utility for assessing which features are relevant for network generation, as well as allowing for a measure of the uncertainty of these estimates given the data (Croft et al., 2011; Goldenberg et al., 2009; Kolaczyk, 2009; Robins et al., 2007a; Welch et al., 2011). This also allows networks to be simulated while accounting for and incorporating this uncertainty which, in the context of infectious disease modelling, can help avoid overfitting epidemic outcomes to observed networks (Reynolds et al., 2015; Rolls et al., 2015; Welch et al., 2011). Despite this utility, less than a third of models being applied to simulate networks for infectious disease modelling were statistical models, with the remaining being mechanistic. This may broadly reflect the contrasting applications of these different model groupings in our included studies; namely, the emphasis on hypothesis testing for the statistical models, particularly ERGMs which were the most well represented model framework in this grouping.

As noted, the major application and strength of statistical models reviewed here was the inference of factors associated with network formation. An important limitation that was not addressed in the reviewed literature is that traditional statistical methods, such as gravity models using OLS/MLE specifications, assume statistical independence between observations. Due to dependencies inherent to network data, such assumptions may not hold, potentially resulting in biased estimates and hence predictions (Broekel et al., 2014; Croft et al., 2011; Lubbers and Snijders, 2007; Silk et al., 2017). While most OLS/MLE specifications of GMs do not explicitly model these dependencies, corrections have been proposed to account for the effects of assumptions about non-independence (summarised by Broekel et al. [2014]). However, to our knowledge, these have not been used in GMs applied to livestock contact networks.

A major strength of ERGMs lies in their ability to explicitly model and account for such dependencies; networks can be modelled and simulated as a function of parameters describing structural characteristics (e.g. transitivity or mutuality effects) in addition to node and edge factors (Goodreau et al., 2009; Lusher, 2013; Silk et al., 2017). ERGMs are therefore a powerful means of assessing the statistical significance of a range of factors on edge formation, as well as for simulating networks from these parameterisations. In practise, however, it is not always possible to generate a well-fitting model. This can be due to issues with ‘model degeneracy’ which can occur when high correlations between network effects result in unrealistically dense or sparse networks (Lusher, 2013; Relun et al., 2017; Silk et al., 2017).

We identified a single model applying random forests to predict and simulate livestock contact networks. More broadly across the network simulation modelling literature, a variety of supervised machine learning approaches have demonstrated high predictive utility when applied to the movements of humans (Robinson and Dilkina, 2017; Spadon et al., 2019) and wild animals (Wijeyakulasuriya et al., 2020). Given increasingly widespread application of machine learning approaches across the network prediction literature and the growing volume and complexity of livestock data including movement data (VanderWaal et al., 2017), there is likely to be considerable scope in applying machine learning methods to predict and simulate livestock contact networks.

This review has highlighted significant variation in how models were calibrated and assessed. This is of course strongly reflective of the availability of empirical network data and the purpose or intended application of models. In the context of simulating networks relevant for epidemiological study however, given the fundamental relationship between network structure and disease transmission dynamics, it is clear that meaningful and realistic outputs rely on simulated networks accurately reproducing epidemiologically-relevant features of the empirical networks. A remaining challenge then, is understanding which structural features are epidemiologically relevant, and which we should therefore seek to reproduce. Indeed, the importance of these features may be highly disease and context specific (Hunter et al., 2008; Pellis et al., 2015; Rolls et al., 2015). Calibration and validation based on a few select network statistics is unlikely to be sufficient to reproduce networks exhibiting similar structure and diffusion patterns as their empirical counterparts (Ball et al., 2013; Green and Kiss, 2010; Ritchie et al., 2014). Comparisons based on multiple structural characteristics are likely to be more robust, especially when the selection of these metrics are based on their relevance for diffusion processes, as is routine practice for ERGMs (Hunter et al., 2008). A highly valuable and interpretable form of validation, where data are available, is the comparison of epidemic outcomes on simulated and empirical networks. Comparison of simulated and observed disease incidence or prevalence is also particularly valuable, given that a transmission network is necessarily a subset of the potentially-infectious contact network (Friedman and Aral, 2001).

This review has some limitations. Despite our efforts to keep search terms broadly relevant to network simulation modelling, the lack of standardisation in terminology means additional papers may have been missed using our search criteria. We have adopted the term 'network simulation model' from Bellerose et al. (2019) and suggest its use in future publications on this topic. This would help to make this area of research more visible and avoid overlap with the related, yet distinct, context in which the term 'network modelling' is commonly applied i.e. simulating disease spread on (empirical or simulated) networks. To keep the scope adequately focussed and the synthesis feasible, we have focussed on models which were used to simulate empirical-like and empirically-informed contact networks of livestock populations. Hence, we highlight that this review does not present a complete compendium of all possible modelling frameworks, nor was it intended to. Alternative frameworks could be identified from the broader literature, such as from related reviews on network simulation models in other contexts (Bellerose et al., 2019; Goldenberg et al., 2009; Keeling and Eames, 2005; Kolaczyk, 2009; Welch et al., 2011).

This review serves to synthesise and categorise the heterogenous group of models that have been applied to simulate the contact networks among livestock populations in the context of livestock disease epidemiology. Despite the important remaining challenges with model validation, this review highlights a number of unique functions afforded by network simulation models which enable us to advance beyond simple descriptive analyses of livestock networks, or infectious disease modelling on empirical networks. With increasing recognition of the need for evidence-based approaches to livestock production and health, particularly in the context of multitudinous high-profile, and often economically devastating, livestock and zoonotic disease outbreaks in recent decades, it seems reasonable to assume that efforts towards livestock network data collection will continue to gain ground. The types of modelling approaches reviewed here are well positioned to derive key insights from this data. Furthermore, such models can be used to inform the design of future empirical studies and livestock tracking systems, in order to optimise their efficiency and utility in generating data needed for effective disease surveillance and control (Chaters et al., 2019; Moon et al., 2019).

2.6 Author contributions

All authors were involved in conceptualising the review and defining the search strategy. WL performed the search and screened records through consultation with GF and JR. WL analysed the data. WL prepared the article with guidance, input, and feedback from GF and JR. All authors have read and approved the final manuscript.

2.7 Acknowledgements

We would like to thank Professor Graham Medley at the London School of Hygiene & Tropical Medicine for his useful discussions and input.

2.8 Data accessibility

The data extracted for this review and the R code used to generate the figures in this review are available from https://github.com/wtm-leung/Network-modelling-review. Database search terms are presented in the supplementary tables.

3 Egocentric characterisation of the swine trading network in Cambodia and implications for disease surveillance and control

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SECTION A – Student Details

Student ID Number	1805783	**Title**	Mr
First Name(s)	William		
Surname/Family Name	Leung		
Thesis Title	Livestock network characterisation in data-scarce settings: the structure of the live pig trade network in Cambodia and implications for influenza transmission dynamics		
Primary Supervisor	James Rudge		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

<u>SECTION B – Paper already published</u>

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SECTION E

Student Signature	William Leung
Date	21/04/2024
Supervisor Signature	James Rudge
Date	21/04/2024

Egocentric characterisation of the swine trading network in Cambodia and implications for disease surveillance and control

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3.1 Highlights

- Swine production is intensifying in Southeast Asia, yet trade networks remain under-characterised
- Node-level, 'egocentric', trade networks of Cambodian swine value chain actors are described
- Data-driven value chain actor typologies are presented with high relevance for disease risk profiling
- Boar service providers, middlemen and breeding farms are well-connected brokers among producers
- Breeding farms supply pigs to all producer types generating a potential for pathogen dissemination
- Egocentric study designs allow integration of network data into epidemiological analyses

3.2 Abstract

Across Southeast Asia (SEA), disease threats such as the ongoing African swine fever epidemic underscore the need for enhanced understanding of pig value chains to elucidate disease risk pathways and to guide disease control and surveillance strategies. This study defines typologies of value chain actors within commercial and smallholder swine production systems in Cambodia and characterises their individual ('egocentric') swine trade networks. Questionnaire-based, cross-sectional surveys were conducted between May 2020 and April 2022, with actors sampled via a multi-stage cluster design. Egocentric networks of 376 actors, involving 4,705 trade partners and 669,363 pigs over six months, are described.

Five producer types were identified based on 51 variables related to herd composition and management, site ownership, and biosecurity: large commercial breeding (n=21) and growing (n=68) farms; family-owned breeding (n=104) and growing (n=77) orientated smallholder producers, and boar service providers (BSP; n=19). Three pig exchanger types were also identified: 'traders' (n=11), mostly purchasing finishing pigs and sows from companies in large volumes; 'middlemen' (n=12) facilitating weaner transfers among smallholders; and 'butchers' (n=51), receiving finishing pigs for slaughter.

Network analysis revealed that BSPs, middlemen and breeding farms were at higher risk of disease introduction and dissemination due to large numbers of inward and outward trade partners or transactions. Logistic regression models provided some support to this risk profiling: compared to breeding orientated smallholders, BSP had 8.1 times greater odds (95% CI: 2.4 - 27.8) of high pig mortality rates. Breeding farms had 6.0 times greater odds (95% CI: 2.0 - 18.6) compared to growing farms.

Farms transported pigs the furthest on average (median >40km; max >120km), while trading partners of smallholders mostly local, but distributions were right skewed (median <5 km; max 114 km). Smallholders sometimes received weaners, sows, and boars from commercial farms therefore linking these contrasting farming systems. Slaughterhouses received pigs from smallholders and farms associated with different companies making them relevant sites for broad-scale swine disease monitoring. This study highlights the merits of egocentric sampling for livestock network characterisation and contributes to the limited knowledgebase on swine trade networks in SEA.

3.2.1 Key words

Network analysis; livestock movement; Southeast Asia; farm typology; swine value chain; egocentric network

3.2.2 Abbreviations

BSP - boar service provider; ODK - open data kit; FAMD - factor analysis for mixed data; HCA - hierarchical clustering analysis; SEA – Southeast Asia

3.3 Introduction

East and Southeast Asia (SEA) are major pig producing regions accounting, respectively, for 49% (47% from China) and 7% of global pig production in 2021 (FAO, 2021; Ritchie et al., 2019). Historically, the pig production landscape in SEA has been dominated by smallholders (Samkol et al., 2006), and while smallholders are still prevalent, there have been recent shifts towards large-scale industrial production (Deka et al., 2014; Mason-D'Croz et al., 2022; Thai, 2018; Thanapongtharm et al., 2016). Pig farming is a major industry in many countries in SEA, with pigs making up the largest share of meat production by mass in Vietnam, Cambodia, Laos, and Timor-Leste in 2021 (FAO, 2021; Ritchie et al., 2019). Within SEA, pig farming further contributes to rural livelihoods, subsistence, and serves important socio-cultural roles (Alawneh et al., 2014; Borin and Henrichs, 2012; Christie, 2007; Huynh et al., 2006).

Over the past two decades, alongside evolving swine sectors, the SEA region has faced recurrent epidemics of transboundary diseases in swine, including foot-and-mouth disease (FMD), highly pathogenic porcine reproductive and respiratory syndrome (HP-PRRS), and porcine epidemic diarrhoea (PED) which continue to circulate in many countries (Kedkovid et al., 2020; Na Ayudhya et al., 2012). Moreover, since its incursion into China in 2018, African swine fever (ASF) has been reported in 18 countries across Asia (FAO, 2023) generating estimated economic losses of between US$55-130 billion (Weaver and Habib, 2020). Infectious agents in swine also threaten public health, not only through their impact on livestock productivity and food security, but by contributing to the risk of emerging diseases in humans, with pigs being an important reservoir for zoonotic disease (Huynh et al., 2006). For example, swine are the main animal reservoir for influenza A virus subtypes H1N1, H3N2, and H1N2 (Trevennec et al., 2011) and play an important role in the generation of reassortant subtypes with pandemic potential (Nelson and Worobey, 2018). This was exemplified by the 2009 H1N1 pandemic (Smith et al., 2009a), and has recently been underscored by the identification - via swine surveillance in China - of a reassortant Eurasian avian-like (EA) H1N1 virus, 'genotype 4' (G4), adapted to infection in humans (Sun et al., 2020).

Within this landscape, there is a pressing need for data-driven approaches to inform cost-effective, setting-specific strategies for disease control, surveillance, and preparedness. This need is particularly acute in resource-limited settings such as Cambodia, where active surveillance for livestock diseases has been limited and heavily dependent on external funding sources (Goutard et al., 2015; Siengsanan-Lamont et al., 2022). While integral to production and distribution, swine movements have been implicated in both local and international spread of swine pathogens including ASF (Kedkovid et al., 2020). Understanding of the swine production and trading practices of value chain actors and, crucially, the structure of the swine trading network within which they are embedded has been highlighted as a priority area for informing ASF control in the Asia-Pacific region (Kalpravidh and Holley, 2019).

The routine, centralised recording of livestock movements, as facilitated by the standardised nature of industrialised swine sectors, has enabled the characterisation of swine movement networks in Europe, Canada, and recently Thailand (Bigras-Poulin et al., 2007; Buttner et al., 2013; Dorjee et al., 2013; Martínez-López et al., 2009; Noremark et al., 2011; S. Rautureau et al., 2012; Smith et al., 2013; Thakur et al., 2014; Wiratsudakul et al., 2022). Contrastingly, in heterogeneous sectors or those with many smallholder producers, extensive informal livestock movements can limit the feasibility and cost-effectiveness of this approach (ACIAR, 2012; Chaters et al., 2019).

In lieu of routinely recorded livestock movement data, targeted network surveys have been used to describe swine trade networks in countries in SEA, e.g. (Baudon et al., 2017a; Poolkhet et al., 2019). In general, network surveys can adopt forms of 'link-tracing' or 'snowball' sampling designs which start with an initial set of respondents, and sample the network through successive waves of contact nominations. These designs are dependent on bespoke sampling schemes and successful contact follow-ups (Keeling and Eames, 2005). An under-utilised alternative within the livestock network literature is the 'egocentric' study design, which captures the personal/local networks of selected nodes (the 'egos'), their trade partners ('alters'), and possibly the connections between alters (Morris and IUSSP, 2004; Robins, 2015). Despite capturing limited structural information compared to a network census or a link-trace sample, such designs are not dependent on contact tracing, do not require unique identification of contacts, and can adopt standard probability-based sampling designs (Morris and IUSSP, 2004; Robins, 2015). This is particularly useful when contact follow up is likely to be impractical or unreliable (e.g. due to dependency on participant recall or challenges with identifying highly mobile actors), or when contacts cannot be described in detail due to commercial interests and privacy concerns (Lindström et al., 2013; Moon et al., 2019; Wiltshire et al., 2019).

Former studies of the Cambodian swine value chain have qualitatively mapped the flows of pigs among different types of value chain actors (ACIAR, 2012; Gross, 2019; Ly, 2016; Tornimbene and Drew, 2012), and partially quantified the number of pigs they trade and mixing patterns among them (ACIAR, 2012; Borin and Henrichs, 2012). However, a comprehensive quantification of pig movements between these types of actors is needed to assess the risk of disease transmission within the heterogeneous swine production sector in Cambodia. Within a larger One Health focussed project aiming to characterise the nature and extent of zoonotic risks from pig rearing systems in Cambodia ('PigFluCam+'), we sought to characterise the swine trading network in Cambodia using egocentric sampling approaches. The objectives of the current study were to (1) generate an updated, data-driven typology of pig producers and exchangers according to their swine trading and management practices; (2) characterise the networks of value chain actors and map swine movement pathways among them; and, (3) demonstrate the use of egocentric sampling methods for livestock network characterisation.

3.4 Methods

3.4.1 Study design

3.4.1.1 Study overview

A questionnaire-based, cross-sectional survey was conducted from May 2020 to April 2022. The survey spanned a two-year period due to the impacts of the COVID-19 pandemic, with travel restrictions necessitating pauses in fieldwork activity (Figure S 8.1). The survey aimed to collect data on value chain actor characteristics and practices relating to swine production, management and trade. Specifically, interviewees ('egos') were asked to provide information on trade partners ('alters') with whom they had exchanged pigs within a set timeframe. No alter-alter ties were recorded. The study design can therefore be described as a 'star egocentric network' design (Almquist, 2012) which we refer to as 'egocentric' throughout.

Ethical approval was received by the Cambodian National Ethics Committee for Health Research (#325), LSHTM Institutional Review Board (#16635 and 17973) and Animal Welfare and Ethical Review Board (#2019-12), the US Army Medical Research and Development Command's Human Research Protections Office (#A-21055) and Animal Care and Use Review Office (#2019-12). Written consent was obtained from all participants. An independent witness observed the consent process for illiterate individuals.

3.4.1.2 Study area and population

The study was conducted in south-central Cambodia; specifically, within Phnom Penh autonomous municipality (containing the capital city, Phnom Penh) and three surrounding provinces: Kandal, Kampong Speu, and Takeo (Figure 3.1). This study area was selected due to the high density of pigs in this region, the diversity of pig production types represented, and for accessibility to field teams in Phnom Penh.

The study population comprised value chain actors (henceforth, 'actors') involved in the raising, transport, or slaughter of live pigs as defined in Table 3.1. Actors could therefore be sites (e.g. farms or slaughterhouses) or people (e.g. pig exchangers). Actor types for sampling were informed by previous value chain analyses and mapping exercises of the Cambodian swine sector (Borin and Hinrichs, 2012; Gross, 2019; Ly, 2016; Tornimbene and Drew, 2012).

Table 3.1. ***Study population:*** *Value chain actor definitions used for sampling, data sources used for sampling frames, and cluster sampling units from which actors were recruited from (i.e. the smallest CSU for each actor type in a multi-stage design.) The number of actors recruited is also shown along with the total number of contacts that they reported for a given type. N.B. contacts do not necessarily represent unique value chain actors. *Indicates actors that were sampled via respondent driven sampling: BSP (n=4) and unregistered pig exchangers (n=4).*

Actor	**Definition | Data sources**	**Cluster sampling unit**	**Recall period**	**Actors n (%)**	**Contacts n (%)**
Farm	Semi-commercial or commercial pig producer raising >=50 pigs. *Census in selected districts provided by provincial authorities.*	Districts	6 months	89 (23.4)	133 (12.1)
Smallholder producer	An individually / family-owned pig production site raising <50 pigs. *Census in selected villages provided by district and village authorities and updated through observations during field visits.*	Villages	6 months	181(47 .5)	491 (44.6)
Boar service provider (BSP)*	Smallholder producers providing a paid service for the hire of boars for breeding. *N/A*	Provinces	14 days	19 (5)	102 (9.3)
Pig exchanger (registered)	Actors who purchase live pigs and sell pigs or carcasses/pig meat to other actors as a form of business. They are licensed to transport pigs and/or sell meat. *Permits and licenses for transporting/moving livestock; or for selling carcasses, held by district authorities.*	Districts	14 days	66 (17.3)	
Pig exchanger (un-registered)*	As above but unlicensed. *N/A*	Provinces	14 days	8 (2.1)	298 (27.1)
Slaughterhouse	A registered site in which pigs are killed. *Permits required for their operation, held by the Department of Animal Production and Health (DAPH) or the Provincial Department of Agriculture.*	Districts	7 days	16 (4.2)	70 (6.4)

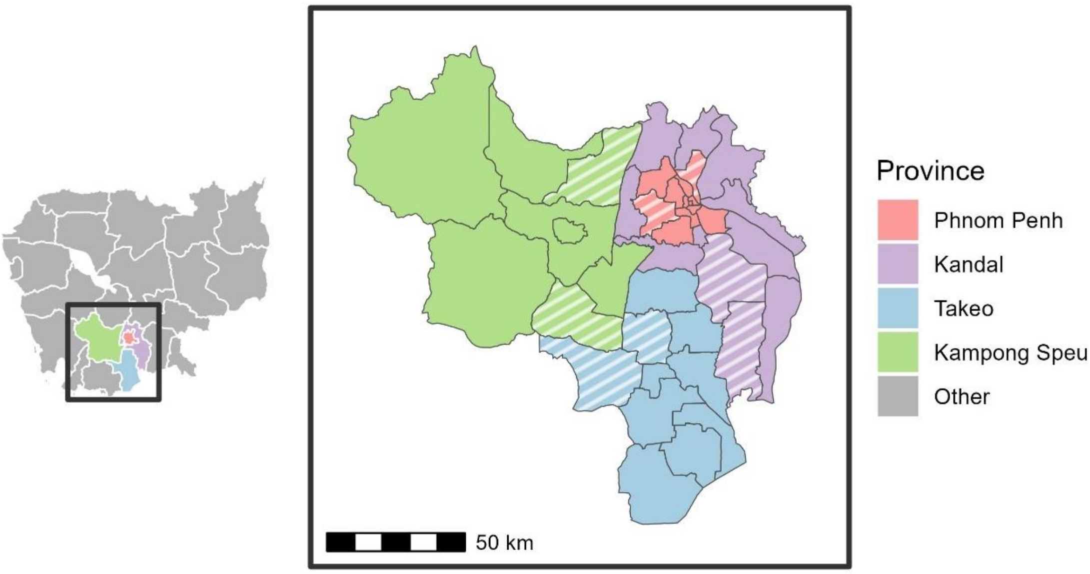

Figure 3.1. ***Study area:*** *Panels show the map of Cambodia (left) and the study area (right) showing the three study provinces and Phnom Penh autonomous municipality (coloured) and selected study districts (striped).*

3.4.1.3 Sampling design

The network survey adopted a similar sampling scheme to two other studies within the PigFluCam+ project: a cohort study of influenza in occupational swine workers, and slaughterhouse surveillance of IAVs in swine (Zeller et al., 2023). Therefore, the sampling design was balanced to meet the objectives of these interlinked studies.

Actors were sampled via a stratified, multi-stage cluster-based design with some adaptations to accommodate varying data availability. Sampling strata and clusters were based on value chain actor types and geographic (administrative) areas, respectively. First, from each of the purposively selected provinces and Phnom Penh municipality (primary sampling units), two districts (secondary sampling units) were selected with probability proportional to pig population size (used as a proxy for the number of value chain actors because actor distributions by geographical unit were not available). Within each selected district, sampling frames were compiled for each actor type through consultation with provincial and district veterinary offices and the National Animal Health and Production Research Institute (NAHPRI) of Cambodia. This task made use of the existing registration requirements of actors, shown in Table 3.1. Details on the sampling approach for each actor type are included in the supplementary information: Section 8.2.1 .

3.4.2 Data collection and management

3.4.2.1 Questionnaires

Structured questionnaires were developed for the different types of actor: 1) producers (i.e. farms, smallholder producers, and BSP), 2) pig exchangers, and 3) slaughterhouses. Questions were mostly closed-ended, with some open-ended to gather additional information when respondents had the option to select 'other'. Questions were related to: 1) actor demographics, site/herd management practices, pig health, and 2) pig trading practices (described in the next section). For producers, the implementation of a predefined set of on-site biosecurity measures was also recorded (Table S 8.2).

All questionnaires were developed in English and translated to Khmer by field teams. Back-translations were performed by an independent translation agency to confirm accuracy and address any inconsistencies. Piloting of each questionnaire was conducted to identify and address any errors in the forms, assess the applicability and clarity of questions within the study population, and to ensure consistency of reporting by field team members. Interviews were conducted in Khmer language, mostly face to face by field teams. Due to the Covid-19 pandemic, some interviews were conducted by phone (n=8; 4 pig exchangers and 4 BSP). Questionnaire data were recorded using tablet computers installed with Open Data Kit (ODK) software (Hartung et al., 2010). Questionnaires are included in the Appendix, sections 9.2 to 9.4.

3.4.2.2 Egocentric network data collection

To facilitate internal validation of egocentric network data, egos were asked to report their alters in aggregate and individually. Aggregate information included: the number of alters of each type (e.g. household, farm, company, pig exchanger, BSP, slaughterhouse) with whom egos had exchanged pigs within a set timeframe, and the number of pigs exchanged according to pig type (e.g. piglets, weaners, growers, finishers, boars – hired or purchased, and sows).

Individual-level alter information included: 1) actor type, 2) relationship (e.g. contract, family, none), 3) location (i.e. smallest known administrative division), 4) whether they had traded pigs with the alter before, and if so, the typical transaction frequency, 5) number of pigs of each type sent by/received from this alter, and 6) contact details (recorded for recruitment purposes). If the alter was a pig exchanger, additional questions were asked about the ultimate origin or destination of pigs (i.e. location and actor type).

For producers (who exchange pigs relatively infrequently) the recall period was 6 months such that at least one production cycle was captured. For pig exchangers and BSP (who trade frequently) a 14 day recall period was adopted to reduce respondent burden and increase reliability of the collected data. For slaughter units, 7 days was used, since their alters were considered to remain consistent over time based on discussions with local livestock authorities and a rapid situational survey among slaughterhouses conducted as part of the inception phase of the PigFluCam+ project.

Slaughterhouses, pig exchangers, and BSP were also asked whether the numbers of pigs they traded varied over the year to assess potential seasonal variations. Actors were asked to report periods during which the number of traded pigs was the highest and the lowest, and to estimate the number of pigs traded in these periods.

3.4.2.3 Data management and validation

Completed ODK questionnaires were sent to an ODK Aggregate server hosted at the University of Health Sciences, Cambodia. Personal identifiable information (i.e. alter name, phone number, and village) was recorded separately for data protection. Pig trading data was checked for errors and internally validated through comparison of aggregated and individually recorded data. Specifically, comparisons were made between the total numbers and types of pigs traded, and actors traded with (purchases and sales). Inconsistencies were addressed through consulting with field teams and by checking field notes.

3.4.3 Actor typology generation

Given the rapid evolution of the swine sector (Thai, 2018), typologies of producers and pig exchangers that have been described previously (e.g. Borin and Henrichs, 2012) may become less applicable over time. Cluster analyses were therefore conducted to generate an updated, data-driven typology of actors based on their pig production and trading practices. This allowed us to categorise actors using a large number of selected variables, moving beyond simple classifications like licensure for pig exchangers or size for producers (e.g. for defining smallholders vs farms). We used factor analysis of mixed data (FAMD) to reduce select categorical and numeric variables into smaller sets of synthetic uncorrelated dimensions. FAMD dimensions are constructed such that the largest fraction of variance is contained within the first dimension, with successive dimensions accounting for successively less variance (Husson et al., 2017).

The FAMD for producers considered 51 variables (i.e. related to site ownership, types and number of pigs raised, herd management, pig trading activity, and biosecurity measures; Table S 8.3). Fourteen growing farms - which are commonly kept empty for around 3 weeks between batches - did not have any pigs at the time of visit so farm size was imputed by taking the mean farm size reported by producers with a similar production type and (where relevant) company association. The FAMD for pig exchangers considered 22 variables related to pig trading (Table S 8.4). Based on the FAMD component values, hierarchical clustering analysis (HCA), was then used to define actor clusters. The number of components used for this analysis was based on identifying an 'elbow' on the scree-graph following methods described by (Jolliffe, 2002). We employed Ward's method using Euclidean distance to assess the level of dissimilarity between actors followed by K-means consolidation. The number of clusters was selected based on a drop in inertia (Husson et al., 2017). All FAMD and HCA analyses were conducted in R software (version 4.2.0) (R Core Team, 2020) and the RStudio environment (Posit team, 2023) using the package FactoMineR (Lê et al., 2008).

3.4.4 Egocentric network analysis

3.4.4.1 Network analysis

In the egocentric networks, nodes represented value chain actors, and edges were pig trades or transfers among actors. Edges were directed and weighted by the number of pigs traded among two nodes. They were defined as 'terminal' if they led to pig slaughter or 'non-terminal' if not.

The following measures of node-level network connectivity were calculated for egos: the number of alters that an ego purchased pigs from (in-degree) and sold pigs to (out-degree), the total number of pigs they purchased (in-strength) and sold (out-strength), and the total number of transactions for purchases (in-transactions) and sales (out-transactions). The number of transactions an ego made with each alter in a 6 month period was estimated by dividing 6 months by the reported transaction frequency. Lent boars, which were by definition returned to their farm of origin after a given time, generated reciprocated edges. Therefore, these movements were included in both in- and out-network measures. All measures were scaled to 6-months (explained in section 3.4.4.2). Euclidean distances between egos and alters were also computed whereby alter locations were the centroid of the smallest reported administrative area to which they were associated.

Alters were reclassified for consistency with the ego types generated above (detailed in the supplementary materials: section 8.2.2). For each ego type in aggregate, the total number of suppliers and recipients of each alter type was then quantified, as was the total number of pigs the egos traded with this alter type. Pig movement pathways among actor types were visualised using directed unweighted networks in which each actor type was a node, and any trade of pigs between actors of two given types, was an edge. Plots were generated using the R packages: igraph (Csardi and Nepusz, 2005), ggplot2 (Wickham, 2016), tidygraph and ggraph (Lin Pedersen, 2023). Minor formatting edits were made in Inkscape software (version 1.2.1).

3.4.4.2 Egocentric network scaling

To compare distributions of degree, transactions, and strength, the periods over which contacts were captured needed to be harmonised across actor types. Therefore, egocentric networks for slaughterhouses (recall: 7 days), pig exchangers, and BSP (recall: 14 days) were re-scaled to 6-months, i.e., the recall period used for producers. We made the simplifying assumption that collected data was representative of other times of year i.e. assuming that in each successive unsampled time period (of length equal to the recall period), the total number of alters an ego had, the types of these alters, and the number of pigs traded would remain constant.

The general principles for rescaling egocentric networks up to 6 months were as follows. When egos made repeated trades with an alter, the expected number of pigs traded with that alter in 6 months was calculated by weighing the observed number of traded pigs by the ratio between 6 months and the recall period. When an ego made only one transaction with an alter during the recall period, additional alters were imputed with identical features to the sampled set of alters, such that degree was maintained for each unsampled time period (see supplementary materials for pseudocode and detailed description: section 8.2.3).

3.4.5 Risk factors for pig mortality

We explored whether producer type was associated with self-reported pig mortalities using univariable logistic regression models. The binary outcome was a mortality risk ≥5% of the current herd size in the previous 6 months. This outcome was selected in preference to morbidity risk due to the reduced subjectivity of the former. Analyses were conducted separately for smallholders and farms to better control for the considerable differences in these producer types. Herd size was not adjusted for as this variable was used in the producer typology construction. Network metrics (e.g. in-degree, in-transactions, in-strength), although not used in the typology generation, were not adjusted for as they were colinear with producer type and were considered to be on the causal pathway between producer type and the outcome. For example, specialisation was expected to mediate the number of inward transactions a producer had (e.g. with the replacement of sows in breeding units likely to generate more transactions compared to growing units), which could in turn influence the chances of disease introduction and hence mortality risk.

3.5 Results

3.5.1 Recruitment, alter imputation, data cleaning and validation

Overall, 379 egos were interviewed and provided information on their transactions with 1,101 alters involving 542,377 pigs. Comparing aggregated and individually recorded trade data, inconsistencies were found and addressed in 29 (3% of) alters. Alters for whom locations were known (n=874; 79%) were distributed in 9 of the 25 Cambodian provinces but 861 (99%) were located within provinces comprising the study area. Most of the missing data was from farms who were able to report the locations of only 32 (16%) of their alters. Of the pig exchanger alters reported by producers, the production origins or ultimate destinations of traded pigs was known for less than half (n=52; 44%).

Re-scaling of networks to 6 months resulted in an imputed dataset involving 4,705 alters and 669,363 pigs. Of these alters, 77% (62% being alters of BSP), and 22% of these pigs, were imputed and used to compare distributions of degree, transactions, and strength. Transfers of artificial insemination doses (n=37) were also reported from BSP to smallholders but were not considered in the network analysis which focused on live pig exchanges.

3.5.2 Actor typologies

3.5.2.1 Producer typology

Producer typology construction was based on two FAMD components explaining 32% of the data variability (PC1=25%; PC2=7%). Variables contributing most to PC1 were related to production system (e.g. biosecurity implementation, ownership, pig breeds raised, and total pigs kept), whereas variables contributing most to PC2 were related to producer specialisation (e.g. the quantity of sows/boars present on site, and the types of pigs purchased and sold) (Figure S 8.2). Four clusters were generated by HCA which then grouped producers according to these two dimensions i.e., broadly describing production system (smallholders vs farms), and stage (e.g. breeding vs growing). BSP (i.e. smallholders lending boars) clustered with other breeding-oriented smallholders. However, due to our specific interest in understanding the position of BSP in the network, this cluster was further partitioned into two subtypes – BSP and other breeding-oriented smallholders – for all downstream analyses. Therefore, five producer types were generated (Table S 8.5).

Cluster 1 - 'breeding farms' (FB; n=21) included those raising pigs directly for market (n=19) and gilt-distributors (n=2) producing replacement gilts. These farms kept a median of 884 pigs (range: 175 – 13,000) which included sows (100%), boars (62%), piglets (38%), and sometimes, weaners (14%). Growers or finishers were not present. These farms mostly received sows/gilts (91%) and sold or sent weaners (76%) and sows/gilts (62%). Most farms were contracted (81%) or owned (5%) by a company. Herd management and biosecurity practices were highly homogenous. Farms generally kept individually-confined pigs (86%; i.e. the separation of sows in pens or farrowing crates separated by metal bars), exclusively used commercial feed (100%), operated an all-in-all-out system by room (86%; i.e. where sows were bred and farrowed in groups), disinfected pig pens weekly (95%), and vaccinated their pigs (100%). Breeding farms had higher levels of biosecurity implementation compared to other producers (Table S 8.2), and approximately 40% always quarantined newly introduced pigs – the highest proportion among all producer types (Table S 8.5).

Cluster 2 - 'growing farms' (FG; n=68) were mostly contracted by a company (96%). They were the largest farms, fattening a median of 2,700 pigs per cycle (range 25-12,000), with 2 cycles per year (range 1-3). They chiefly purchased weaners (94%) and sold growers/finishers (100%) to their contracting company (99%). Most growing farms operated an all-in-all-out production system by room (91%), used commercial feed (100%), and vaccinated their pigs (97%).

Clusters 3a, 3b, and 4 represented smallholder producers, all of which were independently owned. There was a clear divergence in the number of pigs kept by smallholders compared to farms, with 99% of smallholders keeping less than 100 pigs – the updated official threshold used for classification of smallholders in Cambodia (MAFF, 2018; the previous threshold, used for actor recruitment, being 50 pigs) (Figure 3.2). The overall accuracy of this threshold for differentiating smallholders and farms was 99%. Pigs were kept for longer periods than in farms, and were fed a variety of feedstuffs, frequently including swill (62%) from the household or other sources such as restaurants. Biosecurity standards were much lower than in farms. Smallholders also clustered in subgroups according to their general tendency for breeding or growing pigs, although these roles were less strictly delineated compared to farms, with some practising farrow-to-finish production:

Cluster 3a - 'boar service providing smallholders' (BSP; n=19) kept a median of 5 pigs (range 1-30) which, in addition to boars, often included sows (58%), and piglets (32%). By design, all lent boars for breeding, with approximately a quarter also selling weaners. Among smallholders, they reported the highest vaccination adoption level (95%) and disinfection frequency (63% on a weekly basis).

Cluster 3b - 'breeding-orientated smallholders' (SB; n=104) kept a median of 2 pigs (range 1-71), chiefly sows (96%), but rarely boars (5%). Instead, they tended to hire boars (58%), or buy A.I. doses (10%). They mostly purchased from BSP (62%) and sometimes other producers (25%). Half of these smallholders sold weaners (52%). They often did not employ any of the considered biosecurity measures (40%).

Cluster 4 - 'growing orientated smallholders' (SG; n=77) kept the greatest number of pigs of any smallholder type (median 10; range 1-180). They mostly raised growers/finishers (78%) and sows (55%), and rarely kept boars (3%). They mainly purchased weaners (60%) and sold growers or finishers (44%) to pig exchangers (44%). Pigs were usually group housed with a median of 7 pigs per pen (range 1-20).

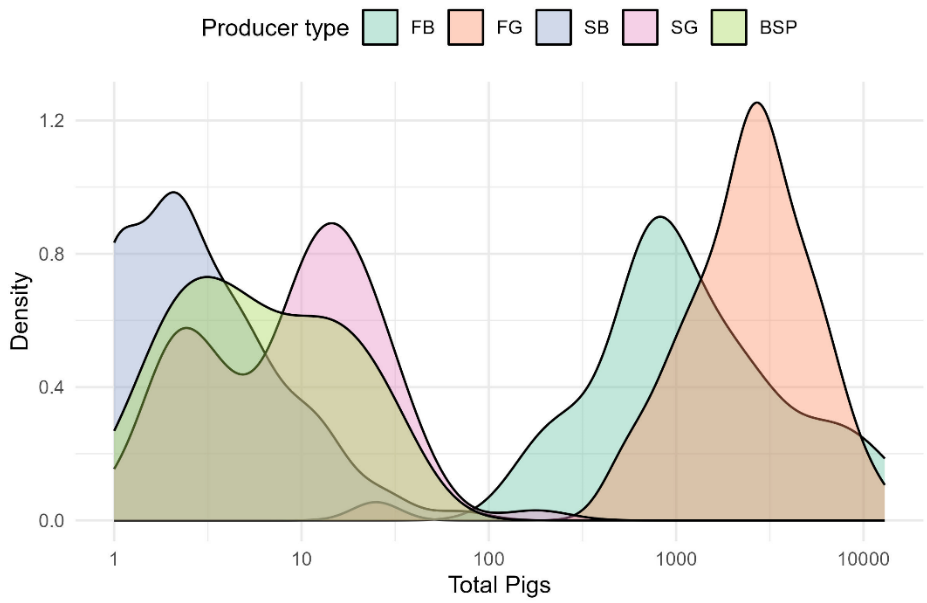

Figure 3.2. ***Distribution of the number of pigs kept by producers at the time of visit:*** *shown for breeding farms (FB), growing farms (FG), breeding orientated smallholders (SB), growing orientated smallholders (SG), and boar service providers (BSP).*

3.5.2.2 Pig exchanger typology

The typology for pig exchangers was based on three components explaining 55.3% of the variation in the dataset (PC1=27.3%; PC2=18.1%; PC3=9.9%). Variables contributing the most to PC1 and PC3 were related to the types of pigs traded, while those contributing most to PC2 were related to the number of pigs traded and the types of actors they traded with (Figure S 8.3). Three clusters broadly separated these actors according to the production stages and volumes of pigs traded (Table S 8.6). Notably, pig exchangers did not cluster completely according to their licensure.

Cluster 1 - 'middlemen' (Mi; n=12) exclusively traded weaners, mostly facilitating trade among smallholders (67% sending and 92% receiving from them). Seven middlemen (58%) also supplied weaners to slaughter points. They did not trade every day (median: 6 out of 14 days). Middlemen transported a median of 10 weaners per trip (range: 1-22) predominantly using a moped/motorbike (83%). Collecting pigs from multiple sites in a single trip was a common practice (only 2 reported never doing this). Middlemen often (50%) or always (33%) entered pig pens/houses to load and unload pigs. Most middlemen kept traded pigs at their homes (92%), where pigs from different origins could mix (75%), for an average of 36 hours and up to a maximum of 5 days. Most were informal actors not holding licences/permits to trade pigs or sell meat (58%).

Cluster 2 - 'traders' (Tr; n=11) purchased and sold finishers (100%) and sows (18%) for slaughter in large numbers (median 120; range 14 to 600 pigs in 14 days) from companies (100%), but also infrequently from smallholders, other pig exchangers, or non-company farms (each 9.1%; n=1). Only two traders (17%) purchased pigs from more than one company. They all sold pigs to other pig-exchangers and had been actively trading every day in the past 14 days. Most used four-wheeled vehicles (82%) to transport a median of 25 pigs (range: 6 to 50 pigs) in a single trip. Most traders reported never collecting pigs from multiple sites in a single trip (n=9; 82%). Around a third of traders (36%) always entered pig holding areas when collecting pigs while over a half never did (55%). Traded pigs were generally kept at a stockyard at the slaughter location (82%) where they were kept on average 10 hours (range: 7-14 hours) and up to a maximum of 18 hours (range: 9-72 hours). All traders held a licence to transport pigs and/sell meat.

Cluster 3 'butchers' (Bu; n=51) received finishers (92%) and sows (18%) for slaughter, mainly from other pig exchangers (65%) and smallholders (26%) and sometimes directly from companies (12%). They rarely sold live pigs onwards with few selling pigs to other pig exchangers (4%). Half of butchers transported pigs (51%). A median of 5 pigs were transported per trip (range 1-50). A minority of butchers (16%) reported sometimes collecting pigs from multiple sites in one trip. Most (96%) held a licence to sell meat. Traded pigs were kept at the slaughter locations (51%) and/or at the butcher's home (24%). Slaughterhouses were rarely mentioned as alters by butchers since they did not sell or transport pigs to the slaughterhouse but rather hired a space in the slaughterhouse to kill pigs.

3.5.3 Network analysis

3.5.3.1 Network sampling summary

Of the 379 interviewed egos, 368 (97%) traded pigs in their surveyed recall periods, with 79% and 92% of egos receiving and sending pigs, respectively. Consequently, 11 egos (3%) were network isolates. These were smallholders (n=8) and butchers (n=3). The butchers were excluded from the network analysis as they provided no data for scaling up 6 months. Hence, the egocentric networks of 376 egos and their swine trading with 4,705 alters, involving 669,363 pigs in 6 months are presented here.

3.5.3.2 Pig movement pathways among value chain actors

With the exception of smallholders, transaction pathways among actor types were mostly non-reciprocated generating a hierarchically organised value chain from producers, to traders and middlemen, and finally to butchers and slaughter locations (Figure 3.3). Breeding farms supplied pigs (i.e. weaners, sows, and boars) to all producer types, but did not receive pigs from other actor types (Figure 3.3a). In aggregate over all breeding farms (n=21), most of their outgoing pigs went to other breeding or growing farms (99%), but notably, a small percentage also went to smallholders and BSP (1%; Figure 3.3a; Table S 8.7). No transactions were reported between farms associated with different companies. Contrastingly, movement pathways among smallholders, BSP, and middlemen were mostly reciprocated (Figure 3.3a). BSP and middlemen played an important role in connecting smallholders, with the majority of their alters being smallholders (Table S 8.7).

Butchers, traders, and slaughterhouses were exclusively involved in terminal movements which did not include any transfers of pigs towards producers (Figure 3.3b). Some bi-directional flow of pigs was observed between slaughterhouses and traders, representing the collection of pigs in slaughterhouses (n=2) by traders prior to the transfer of pigs to other slaughter points. Most pigs supplied to slaughterhouses were directly from traders (86%), butchers (14%), and smallholders (<1%), with the pigs from butchers and traders originating from six different companies. Killing points, i.e. unofficial slaughter locations processing a small number of pigs, were not directly surveyed. However, two smallholders and four middlemen reported supplying pigs to killing points, and 14 smallholders stated that pigs they sold to butchers (n=13) and middlemen (n=1) ultimately ended up at killing points.

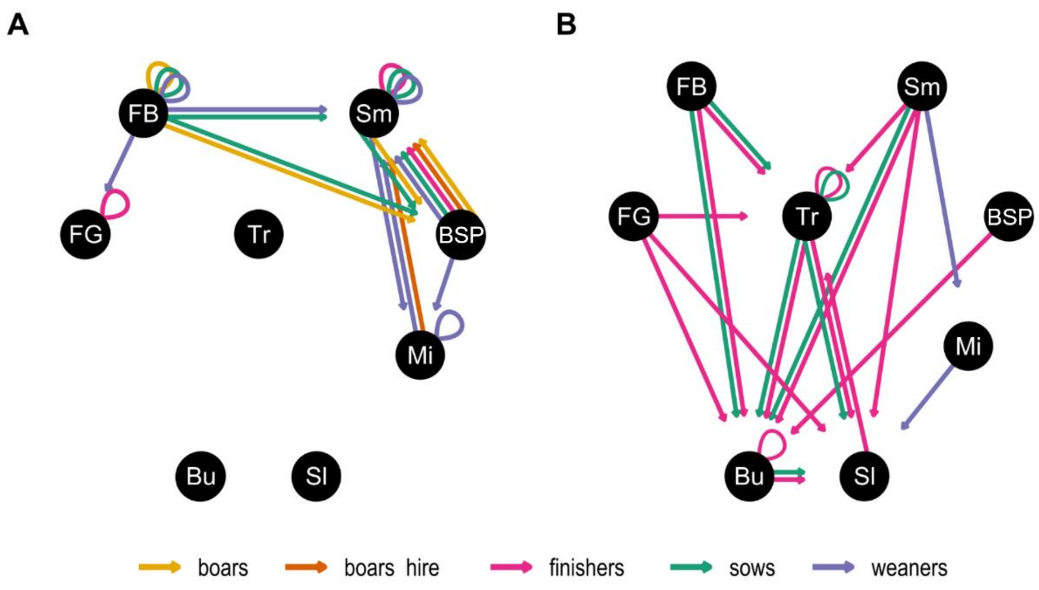

Figure 3.3. ***Pig movement pathways among actor types:*** *Panels show non-terminal (A) and terminal (B) movements. Nodes are breeding farms (FB), growing farms (FG), smallholders (Sm; incudes both breeding-orientated and growing-orientated as it was not possible to differentiate smallholder alters along these boundaries), boar service providers (BSP), middlemen (Mi), traders (Tr), butchers (Bu) and slaughter points (Sl).*

3.5.3.3 Distributions of degree, transactions, and strength

Based on network degree and transactions, actor types were considered 'sinks' when they had many inward connections but no or few outward connections, or 'brokers' when they had many inward and many outward connections with producers. Breeding and growing orientated smallholders were weakly connected to the swine movement network having ≤2.1 suppliers and recipients on average (Figure 3.4a). Contrastingly, BSP - who had the highest number of contacts of any node type - were brokers, having approximately 160 suppliers and recipients on average. Middlemen were also brokers, but had considerably fewer contacts than BSP: 20 suppliers and 14 recipients on average.

Farms were rarely able to report each individual farm contact during transactions with companies meaning their network degree was unreliable. We instead interpreted farm connectivity based on the number of transactions they made and the number of pigs they traded. Breeding farms were also brokers, with the highest number of inward and outward transactions of any producer type and trading large numbers of pigs (464 pigs received and 5,546 pigs sent on average) (Figure 3.4 b-c). Growing farms, contrastingly, made few transactions which recurred on a 6-monthly basis (i.e. 2 fattening cycles per year; Table S 8.8) reflecting their all-in-all-out production practices.

Most butchers (96%; n=49/51) and slaughterhouses (81%; n=13/16) were sinks, having no outward pig movements (Figure 3.4a-c). Traders had large numbers of inward and outward transactions but exclusively supplied pigs to sinks (Figure 3.4a-c; Figure 3.3b).

With the exception of smallholders, actors tended to make repeat transactions with the same trade partners. For example, 48% of breeding-orientated smallholders' recipients, and 64% of growing-orientated smallholders' suppliers were alters that they had never traded with before (Table S 8.8).

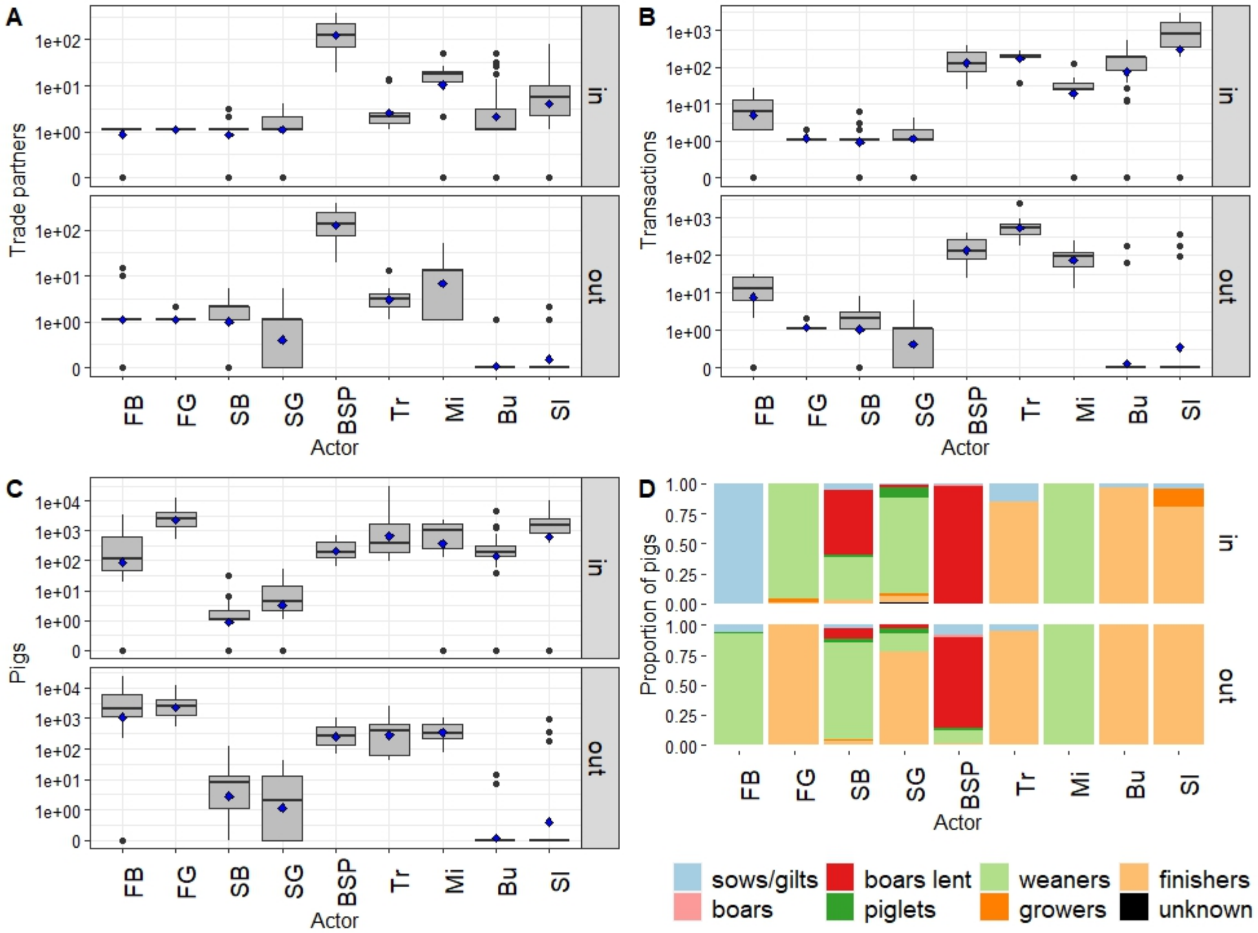

Figure 3.4. ***Egocentric network statistics by actor type:*** *Panels show distributions of degree (A), strength (B; i.e. pig weighted degree), and the number of transactions made (C) scaled to 6 months; and according to (D) pig categories purchased and sold by actors (N.B. FB received 4 boars [0.05% of the pigs they received]). Actor types are breeding farms (FB), growing farms (FG), breeding smallholders (SB), growing smallholders (SG), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu) and slaughterhouses (Sl). Mean values are shown as blue diamonds; outliers, shown as black points, are values beyond 1.5 times the interquartile rage. A modified logarithmic scale is used in plots A-C whereby zero values are not log transformed.*

3.5.4 Spatio-temporal characteristics of pig trading

3.5.4.1 Spatial movements

Locations were recorded for alters at province level (79% of alters), district level (76%), and commune level (68%). Egos mostly traded with alters in the same province (84% of dyads for which alter location was known), district (74%), and often, commune (50%). However, distributions of distances connecting egos and alters were often right-skewed, especially for non-terminal movements (Figure 3.5).

Farms rarely knew the locations of their alters (16%), but reported the longest domestic transportation distances on average, with breeding farms sending pigs a median 46 km (maximum=126 km) and growing farms correspondingly sourcing pigs from a median 41 km (maximum= 138 km) (Figure 3.5). Contrastingly, smallholders mostly traded pigs locally (median <5 km) but sometimes sourced and sent non-terminal pigs at large distances (e.g. up to 114 km for growing smallholders).

Most BSP lent boars to customers locally, but sometimes had customers in multiple districts (26%; n=5) and frequently, communes (84%; n=16) within a two-week period. Compared with smallholders, middlemen tended to source pigs from more distant alters on average. They would then either supply these weaners to their local smallholders (non-terminal movements) or to more distant slaughter locations (terminal movements) (Figure 3.5).

Cross-border movements of terminal pigs were reported by slaughterhouses in Phnom Penh (n=3) and Kandal (n=3). These actors received pigs from Thailand via 26 pig exchanger alters, 23 (88%) of whom were daily contacts. No imports were observed from other countries.

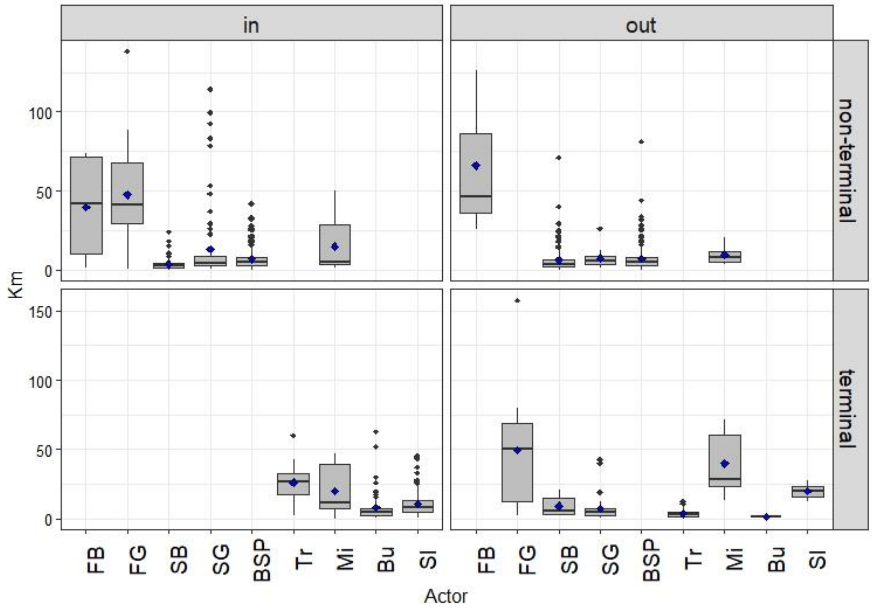

Figure 3.5. ***Euclidean distances between egos and their alters****: Plots are stratified by pigs that egos received (in) and sent (out), and according to whether movements were terminal (i.e. movements for slaughter) or non-terminal. Mean values are shown as blue diamonds; outliers, shown as black points, are values beyond 1.5 times the interquartile rage.*

3.5.4.2 Temporal variation in pig trading activity

All slaughterhouses reported temporal variation in the number of pigs received (100%; n=16). Most slaughterhouses reported peaks in April and October, and some in late January (Figure S 8.4a), corresponding respectively with Khmer New Year (Songkran), Pchum Ben, and Lunar New Year. Butchers and traders experienced similar peaks in their pig trading activities (Figure S 8.4c). Middlemen reported peak trading periods between January and April (Figure S 8.4e). Most BSP (83%) reported no temporal variation in their business.

3.5.5 Producers' pig health status and risk-factor analysis

Overall, 102 (35%) producers reported pig morbidity. When asked if they knew or suspected the cause of morbidity, two farms reported salmonella as the causative agent, while growing orientated smallholders reported salmonella (n=1 smallholder), PRRS (n=1), Classical swine fever (n=1), and FMD (n=1). BSP were the only producer types who reported ASF as the causative agent (n=3). In total, only 9 (8% of producers reporting pig morbidities) were able to report the diseases affecting their pigs.

Overall, 19 (27%) farms and 22 (12%) smallholders reported a mortality risk ≥5% of their current herd size in the past 6 months (Table 3.2). Producer type was significantly associated with odds of high (≥5%) pig mortalities based on univariable logistic regression. Compared to breeding-orientated smallholders, BSP had 8.1 times greater odds (95% CI: 2.4 - 27.8) of self-reported pig mortalities affecting 5% of their current herd size in the past 6 months (Table 3.2). Breeding farms meanwhile had 6.0 times (95% CI: 2.0 - 18.6) greater odds of the outcome compared to growing farms.

Table 3.2. ***Univariable logistic regression.*** *Univariable logistic regression of the odds of self-reporting a mortality risk ≥5% of the current herd size in the previous 6 months (based on the herd size at interview). Separate analyses for smallholders and farms are shown.*

	Mortality risk ≥5%	**Univariable logistic regression**		
Variables	**n (%)**	**Odds ratio**	**95% CIs**	**p-value**
Smallholder analysis				
Smallholder type				
Breeding oriented	7 (6.7)	reference		
Growing oriented	8 (10.4)	1.6	(0.55 - 4.78)	0.38
BSP	7 (36.8)	8.1	(2.4 - 27.8)	<0.001
Farm analysis				
Farm type				
Growing	9 (13.2)	reference		
Breeding	10 (47.6)	6.0	(2.0 - 18.6)	0.002

3.6 Discussion

This study provides the first quantitative description of the pig trading network in Cambodia and updates previous characterisations of the swine production landscape and value chain (e.g. Borin and Henrichs, 2012; Gross, 2019; Ly, 2016; Tornimbene and Drew, 2012). In light of multiple disease threats, such as the ongoing ASF epidemic and pandemic risks associated with swine IAVs (Vijaykrishna et al., 2011), the findings from this study have high relevance for informing swine disease management strategies in Cambodia.

The producer typology classified producers by production system (smallholders or farms), and specialisation (breeding, growing, or BSP). We find that these actor types vary in their node-level network connectivity, and in their odds of experiencing pig mortalities, suggesting a high relevance for disease risk-stratification. Notably, the data-driven typologies aligned well with official classifications in terms of production type and specialisation, supporting their practical utility. For example, our findings are consistent with recently updated official classifications which define producers with 100 or more pigs as farms, and others as smallholders (MAFF, 2018). Our farm specialisations also closely matched official records held by government veterinarian offices. Smallholders similarly (albeit less distinctly) clustered according to their specialisation towards breeding or growing; however, unlike farms, such heterogeneities are not currently captured in official classifications of (or registry data on) smallholders. We also identified pig exchanger types which could not be determined by licensure alone. Together, these findings illustrate the value of data-driven approaches to typology generation for risk stratification.

A key finding of this study is the identification of BSP, middlemen, and breeding farms as brokers between producers, meaning they are likely to be at an increased risk of disease introduction (or contamination), and subsequent dissemination if infected or contaminated. Risk factor analysis lent some support to this given that BSP and breeding farms were more likely to report mortalities. Notably, BSP had the highest mean degree of any actor. This reflects the common practice among smallholders, who typically do not own boars, of hiring these pigs for breeding; practices mirrored in smallholder swine production systems across SEA (Baudon et al., 2017a; Chea et al., 2020; FAO, 2011; Huynh et al., 2006; Leslie et al., 2015) as globally (Beltrán-Alcrudo et al., 2018; Kouam et al., 2020; Okoth et al., 2013). Although the degree of middlemen was much lower than BSP, several practices were identified that potentially facilitate disease transmission along the value chain including holding weaners from diverse sources for several days before resale, collecting and delivering pigs to multiple sites in a single trip, and commonly entering pig holding areas. The role of middlemen mirrors findings from studies on swine traders in other provinces (Chea et al., 2020) and livestock traders across Cambodia (ACIAR, 2012; Poolkhet et al., 2016).

In the context of the ongoing ASF epidemic in Cambodia, extensive informal live pig movements via BSP and middlemen, while serving important roles for production, presents a major challenge to effective disease control, as has been recognised more broadly in smallholder production settings (Chenais et al., 2022; Costard et al., 2015; Kedkovid et al., 2020). The reporting of ASF outbreaks by BSP in this study underscores the transmission risk via this route. In other settings, the movement of boars and sows between villages has indeed been identified as an important risk factor for ASF introduction to a farm (Kalenzi Atuhaire et al., 2013; Nantima et al., 2015). The promotion of artificial insemination, already adopted by some smallholders and associated with improved smallholder productivity and profitability (e.g. Am-in et al., 2010; Sharma et al., 2020; Singh et al., 2022), could aid in addressing this challenge (Chea et al., 2020). However, this approach would require appropriate pathogen screening and sanitary measures given the potential for ASF transmission via artificial insemination (FAO et al., 2010; Friedrichs et al., 2022). Consideration of the social and cultural aspects of ASF control is crucial in smallholder settings (Chenais et al., 2022). In Cambodia, boar lending is under-recognised as a disease pathway among pig smallholders (Tornimbene et al., 2014). Therefore, targeting highly connected nodes such as BSP and middlemen with preventive measures like biosecurity training and animal health education serves as an important complementary approach to ASF control in the country.

In addition to being brokers among producers, breeding farms had non-reciprocated pig movement pathways towards all other producer types, further increasing their potential for pathogen dissemination through the value chain. Notably, smallholders and BSP infrequently received weaners and breeding stock (i.e. sows and boars) from large breeding farms, as is consistent with observations in other Cambodian provinces (Chea et al., 2020). While this practice facilitates the sourcing of pigs from higher biosecurity suppliers (Chea et al., 2020), it also connects these highly contrasting production systems, which may have epidemiological implications. For example, several studies have found IAV prevalence to be higher in commercially produced pigs (Baudon et al., 2017b) including in our study area (Hidano et al., In prep.). Such movements may therefore increase risk of IAV introduction in smallholders where conditions are fertile for inter-species (e.g. pig-poultry) transmission and viral reassortment. Given the purported role of smallholders as drivers for ASFV transmission (Chenais et al., 2022; Costard et al., 2015; Kedkovid et al., 2020), pig movements from large farms to smallholders may further serve as an indirect route of ASF transmission from smallholders to farms via contaminated vehicles, equipment or personnel. Further research would be needed to evaluate the potential for indirect transmission to commercial farms via this route.

We were unable to determine how many suppliers growing farms had (i.e. when they reported a single company as their supplier). In other commercial pig production settings, growing farms have been reported to have high in-degree relative to other farm types (Buttner et al., 2013; Dorjee et al., 2013; S. Rautureau et al., 2012; Thakur et al., 2016). Further work is needed to better characterise swine movements among commercial swine producers. All farms specialised in a single production stage, either breeding of market pigs or replacement gilts, or finishing, with no farrow-to-finish farms identified. This contrasts with industrialised pig sectors in countries like Sweden, Canada, and France (Dorjee et al., 2013; Noremark et al., 2011; S. Rautureau et al., 2012). The high specialisation within the study area here, leads to frequent transport of large numbers of pigs between farms, sometimes over long distances.

Slaughterhouses sourced pigs from a variety of companies as well as smallholders, while few actors sent pigs to unofficial killing points. These findings indicate that, with appropriate selection, slaughterhouses can be an effective means for disease monitoring and surveillance across diverse production types and companies. Despite some caveats, such as potential challenges with identifying the origins of pigs (e.g. Siengsanan-Lamont et al., 2022), and/or their point of exposure, slaughterhouse surveillance can serve as a cost-effective approach to assess pathogen diversity. It also limits the need for on-farm visits which pose biosecurity concerns.

This study had some important limitations. The use of different recall periods for producers, exchangers, and slaughterhouses required imputation to re-scale egocentric networks to equal recall periods. This may have introduced a degree of error to measures of node-level connectivity, but was deemed necessary to ensure data reliability and to minimise respondent burden. Furthermore, lists of BSP and middlemen operating in the study area were not available, meaning some were selected via the contact details of egos. Such link-trace sampling may overestimate the connectivity of these nodes by virtue of high-degree nodes being more likely to be sampled (Robins, 2015), however, this constituted a small fraction of sampled egos. Moreover, such methods were necessary to identify and therefore characterise these actors.

Finally, the results presented here capture multiple snapshots of the swine trading network during a period of significant disruption due to the concurrent COVID-19 and ASF epidemics. The COVID-19 pandemic, in particular, complicated data collection, necessitating surveys at different times across multiple years for various actors. Moreover, both likely influenced pig supply, demand, and consequently trading patterns and behaviours (e.g. Cameros et al., 2022; Qiu et al., 2020). The ongoing shift towards large-scale commercial swine production in Cambodia and Southeast Asia (Asian Development Bank, 2022; Hin et al., 2022; Thai, 2018), as accelerated by the impacts of ASF (Mason-D'Croz et al., 2022), is likely to result in increasing value chain restructuring, as was observed even before the first detection of ASF in Cambodia (Thai, 2018). Further research would be needed to assess the impacts of diseases such as ASF and COVID-19 on the restructuring of the swine production system and the reciprocal effects of value chain restructuring on infectious disease risks (e.g. Waage et al., 2022).

Despite these limitations, this study demonstrates the utility of egocentric sampling for quantifying node-level network metrics such as degree, strength, and transaction frequencies which have high relevance for disease transmission (Kiss et al., 2006; Lebl et al., 2016; Volkova et al., 2010). Unlike network censuses or link-trace sampling, egocentric sampling strategies do not directly quantify global network statistics such as clustering, and component sizes but methodological developments in statistical network simulation modelling present opportunities to infer whole network properties from egocentric networks and will be the subject of Chapter 4 (Krivitsky and Morris, 2017; Robins, 2015; Smith, 2012). A clear advantage of egocentric sampling, particularly in livestock systems characterised by informal animal movements, is in obviating the need for contact tracing of trading partners – a task with which we and others had limited success (Baudon et al., 2017a). Egocentric sampling methods facilitate the joint collection of epidemiological and network data on farms, enabling their joint analysis. We highlight that this further permits repeated surveys of the same actors (e.g. via mobile devices) which could be harnessed to study temporal changes to a network. Such approaches are therefore well positioned to address a lack of data on livestock trade networks in resource constrained settings, especially if paired with modelling approaches to address shortcomings of egocentric data.

3.7 Acknowledgements

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3.8 Declaration of interests

None.

3.9 Author contributions

Study conception: WTML, GF, YCSF, GJS, JWR. Study design: WTML, GF, PM, TC, JWR. Data acquisition for sampling frames: PM, TC, SV, SH, SP, ST, JWR. Questionnaire development: WTML, GF, PM, TC, AH, HH, SV, SH, JWR. Conducting network surveys: WTML, AH, SV, SH, SP, ST, MC. Data analysis and interpretation: WTML. Writing - original draft: WTML. Writing - reviewing and editing: all authors.

4 Using egocentric data to model influenza transmission within Cambodia's swine trade network

RESEARCH PAPER COVER SHEET

Please note that a cover sheet must be completed <u>for each</u> research paper included within a thesis.

SECTION A – Student Details

Student ID Number	1805783	**Title**	Mr
First Name(s)	William		
Surname/Family Name	Leung		
Thesis Title	Livestock network characterisation in data-scarce settings: the structure of the live pig trade network in Cambodia and implications for influenza transmission dynamics		
Primary Supervisor	James Rudge		

If the Research Paper has previously been published please complete Section B, if not please move to Section C.

<u>SECTION B – Paper already published</u>

Where was the work published?			
When was the work published?			
If the work was published prior to registration for your research degree, give a brief rationale for its inclusion			
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Stage of publication	Not yet submitted

SECTION D – Multi-authored work

For multi-authored work, give full details of your role in the research included in the paper and in the preparation of the paper. (Attach a further sheet if necessary)	All authors were involved in conceptualising the study. I conducted the analyses, including ERGM analyses, infectious disease modelling. I developed the ABM modelling framework based on R code from a short course from GF. I prepared the article with guidance input and feedback from GF and JR.

SECTION E

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Using egocentric data to model influenza transmission within Cambodia's swine trade network

4.1 Abstract

Across Southeast Asia (SEA), influenza A virus (IAV) surveillance in swine populations is crucial for pandemic preparedness but needs to be risk-based and setting-specific. The effective use of data-driven epidemic models to inform such strategies is constrained by a lack of detailed livestock movement data. This study utilised a subclass of exponential random graph models (ERGM) to analyse and simulate complete networks from egocentric swine trade data in Cambodia. An agent-based model assessed IAV transmission dynamics on ERGM-simulated networks, while considering direct contacts via pig transfers, and indirect contacts via shared visits from pig exchangers and boar service providers (BSP). Model scenarios assessed the impact of different seed nodes and transmission probabilities.

ERGMs revealed that the actor type(s) in a dyad were an important factor for network formation, as were the mixing patterns among actor types. For company-affiliated nodes, there was a strong propensity for within-company trades. Due to missing data, the impact of geographical distance could not be evaluated. ERGM-simulated networks achieved a good fit to the degree distribution of the empirical network; both globally, and stratified by each actor type. The probability of a sustained epidemic was highest when seeding in breeding farms (at least five times higher than other actors) and could be attributed to their upstream positioning within the value chain.

Node-level prevalence at epidemic stationarity was highest for breeding farms followed by growing farms and very low in smallholders and BSP. The relative differences in infection prevalence between large farms and smallholders was qualitatively consistent with pig-level IAV prevalence reported from slaughterhouse sampling in the same study area, however further work is needed to validate model predictions.

Despite this, these findings highlight breeding farms as possible targets for IAV virological surveillance – both for early detection of novel subtypes, and during endemic phases. The methods adopted here present a framework for applying egocentric data to infectious disease models are well positioned to bridge knowledge gaps where livestock network data are scarce.

4.2 Introduction

The movement of livestock between holdings is recognised as an important transmission route with broad relevance for infectious diseases, including foot and mouth disease (FMD), African swine fever (ASF), and Influenza A viruses (IAVs) (Cheung et al., 2022; Costard et al., 2013; Fèvre et al., 2006; Kedkovid et al., 2020; Nelson et al., 2015). Infectious disease models incorporating data on livestock movements can enhance our understanding of transmission dynamics among livestock, improve model predictions, and therefore inform optimal strategies of disease control and surveillance (Craft, 2015; Danon et al., 2011; Dube et al., 2011; Keeling and Eames, 2005; Martinez-Lopez et al., 2009).

Swine IAVs stand as one such disease for which data-driven models accounting for the structure of livestock trade networks would be of considerable value. In affected pig herds, swine IAVs limit productivity and reproductive performance (Gumbert et al., 2020; Janke, 2013). Moreover, pigs are considered important mixing vessels for the reassortment of novel IAVs with pandemic potential as they can become co-infected with IAVs of avian, human, and swine origin (Scholtissek, 1990). Swine production systems are important reservoirs for IAV genetic diversity, while swine value chains provide a means for local- and global- IAV dissemination (Cheung et al., 2022; Hennig et al., 2022; Nelson et al., 2015; Nelson and Worobey, 2018; Smith et al., 2009a; Vijaykrishna et al., 2011).

Given the pandemic risk posed by swine IAVs, there is a global need for enhanced surveillance in pig populations (Nelson et al., 2015; Smith et al., 2009b; Van Reeth et al., 2008). Southeast Asia (SEA), with its dense populations of pigs, poultry, and humans, is considered a high priority area for such surveillance efforts (Wei et al., 2015). There is a well-established need for cost-effective, tailored, and risk-based IAV surveillance strategies across the region (Trevennec et al., 2011; Wei et al., 2015), including in Cambodia (Goutard et al., 2015; Netrabukkana et al., 2015; Zeller et al., 2023a). In Cambodia, as the swine sector expands and intensifies (Asian Development Bank, 2022; Mason-D'Croz et al., 2022; Thai, 2018), the need for data-driven approaches to inform disease surveillance and control strategies has become increasingly acute.

In a previous study, we described the egocentric networks of swine value chain actors in Cambodia, comprised of interviewed 'egos', and their immediate trade partners, 'alters' (Chapter 3). This type of network data, provides insights into node-level statistics like degree, strength, and nodal assortativity, but lacks information on network-level features like path lengths, community structure or component sizes (Eames et al., 2015; Perry et al., 2018; Robins, 2015). The use of egocentrically sampled data in infectious disease network modelling has therefore remained an outstanding challenge (Danon et al., 2011; Eames et al., 2015). One solution has been to mechanistically calibrate network-simulation models, such as configuration algorithms, to egocentric statistics (Danon et al., 2011; Read et al., 2008). Methodological advancements in statistical network modelling present opportunities for complete network inference form egocentrically sampled networks (Gjoka et al., 2014; Handcock and Gile, 2010; Koskinen et al., 2013; Robins, 2015; Smith, 2015, 2012). In this study, we employ a recently described subclass of exponential random graph models (ERGMs) which can be estimated from the simplest form of 'star' (Almquist, 2012) egocentric data in which alters are not uniquely identifiable and edges between alters are not observed (Krivitsky and Morris, 2017).

ERGMs are a family of generative statistical network models in which the observed network is modelled as a function of local processes hypothesised to be relevant for network formation (Lusher, 2013). A fitted ERGM defines a probability distribution of a set of random graphs given a set of nodes and their attributes. Hence, by drawing from this distribution, networks can be simulated consistent with the generative processes specified by the model. The application of ERGMs to livestock trade networks has mostly employed complete livestock movement data collected via national-scale livestock traceability systems (Leung et al., 2023). In the absence of such data in Cambodia, we apply the ERGM method described by Krivitsky and Morris (2017) to analyse egocentrically-sampled data on Cambodian swine trade (Chapter 3), and reconstruct sociocentric networks. We then model IAV transmission on the simulated sociocentric networks to explore whether IAV risk varies among different value chain actors and to therefore identify potential targets for surveillance.

The specific objectives of this study were to: (1) determine the mechanisms and key drivers shaping the organisation of the observed swine trade network in Cambodia; (2) develop a network-based simulation modelling framework of IAV transmission among swine populations/premises based on egocentric livestock movement data; and (3) compare value chain actors' susceptibility to, and potential for spreading IAVs. This study further serves as a proof of concept to demonstrate the utility of egocentric ERGMs for generating networks relevant for infectious disease modelling within livestock populations.

4.3 Methods

4.3.1 Egocentric data

Network data was collected via a star-egocentric network survey conducted in south-central Cambodia described previously (Chapter 3). The study area included Phnom Penh autonomous municipality and three surrounding provinces: Kandal, Kampong Speu, and Takeo. Egocentric data was comprised of swine value chain actors ‘egos’ (n=379) and the trading partners ‘alters’ (n=1,101) they had exchanged live pigs with within a defined recall period. Each node represented a given value chain actor type described previously (Chapter 3). These were either 1) Producers: breeding farms (FB), growing farms (FG), smallholders (Sm), and boar service providers (BSP); 2) Pig exchangers: traders (Tr), middlemen (Mi), and butchers (Bu); or finally, 3) Slaughterhouses (Sl).

Survey recall periods for producers (six months), pig exchangers, BSP (two weeks), and slaughterhouses (seven days) were standardised to two-week intervals prior to ERGM-fitting. This period was used since it was considered appropriate in relation to the minimum expected infectious period of influenza within producer nodes (elaborated in section 4.3.3.3). Standardisation of recall periods was achieved following the methods described previously (Chapter 3, section 8.2.3) and generated a dataset with 379 egos and 669 alters.

4.3.2 Egocentric ERGMs

4.3.2.1 Method overview

In this study, we use a recently described sub-class of exponential-family random graph models (ERGMs) which can be estimated from star-egocentric samples of a network (Krivitsky and Morris, 2017). Here, we highlight some key methodological differences in this statistical framework compared to ERGM inference from complete networks. See Krivitsky and Morris (2017) for a complete technical description.

$$P_{\theta}(Y = y | n\ nodes) = ce^{\theta_1 z_1(y) + \cdots + \theta_k z_k(y)} \quad \text{Equation 1}$$

ERGMs define the probability of a random network, *Y*, given a set of $n\ nodes$ and their attributes, as an exponential function of covariates which are (population-level) network statistics, $z_k(y)$ from the observed network, y, hypothesised to be relevant for network formation, that is, which are more or less common than would be expected in the equivalent random graph. This is presented in Equation 1, with c being the normalising constant and θ, the coefficients.

The ERGM method in Krivitsky and Morris (2017) applies a parameterization of dyad-independent statistics (described in Krivitsky et al. [2011]), that allows ERGMs to be fit in a way that is invariant to network size, using an offset-term. Population-level network statistics (covariates in the model) can be extracted from observed egocentric networks according to known scaling with network size. Models are then fit to a pseudo-network matching the distribution of nodes and their attributes defined by the survey weights where relevant, and with statistics that would have been observed from the complete network. Given a fitted model, resulting coefficients can be scaled to any population size specified, or else retuned as 'per-capita' estimates. This is achieved using the offset term – equal to pseudo-population size divided by population size when applied to weighted surveys – which has the effect of preserving mean degree with scaling to network size. This allows models to be fit to networks of a smaller pseudo-population size that the complete network, easing computation.

When fitting ERGMs to egocentric data, covariates are restricted to network statistics that are observable in the egocentric sample. With the star-egocentric design, this includes: nodal attribute effects (e.g. farm size, farm type), nodal mixing effects (i.e. mixing patterns across different levels of nodal attributes such as mixing by production type), homophily effects (i.e. the tendency for edges to form within a nodal attribute group), and network degree effects (i.e. a model term can be added for defined values of degree; e.g. degree[0] applies the count of network isolates as a covariate). In contrast to fitting ERGMs to completely observed networks, edge effects (e.g. geographic distance between farms) cannot be modelled as independent variables. Some structural statistics (e.g. triadic terms) can be estimated if data are available on edges between alters, however, this was not the case in the dataset used here. Pseudo-maximum-likelihood estimates for model coefficients are generated using Markov chain Monte Carlo (MCMC) algorithms.

4.3.2.2 Survey weighting

Survey weighting was applied to account for the stratification of sampled actors (Chapter 3). Population distributions for actors within the study area were informed by census data (Ministry of Agriculture Forestry and Fisheries, 2019) and sampling frames collected during field visits (Chapter 3; summarised in Table 4.1), with weights generated by post-stratification (Lumley, 2010). A detailed justification of actor population distributions are presented in Supplementary Information (section 8.3.1) and is summarised in Table 4.1.

Table 4.1. ***Population distribution by actor type.*** *Data and summary of calculations used to inform the distribution of actors (nodes) in the study population in Phnom Penh autonomous municipality, Kandal, Kampong Speu, and Takeo. *See Supplementary information (section 8.3.1 for detailed explanation of calculations).*

Actor class	**Nodes estimated in population, n**	**Nodes in sample, n (% of population)**	**Justification***
Farms	**(358)**	**(89 [25])**	Total farms informed by Ministry of Agriculture Forestry and Fisheries (2019)
breeding	129	21 (16)	Proportion of breeding farms informed by sampling frames
growing	229	68 (30)	Proportion of growing farms informed by sampling frames
Smallholders	**(10,834)**	**(200 [2])**	Total smallholders informed by Ministry of Agriculture Forestry and Fisheries (2019). This value was reduced by two thirds to match field observations and reductions reported by Asian Development Bank (2022)
BSP	30	19 (63)	Calculation based on the number of BSP required to serve all smallholders in the study area
breeding/growing	10,804	181 (2)	Calculation based on total smallholders minus no. of BSP
Pig exchangers	**(586)**	**(90 [14])**	(The sum of below)
middlemen	89	12 (13)	Calculation based on the number of middlemen required to serve all smallholders in the study area
traders	100	11 (11)	Sampling frames
butchers	397	51 (13)	Sampling frames
Slaughterhouses	63	16 (25)	Sampling frames
Totals	**11,871**	**379 (3)**	

4.3.2.3 Model specification

Based on descriptive network analysis (Chapter 3), the following features were hypothesised to be relevant for edge formation: 1) actor type, 2) the types of actors forming a dyad, 3) the company membership of actors forming a dyad (i.e. more frequent trade between actors affiliated to the same, than to a different, company). The geographical distribution of nodes could not be accounted for as locations were known for only 16% of farms' alters. Nodal attributes used in this analysis are presented in Table 4.2.

Models were constructed using a step-wise cumulative process, retaining model terms that achieved statistical significance at $p<0.05$. Model building began with a null, Erdős-Rényi model (model 1) with only one term, the network density. Next, following standard methodology (Harris, 2013), a nodal attribute effect was added for actor type (model 2). Finally, two nodal mixing terms were added, beginning in the order of their anticipated importance based on trends observed in descriptive analyses (Chapter 3). The first was a nodal mixing effect by actor which included one network statistic for each pairwise combination of actor types, and tested the hypothesis that edges were more/less likely between certain actor pairings (model 3). To avoid challenges with model convergence due to sparse data, all pairwise combinations of actor types with at least 1, but less than 10 connected dyads, were combined into a single level and constituted the baseline group (with pairwise actor combinations with zero observations having a fixed odds of zero i.e. not being estimated by MCMC). Next, a term for uniform homophily by company (model 4) was added, relevant only to nodes affiliated with a company. All terms were dyad-independent i.e. where the probability of an edge is independent on the state of other dyads.

A pseudo-population size equivalent to the sample size divided by smallest survey weight was applied, as recommended in Krivitsky (2023). Model coefficients were rescaled to the total population size (i.e. 11,871 nodes; Table 4.1). The MCMC algorithms for each model were run with 3 chains with 25,000 samples and a burn-in of 12,000 samples. All ERGM analyses were carried out in R version 4.2.0. (R Core Team, 2020) and the RStudio environment (Posit team, 2023), using the Statnet packages: ergm.ego and ergm (Handcock et al., 2023; David R. Hunter et al., 2008; Krivitsky, 2023).

Table 4.2. ***Nodal attributes.*** *Description of nodal attributes used in the ERGMs.*

Nodal attributes	**Description**
Actor type	A categorical variable representing each of the eight actor types: breeding farms (FB), growing farms (FG), smallholders - not differentiated by breeding and growing orientated (Sm), smallholder boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl).
Company	A categorical variable representing the company actors were associated with (via a contract or direct ownership). Due to data sparsity, company was simplified to 1) nodes with no company affiliation, 2) company A, 3) company B (the two most common companies in the observed network), and 4) all other companies combined.

4.3.2.4 Model selection and goodness of fit

For each fitted model, MCMC chain mixing and convergence was assessed by visual inspection of trace plots. Following standard ERGM methodology, model calibration and goodness of fit was assessed by comparing network statistics calculated on the observed network, with the distribution of equivalent statistics from ERGM-simulated networks (n=100). For clarity, ‘network statistics’ are simply counts of network configurations. For example, the total number of edges in a network, the number of nodes with a specified number of edges to other nodes (nodal degree), or the number of dyads involving nodes with specified combinations of nodal attributes. Model calibration was assessed by comparing the fit of the model to statistics included as terms in the ERGM. Goodness of fit was assessed by comparison to global structural statistics which were not included as terms in the model. With egocentric data, estimation of such measures is restricted to degree distribution, which we compared globally, and stratified by actor type. This functioned as a measure of internal validity to assess whether a useful model had been specified. Sociocentric ERGM simulated networks were also plotted and visually compared using the R package: igraph (Csardi and Nepusz, 2005).

4.3.3 Infectious disease modelling

4.3.3.1 Model overview

A discrete-time, stochastic, agent-based network model (ABNM) was applied to simulate the transmission of a novel IAV subtype within the Cambodian swine trade network. Within-farm transmission dynamics were not explicitly modelled. This approach aligns with other studies modelling highly infectious diseases in livestock populations, including influenza (Andraud and Rose, 2020; Bernini et al., 2019; Dorjee et al., 2016; Masuda and Holme, 2013).

A susceptible-infectious-recovered-susceptible (SIRS) model framework was used. Nodes could transition from susceptible to infectious if they were in contact with an infectious node in a previous timestep; from infectious to recovered after a defined infectious duration had elapsed; and returned to susceptibility after a specified immunity duration had elapsed.

4.3.3.2 Transmission process

Transmission of influenza virus among pigs primarily occurs via pig movements i.e. 'direct' contact (Torremorell et al., 2012) but can also occur by 'indirect' contact through fomites, as evidenced by experimental studies (Allerson et al., 2013; Desrosiers, 2021; Thompson and Bennett, 2017) and field observations (Desrosiers, 2004; Poljak et al., 2008b). In the model, producer nodes were the epidemiological units and transmission could occur via either of these routes. Direct contact occurred from a supplier (i) to a recipient (j) producer via swine transfers (i→j), while indirect contact could occur via two routes: The first route was from a recipient to a supplier (i←j) based on an assumption of shared use of equipment or personnel e.g. a recipient sending their vehicles to collect pigs. Indirect contact from i to j was deemed negligible compared to direct transmission, hence disregarded. The second route was between producers connected, in a single same time step, to the same pig exchanger or BSP (detailed in section 4.3.3.4.2). The transmission process is presented in detail in supplementary information: section 8.3.2

4.3.3.3 Network edge dynamics

ERGM-simulated networks were static networks in 2-week snapshots. This aligned with the minimum duration of node-level influenza persistence (equivalently, node-level infectious period) which, according to within-herd infectious disease modelling of influenza in Cambodian pig producers, was 2-weeks for smallholders (Hidano et al., 2022). Aggregation over a longer period would generate a more highly connected network than the contagion could actually transmit along (Craft, 2015; Cross et al., 2005; Keeling and Eames, 2005; Reynolds et al., 2015).

During the disease simulation, a new ERGM-simulated network was used in each time step, creating a sequence of static networks. This approach did not account for network autocorrelation (i.e., repeatability of trades among the same producers). However, this simplification was deemed reasonable given that producers typically made repeat trades with the same partners over large time intervals (e.g. 6 months; Table S 8.8) relative to the infectious duration of nodes.

4.3.3.4 Network pre-processing

ERGM-simulated networks were undirected and comprised of producer, pig exchanger, and slaughterhouse nodes. These networks were therefore altered to generate directed networks of producers. The complete analysis steps are summarised in Figure 4.1.

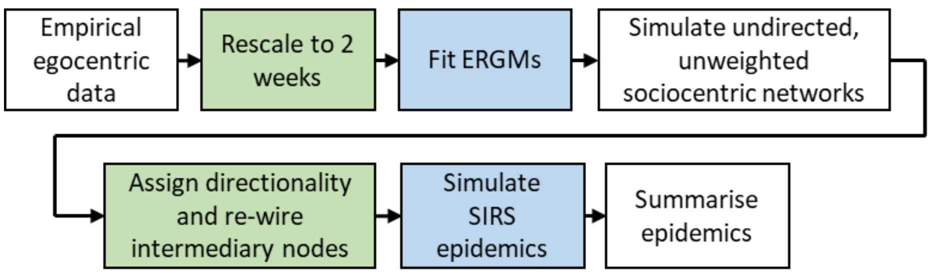

Figure 4.1. ***Flow diagram of analysis steps.*** *Modelling steps shaded blue; model pre-processing steps are shaded green.*

4.3.3.4.1 Edge directionality

Edge directionality was assigned based on a set of rules to reproduce the observed pig movement pathways among actors (Table S 8.10). Edges among actor types were mostly non-reciprocated in the empirical network (Chapter 3), and when edge direction was uncertain, such as when two actors in a dyad were of the same actor type, edge direction was randomised using a Bernoulli trial with probability 0.5.

4.3.3.4.2 Network re-wiring

ERGM-simulated networks were re-wired to account for (direct or indirect) contacts among producers mediated by pig exchangers or BSP (termed 'intermediary nodes'; Figure 4.2). Assuming that an intermediary node could remain contaminated for an entire 2-week time step, a producer was *indirectly* connected to other producers visited previously by the same intermediary, with the sequence of visits being generated randomly (Figure 4.2; column 4). This is similar to how others have accounted for indirect contacts among farms, based on partial information on shared truck usage or personnel visits (Bernini et al., 2019; Rossi et al., 2017a; Salines et al., 2017).

Direct contacts were generated differently according to the type of intermediary node (Figure 4.2; column 3) based on their observed roles in transferring pigs among producers (Chapter 3). BSP lent boar(s) to smallholders for mating. Edges were drawn among producers in an identical way as for indirect contacts, to replicate the sequence of visits a BSP would make to their customers. Middlemen transferred weaners among smallholders, so half their producer alters (all smallholders) were randomly selected as suppliers and half as recipients and directed edges were drawn among them. Traders and butchers received but never supplied pigs to producers so no edges were generated among their producer alters. After rewiring, all edges to non-producer nodes were removed, except in networks used in the initial time step, such that seeding of infection could occur in non-producer nodes.

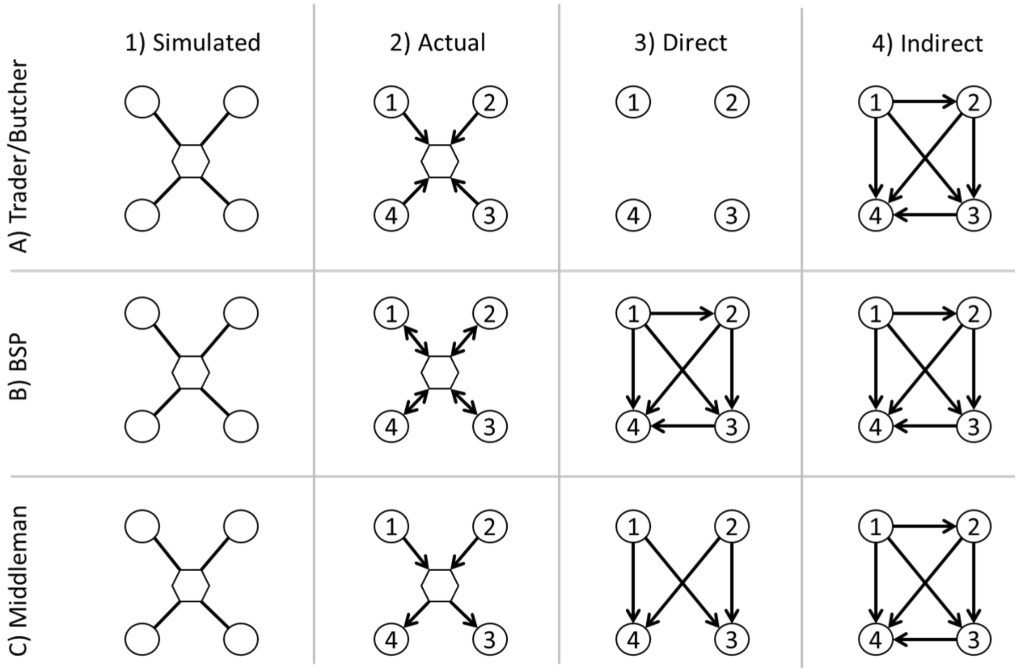

Figure 4.2. ***Network rewiring strategy.*** *Direct and indirect connections generated by visits of intermediary nodes (hexagons) to their producer alters (circles). Columns show (1) Simulated networks which generate undirected connections among intermediaries and their producer alters, (2) an example of actual pig transfers that could have been generated by such connections (numbers indicate sequence of visits), (3) how this is represented in the ABNM in terms of direct contacts and (4) indirect contacts among the producer contacts. N.B. edges to pig exchangers (traders, butchers, and middlemen) were removed after rewiring.*

4.3.3.5 Global network structure of simulated and rewired networks

Global, sociocentric, network statistics were computed for ERGM-simulated networks (n=100), and rewired, direct and indirect contact networks (n=100). Six statistics were computed: 1) The number of weakly connected components (WCC), defined as sets of at least two nodes which are all reachable from one another irrespective of edge directionality. A large number of components would indicate a fragmented network. 2) The number of nodes in the largest weak component. 3) The average of the shortest path lengths, or 'geodesics', between pairs of nodes and calculated for the largest weak component when a network was incompletely connected. 4) Global clustering coefficient i.e. the proportion of closed triplets in the network. Finally, for the rewired networks, two additional statistics relevant to directed networks were calculated: 5) the number of strongly connected components (SCC) – directed subgraphs in which every node is reachable from every other node, and 6) the size of the largest SCC. All network statistics were computed using the R packages: sna (Butts, 2008) and igraph (Csardi and Nepusz, 2005).

4.3.3.6 Infectious disease modelling parameters

4.3.3.6.1 Duration of infectiousness

The infectious period was defined as the duration of IAV persistence within a given node type. For producers, these parameter values were informed by the within-herd epidemic model for IAV mentioned previously (Hidano et al., 2022). Transmission parameters are presented in Table 4.3.

4.3.3.6.2 Duration of immunity

The duration of immunity was based on the frequency of pig replacements via births or purchases. Waning immunity in pigs was not accounted for in the model; this was considered to have a negligible effect on herd-level immunity relative to the high frequency of batch replacements.

Growing farms practiced all-in-all out production in which all pigs are replaced together, so node-level immunity lasted the duration of a single production cycle (~5 months). The same period was used for smallholders and BSP as they mostly had two farrowing or fattening cycles per year. For breeding farms, the duration of immunity was two time-steps (four weeks), based on a typical farrowing frequency of three weeks based on field observations.

4.3.3.6.3 Probability of transmission

The probability of transmission following direct or indirect contact is likely to vary according to a variety of factors including within-herd prevalence, batch sizes, and biosecurity practices. Indirect contact may further vary according to the frequency and effectiveness of vehicle or equipment cleaning, climactic conditions, and the type(s) of surface contaminated (e.g. Allerson et al., 2013; Desrosiers, 2021; Thompson and Bennett, 2017). Due to a lack of data on transmission probabilities, previous studies modelling influenza among swine herds have used assumed direct transmission probabilities ranging from 1 (Dorjee et al., 2016; based on assumptions derived from experimental studies), and 0.2 (Mateus-Anzola et al., 2019), and 0.01 (Dorjee et al., 2016; based on expert opinion elicitation) for indirect contact. In this study, three values for direct and for indirect transmission were explored, with this range including the values used in Dorjee et al. (2016) (Table 4.3).

Table 4.3. Infectious disease modelling parameter values used for the simulation of between-herd spread of influenza A virus among pig producers in Cambodia.

Parameter	Value used	Justification
Duration of infectiousness (weeks)		
Breeding farm	52 22 78	1 year based on Hidano et al. (2022) Assumed for sensitivity analyses Assumed for sensitivity analyses
Growing farm	22	Batch production cycle
Smallholders and BSP	2	(Hidano et al., 2022)
Duration of immunity (weeks)		
Breeding farm	4	Batch production cycle
Growing farm	22	Batch production cycle
Smallholders and BSP	22	Batch production cycle
Transmission probability		
Direct: high Direct: medium Direct: low	1 0.8 0.6	Dorjee et al. (2016) Assumed Assumed
Indirect: high Indirect: medium Indirect: low	0.2 0.1 0.01	Assumed Assumed Dorjee et al. (2016)

4.3.3.7 Model scenarios and sensitivity analyses

Nine transmissibility scenarios were considered based on the combination of direct and indirect transmission probabilities (Table 4.3). Infection was seeded in a single node, either randomly selected from a specified actor type, referred to as random actor seeding (n=8 set of seeds), or else randomly selected from all nodes, referred to as total random seeding (n=1). Therefore 81 possible scenarios were run (9 sets of seed actors; 9 transmissibility parameter sets). Each scenario was executed for 100 iterations over 5 years (130 time steps), or until node-level infection prevalence reached stationarity (max 20 years; 520 time steps).

It was anticipated that the duration of infectiousness of breeding farms could vary due to factors such as herd size and pig management practices. Therefore, the sensitivity of the main model outcomes to durations of infectiousness for breeding farms was also assessed by using a maximum value of 78 weeks, and a lower value of 22 weeks, i.e. the same duration used for growing farms.

4.3.3.8 Model outcomes

Due to the stochastic nature of the model, some scenario iterations could result in sustained transmission for the duration of the simulation resulting in large epidemic sizes. In other iterations, the infection process could stop before the end of the simulation resulting in relatively small epidemic sizes. This generated a bimodal distribution which was plotted to find an appropriate threshold for defining an 'epidemic'.

Four infectious disease modelling outcome metrics were computed (Table 4.4). Following total random seeding, the epidemic attack rate, and its evolution over time, was used as an indicator of actors' susceptibility to infection. The probability of an epidemic occurring after seeding in a given actor type was used as an indicator of that actor type's propensity for onward transmission.

Table 4.4. ***Infectious disease modelling outcomes.*** **calculated only for simulations that resulted in an epidemic.*

Model outcome definitions	
Probability of an epidemic	The proportion of simulations generating an epidemic
Attack rate*	The proportion of nodes that were ever infected at time step, t
Time to epidemic stationarity*	The time to reach stationarity (defined numerically as the time step at which the median prevalence, calculated across all time steps, was reached; confirmed graphically)
Prevalence at stationarity*	The average proportion of infectious nodes from the time epidemic stationarity was reached until the simulation end
Proportion recovered at stationarity*	The average proportion of recovered nodes from the time epidemic stationarity was reached until the simulation end

4.4 Results

4.4.1 Egocentric ERGMs

MCMC diagnostics for all models indicated that chains were well mixed and distributed randomly among the observed values (Figure S 8.5 to Figure S 8.8). All models were well calibrated to the data (Table S 8.11; Figure S 8.9). Models 2-4 achieved a good fit to the data based on comparison of empirical and simulated degree distributions, when considering all actors (Figure S 8.10; Table S 8.12) or stratifying by actor type (Figure S 8.11). Model 1 contrastingly, achieved a poor fit. Compared to model 2, inclusion of actor mixing terms in models 3 and 4 improved the fit of the degree distribution for breeding farms and BSP (i.e. better able to reproduce the right skewed degree distribution) but generated a worse fit for slaughterhouses or traders. None of the models were able to reproduce the observed level of overdispersion in slaughterhouses' degree distribution (Figure S 8.11).

A differential tendency for edge formation by actor type, selective mixing by actor type and company membership (model 4) were all significant effects (Table 4.5 for odds ratios; Table S 8.13 for coefficients). Compared to model 2, the addition of actor mixing terms (model 3) increased the node factor coefficients for most actors, however, this could be explained by a large reduction in the coefficient of the ‘edges’ term (i.e. the baseline edge probability; Table S 8.13). The single exception was the node factor effect for BSP for which the coefficient decreased. This can be explained by a very large positive coefficient for mixing between BSP and smallholders, suggesting that a high tendency for BSP-smallholder trades accounted for some of BSP’s high node factor effect in model 2. In model 4, all actors had a higher tendency to form edges than smallholders after controlling for actor mixing and company homophily (odds ratios>1 in Table 4.5). All other network properties being held constant, a smallholder and a BSP had 600 (95% CI: 76-4716) times greater odds of being in a connected dyad compared to the baseline. Two actors affiliated to the same company had 12 (95% CI: 3-48) times greater odds of being connected together than actors belonging to different companies. Addition of the company homophily term (model 4 vs model 3) attenuated node factor effects for breeding and growing farms (the vast majority of which were company affiliated) and nodal mixing effects between breeding farms (with odds confidence intervals of this effect including 1) suggesting these effects were largely or entirely be explained by company homophily. Due to the added information captured by model 4, this model was taken forward for the ABNM analyses.

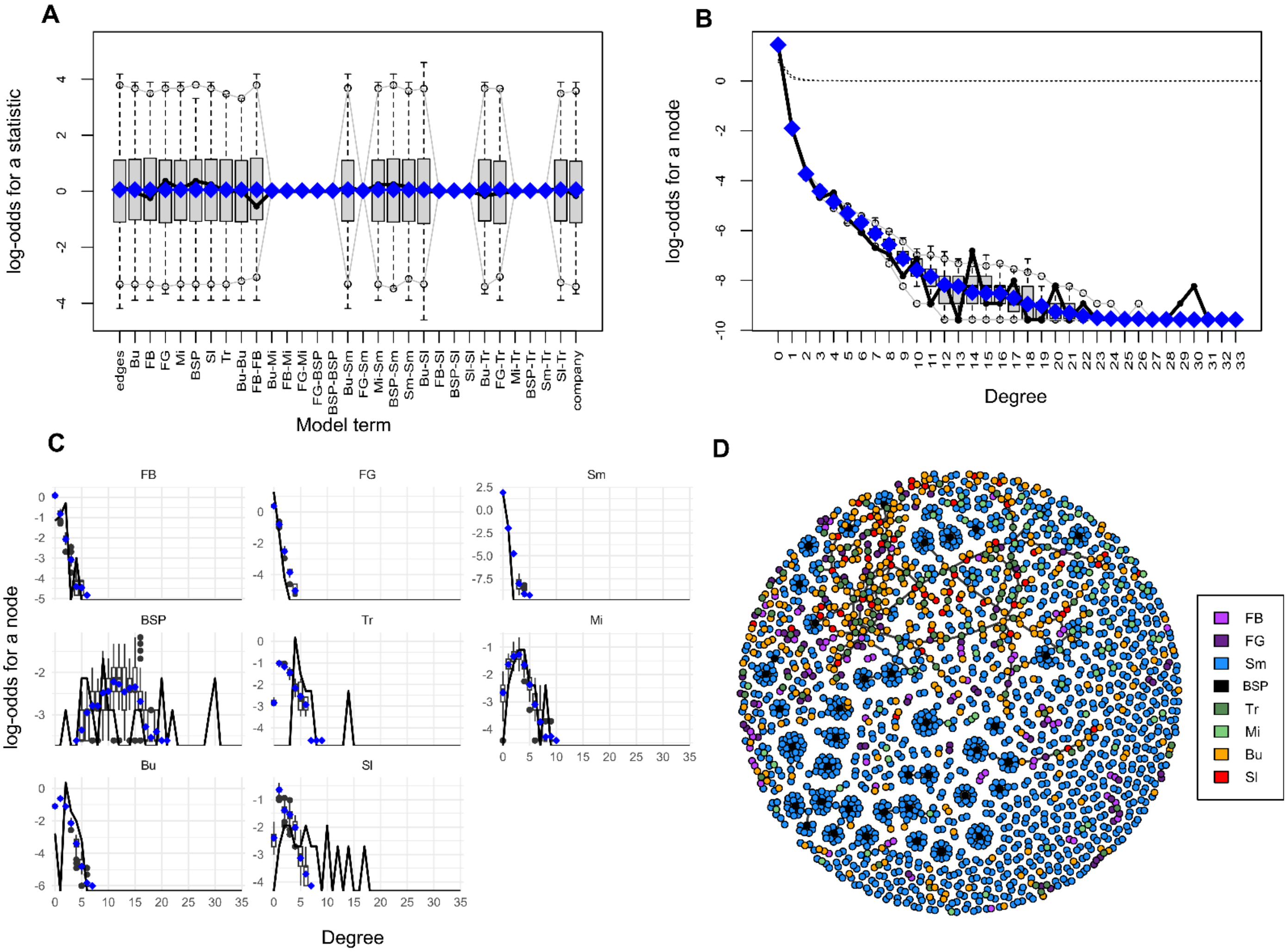

Figure 4.3 ***ERGM goodness of fit for model 4.*** *(**A**) Observed network statistics (black lines) relative to the normalised distribution of simulated network statistics (boxplots) centred at zero. (**B-C**) Observed degree distribution (black lines) relative to the global (**B**) and actor-stratified (**C**) degree distribution of simulated networks (boxplots). Boxplots show model statistics from 100 simulated networks with mean values displayed as blue diamonds. Blank spaces denote model terms with no observations and which were fixed at an odds of zero. (**D**) An example of a simulated network is also shown: isolates have been removed for viewability and nodes are arranged using the Fruchterman-Reingold algorithm and coloured by actor type.*

*Table 4.5. **ERGM odds ratios**. Odds ratios and 95% confidence intervals for ERGM terms. Actor types are breeding farms (FB), growing farms (FG), smallholders (Sm), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl). *Baseline is all pairwise actor combinations with 0<observations<10 (Bu-FB, Bu-FG, FB-FG, FG-FG, Mi-Mi, Bu-BSP, FB-BSP, Mi-BSP, FB-Sm, FG-Sl, Mi-Sl, Sm-Sl, FB-Tr, and Tr-Tr). Pairwise actor combinations with zero observations were not estimated by MCMC and had a fixed odds ratio of zero (shown as NA). The edges term and ERGM results for model 1 (edges only model) are not shown.*

	Model 2: actor		**Model 3: + actor mix.**		**Model 4: + company hom.**	
	OR (95% CI)		**OR (95% CI)**		**OR (95% CI)**	
Node factor effects: Actor						
Sm	Reference		Reference		Reference	
Bu	15.5	(10.5 - 22.8)	34	(5.3 - 217.9)	54.1	(6 - 483.9)
FB	10.5	(6 - 18.5)	150.5	(26 - 872.4)	78.8	(11.8 - 523.9)
FG	4	(2.3 - 6.9)	80.6	(15.7 - 414.8)	28.3	(4.7 - 171.1)
Mi	20.4	(11.7 - 35.6)	226.2	(43.3 - 1182.4)	182.6	(33 - 1008.5)
BSP	101.2	(62.8 - 163.2)	41.4	(5.6 - 306.6)	33.4	(3.6 - 308.1)
Sl	40.8	(26.1 - 63.8)	166	(18 - 1531.3)	173.6	(11.2 - 2701.3)
Tr	38.6	(24 - 62.2)	191.6	(25.7 - 1426.2)	187.3	(21.8 - 1611.1)
Nodal mixing: Actor						
Other actor pairings*			Reference		Reference	
Bu-Bu			9.1	(1.5 - 56.9)	2.6	(0.3 - 22.2)
FB-FB			7.6	(2 - 28)	3.7	(0.8 - 17.5)
Bu-Mi			NA		NA	
FB-Mi			NA		NA	
FG-Mi			NA		NA	
FG-BSP			NA		NA	
BSP-BSP			NA		NA	
Bu-Sm			28	(3.9 - 200.4)	12.8	(1.6 - 104.2)
FG-Sm			NA		NA	
Mi-Sm			21.9	(3.4 - 141.4)	19.7	(2.3 - 171.8)
BSP-Sm			668	(99.5 - 4486.8)	600.3	(76.4 - 4715.9)
Sm-Sm			121.6	(4.1 - 3596)	88.2	(2.1 - 3715.8)
Bu-Sl			33.1	(10.7 - 101.8)	14.4	(3 - 69.8)
FB-Sl			NA		NA	
BSP-Sl			NA		NA	
Sl-Sl			NA		NA	
Bu-Tr			25.4	(7.1 - 91.4)	11.8	(3.5 - 40.3)
FG-Tr			4.3	(1.3 - 14.4)	9.1	(2.6 - 32.1)
Mi-Tr			NA		NA	
BSP-Tr			NA		NA	
Sm-Tr			NA		NA	
Sl-Tr			12.8	(3 - 54.8)	9	(1.9 - 42.9)
Nodal homophily effects						
Different company					Reference	
Same company					12.2	(3.1 - 47.9)

4.4.2 Structure of simulated and re-wired networks

Networks simulated from model 4 had a median density of 2.9×10^{-5} and a high proportion of isolates (median 81%; Table 4.6 for IQR). A large number of WCCs (median 390) indicated networks that were quite fragmented, but a large WCC comprising 1022 nodes was also present, comprising 8.6% of total nodes. This was much larger than model 1 which comprised a random graph with equivalent density. In the largest WCC, which had a median density of 2.2×10^{-3} (IQR: 2.1×10^{-3} - 2.3×10^{-3}), average geodesics were 9.6 (IQR: 9.1 - 10.5), and clustering coefficient was 1.5×10^{-3} (IQR: 7.3×10^{-4} - 2.1×10^{-3}). These values were similar to random graphs (n=100) generated with an equivalent number of nodes and edges as the WCC: average geodesics were 7.9 (IQR: 7.8 - 8.1) and clustering coefficients were 2.1×10^{-3} (IQR: 1.1×10^{-3} - 3.1×10^{-3}). The inclusion of nodal mixing and homophily terms in models 3 and 4 increased the global clustering coefficient, and decreased the size of the largest WCC compared to model 2 (Table 4.6).

Rewiring networks from model 4 to direct- or indirect-contact networks of producers generated networks with much higher clustering (near 1). The largest WCC of rewired networks was also an order of magnitude smaller than ERGM-simulated networks (Table 4.6). This was due to a large proportion of non-producer nodes in the largest WCCs of ERGM-simulated networks (Figure 4.3d). The density of the large WCC in the direct contact layer was 0.1 (IQR: 0.1 - 0.1). Clustering in the WCC was much higher than an equivalent random graph: 0.9 (IQR: 0.9 - 0.9) vs 0.2 (IQR: 0.1 - 0.2) respectively. The density of the large WCC of the indirect contact layer was 3.3×10^{-5} (IQR: 3.2×10^{-5} - 3.4×10^{-5}). Clustering was again much higher than an equivalent random graph: 0.9 (IQR: 0.9 - 0.9) vs 0.1 (IQR: 0.1 - 0.2). The direct contact layer had a median of 26 SCCs, the largest of which included a median 83 (0.74% of) producers. The indirect contact layer did not have any SCCs; average geodesics were short. The producer-producer contact network was therefore fragmented, but a large, highly clustered large WCC and short path lengths suggested that disease could spread quickly in this component within the two week timeframe that this network represented.

Table 4.6. ***Structure of ERGM-simulated and rewired networks.*** *Summarised network statistics across simulated contact networks (n=100): median (IQR). Comparison are made between ERGM specifications: models 1-4, and direct and indirect contact networks generated by rewiring networks simulated from model 4. WCC=weakly connected components; SCC=strongly connected component. Grey cells indicate statistics for directed networks that are not relevant for undirected networks simulated from models 1-4. *Calculated for the largest WCC.*

	Density	Global clustering coefficient	Proportion isolates	No. WCC	Size of largest WCC	No. SCC	Size of largest SCC	Average geodesic*
Model 1 (Erdős–Rényi)	3.1e-05 (3.0e-05-3.2e-05)	0.0e+00 (0.0e+00-0.0e+00)	0.69 (0.69-0.70)	1470 (1450-1491)	11 (10-13)			3.15 (2.88-3.40)
Model 2	2.9e-05 (2.8e-05-3.0e-05)	8.0e-04 (2.7e-04-1.9e-03)	0.81 (0.81-0.81)	338 (327-354)	1427 (1382-1467)			8.06 (7.50-9.48)
Model 3	2.9e-05 (2.8e-05-3.0e-05)	1.9e-03 (5.0e-04-3.2e-03)	0.81 (0.81-0.81)	396 (385-408)	1060 (978-1142)			9.97 (9.45-10.49)
Model 4	2.9e-05 (2.8e-05-3.0e-05)	1.9e-03 (6.4e-04-3.5e-03)	0.81 (0.81-0.81)	390 (378-406)	1022 (953-1113)			9.64 (9.11-10.45)
Model 4: Direct	3.9e-05 (3.8e-05-4.1e-05)	9.5e-01 (9.4e-01-9.5e-01)	0.87 (0.87-0.88)	402 (388-414)	100 (78-125)	26 (24-28)	83 (65-110)	4.10 (3.52-4.57)
Model 4: Indirect	3.7e-05 (3.6e-05-3.9e-05)	9.4e-01 (9.4e-01-9.5e-01)	0.86 (0.86-0.87)	411 (398-422)	106 (89-129)	0 (0-0.50)	1 (1-1.50)	1.62 (1.53-1.73)

4.4.3 Infectious disease modelling

4.4.3.1 General epidemic features

Although the simulated networks had a large fraction of isolated nodes, the dynamic process of edge formation meant that if an epidemic was sustained, all nodes could eventually become infected. Simulations reached stationarity in a median of approximately 4-7 years (115-180 time steps), and reached an overall producer-level virological prevalence between 0.75% to 1.4% depending on transmissibility (Figure S 8.8.13). The actor type of the initial seed node appeared to have little impact on the prevalence at stationarity (Figure S 8.8.13). However, few simulations resulted in epidemics when seeding in most actor types, meaning these trends were difficult to assess. Prevalence at stationarity, however, varied by transmissibility, with higher transmissibility scenarios resulting in higher prevalence (Figure S 8.8.13).

4.4.3.2 Epidemic probability

Epidemic probability varied by actor type in which the infection was seeded with seeding in breeding farms consistently generating the highest epidemic probabilities across transmissibility scenarios (Figure 4.4). See Figure S 8.17 for the total set of transmission probabilities tested. When indirect transmissibility was relatively high, seeding in growing farms and BSP was also associated with slightly higher epidemic probabilities relative to other actors (Figure 4.4a). When indirect transmissibility was low, epidemic probability was low to zero unless the seed node was a breeding farm. This was true regardless of direct transmission probability. The relative differences in epidemic probabilities across seed nodes were robust to sensitivity analyses varying the duration of infectiousness of breeding farms (Figure S 8.14).

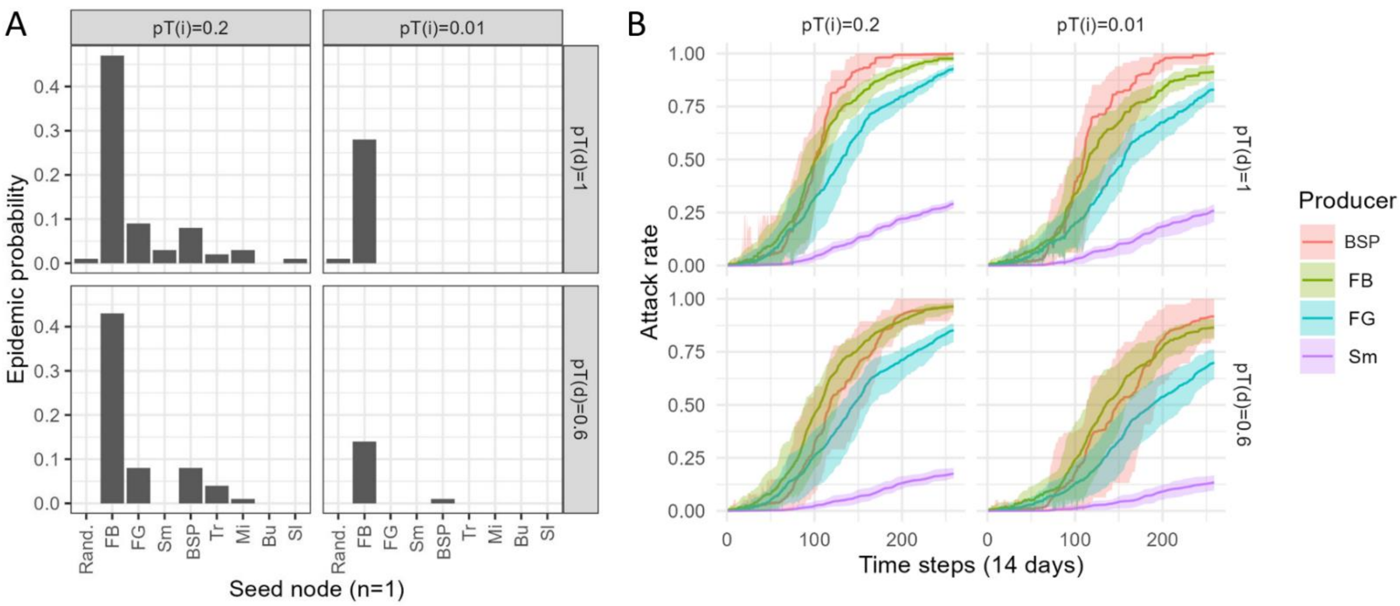

Figure 4.4. ***Infectious disease modelling outcomes.*** *(A) Epidemic probability following seeding infection in different actor types: Proportion of iterations (n=100) generating epidemics after total random seeding (Rand.) or random actor seeding. (B) Node's susceptibility to infection: Evolution of attack rate over time by actor type. Infections were seeded in breeding farms to ensure most simulations led to sustained transmission. Lines show means and shaded areas show the 5th and 95th percentiles of simulations (n=100). BSP=Boar service provider, FB=breeding farm, FG=growing farm, Sm=smallholder. For plots A and B, results are shown for scenarios with different direct (d) and indirect (i) transmission probabilities (pT) .*

4.4.3.3 Node susceptibility to infection

Based on the evolution of the attack rate over time, BSP and breeding farms were most susceptible to infection followed by growing farms (Figure 4.4b; Figure S 8.16 for the total set of transmission probabilities). While there was notable overlap in the inter-95 percentiles of this model output between breeding farms and BSP, breeding farms tended to become infected more quickly at the early stages of the simulation (i.e. within the first 50 time steps) but the attack rate for BSP reached 100% sooner when direct transmission probability was 1 or 0.8 (Figure S 8.16). Smallholders became ever infected at a much slower rate relative to other actors. These trends were consistent across the range of values explored for duration of infectiousness in breeding farms in a sensitivity analysis (Figure S 8.15).

4.4.3.4 Node-level prevalence over time

The average node-level prevalence reached at epidemic stationarity was highest for breeding farms (50-60%) followed by growing farms (10-14%); these trends were consistent across transmissibility scenarios (Figure 4.5a-b; Figure S 8.19). The average prevalence for BSP, and especially smallholders, was much lower (<3%), but prevalence among BSP exhibited greater temporal fluctuation around this mean value, sometimes reaching around 10%. BSP and growing farms had the largest fraction of recovered ('immune') nodes, with the former varying considerably around this average value at stationarity (Figure 4.5c-d). Smallholders and breeding farms had the lowest fraction of recovered nodes. These relative trends across actor types remained regardless of infectious duration of breeding farms, however, decreasing (or increasing) infectious duration led to corresponding decreased (or increased) breeding farm prevalence as expected (Figure S 8.18).

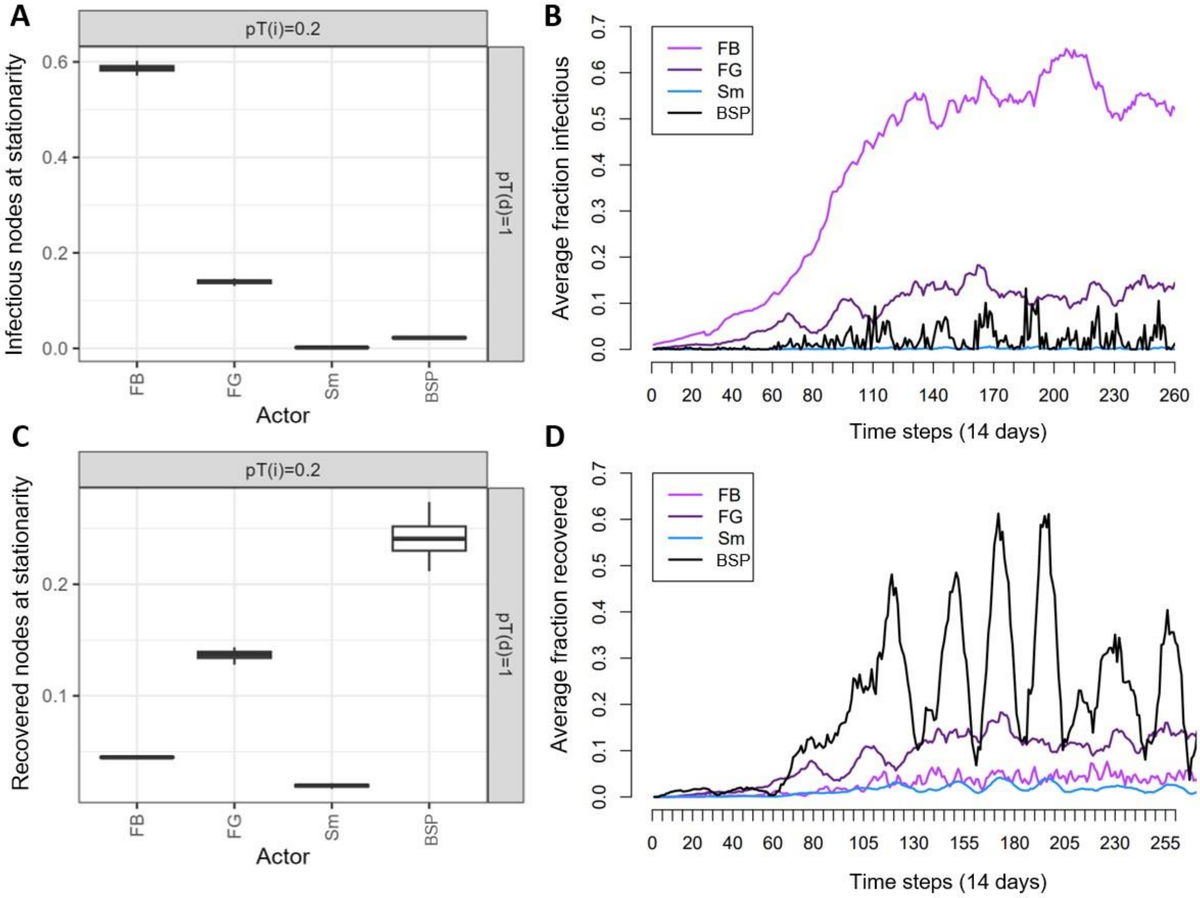

Figure 4.5. ***Infectious disease dynamics by actor.*** *The proportion of infectious (**A**-**B**) and recovered (**C**-**D**) nodes at stationarity for each actor type. Plots **A** and **C** show the mean proportion at stationarity averaged over simulations resulting in an epidemic. Results are shown here for model 4 and high direct and indirect transmission probabilities after seeding in breeding farms.*

4.5 Discussion

This study employed Exponential Random Graph Models (ERGMs) to analyse egocentric swine trade networks. This analysis permitted the assessment of factors relevant for network formation, along with the simulation of sociocentric networks comprised of swine producers, exchangers, and slaughterhouses, and calibrated to the egocentrically observed network statistics. Simulated networks were then used to explore the potential transmission dynamics of influenza within the Cambodian swine sector, following the rewiring of networks to producers and their contacts from swine movements and shared visitors.

ERGM analysis revealed that the formation of the Cambodian swine trade network was driven by the differential propensity for edge formation by actor, mixing patterns among actors, and the tendency for commercial farms to trade with farms of the same company. Similar factors have also been found to drive the organisation of swine trade networks in other settings (Hammami et al., 2022b; Relun et al., 2017).

In the current analysis, fitted ERGMs were able to well reproduce the overall degree distribution of the observed network, and reasonably well reproduce the degree distribution of each actor type, giving some internal validity to the fitted models. However, the use of star egocentric data inherently limits the quantification of structural network statistics beyond density and degree. Consequently, it was not possible to explore the importance of other local structural statistics for network formation, nor to assess the goodness of fit of models to higher order structural statistics like the distributions of edgewise shared partnerships, and geodesic distances, which are routinely used in ERGM goodness of fit assessment (David R Hunter et al., 2008). While previous ERGM analyses of livestock trade networks have found that higher order statistics can be well reproduced in models lacking local structural terms beyond density (Hammami et al., 2022b), others have found that these terms are needed to achieve optimal fit (Kukielka et al., 2017; Ortiz-Pelaez et al., 2012; Relun et al., 2017).

Despite uncertainty surrounding the extent to which the ERGM-simulated networks reproduced unobserved, higher order network statistics in the Cambodian swine sector, our study demonstrates their potential to capture at least some key structural properties and heterogeneities in livestock trading networks between different types of actors. Such heterogeneities are likely to be important determinants of infectious disease dynamics, and heterogeneities in risks associated with different actors, as illustrated by our simulations of influenza transmission on the modelled networks. The egocentric-ERGM approach presented here therefore represents an important advancement for exploring infectious disease dynamics in relation to livestock value chains, particularly in settings where routine or sociocentric trading data are unavailable and/or extremely challenging to obtain. At the very least, the ERGM-simulated networks presented in this study offered a more nuanced approach for modelling influenza transmission among swine herds compared to previous studies which used fixed, uniform contact probabilities among units (Dorjee et al., 2016; Mateus-Anzola et al., 2019). Nonetheless, these networks are based on the best fit given data limitations meaning results should be interpreted with caution.

In simulations of swine influenza transmission on the modelled contact networks, the highest epidemic probabilities were generated after seeding in breeding farms, even after reducing the infectious duration on those farms. This finding may therefore be explained by the upstream positioning of breeding farms within the value chain characterised by chiefly non-reciprocated pig movement pathways among actor types (Chapter 3). These findings collectively highlight the potential importance of breeding farms in epidemic generation, and suggest that interventions that limit influenza persistence in breeding farms could reduce the likelihood of sustained epidemics and have a large impact on the burden of influenza through the entire production system. Breeding farms may therefore be effective targets for disease control interventions such as vaccination or antivirals. Pig vaccination, especially of sows, has indeed been a primary focus of control of influenza in pigs in the USA, with approximately 70% of large sow farms adopting such measures (Allerson, 2013; Beaudoin et al., 2012). In Cambodia, influenza vaccination in pigs is currently negligible (Osbjer et al., 2017) and antivirals have been highlighted as an useful intervention due to a lack of strain specific vaccines (Dong et al., 2015; Osbjer et al., 2015).

Following seeding in actors other than breeding farms, large epidemics were very unlikely when the probability of transmission via indirect contact was low (i.e. pT(i)=0.01). This finding further reflects the hierarchically organised value chain, which effectively constrains the length of potential infection chains that can occur via direct contact alone suggesting that indirect transmission can be an important mechanism for epidemic generation. This is further reflected by the small size of the largest SCC in comparison to the largest WCC – with the latter describing maximally connected subregions irrespective of edge direction, which is relevant when transmission can occur bidirectionally between suppliers and recipients. The organisation of swine movement networks in other settings have similarly been suggested to limit transmission potential. For example, Rautureau et al. (2012) found that the hierarchical structuring of the swine trade network in France resulted in a network that was fragmented, and comprised of strong components that were small in size i.e. less than 30 holdings when considering monthly farm-farm contact networks. In the current study, the rewiring of networks of ERGM-simulated networks necessitated some important assumptions such as the sequence of visits an intermediary node could make, the direct and indirect contacts such visits could generate, and the assumption that suppliers were indirectly connected to their recipients. Nonetheless, these findings emphasise the potential importance of considering indirect contacts as potential routes for influenza transmission among pig farms, even if the probability of transmission following such contact is low.

Longitudinal IAV virological and serological sampling in pigs within the slaughterhouses studied here was recently conducted via the PigFluCam+ project within which this study was embedded. This activity revealed limited circulation in smallholders compared to commercial farms, with smallholder pigs showing significantly lower pig-level seroprevalence (3.1% vs. 37.7%) and infection prevalence (0.6% vs. 1.5%) (Hidano et al., In prep.). In the current study, we did not attempt to fit the ABNM to this epidemiological data due to challenges in linking batch-level epidemiological data to the fraction of recovered and infectious herds predicted here. Specifically, batches of pigs arriving at slaughterhouses do not reflect the full diversity of pigs on a farm. For instance, sampling only sows at slaughterhouses does not provide a complete estimate of the status of breeding farms, as piglets, weaners, and gilts remain unsampled. Additionally, the fraction of recovered nodes in the ABNM did not always relate to herd-level seroprevalence. This is because nodes transition from recovered to susceptible compartments based on batch replacement frequencies meaning that the fraction of recovered nodes corresponds to seroprevalence of batches of fattening pigs or farrowed piglets. Finally, the use of virological data was also complicated due to evidence of transmission within the slaughterhouse or during transport (Hidano et al., In prep.). Nevertheless, in the ABNM presented here, compared to other actor types, smallholders became ever infected at the slowest rate and had the lowest prevalence at stationarity, while farms - especially breeding farms - became infected sooner, and reached a higher prevalence at stationarity. These qualitative features therefore give some external validity to the results presented here and demonstrate how the differential node-level IAV prevalence and seroprevalence in these producer types can result from their differing infection processes and network positions, highlighting the value of characterising swine contact networks. These observations are also in line with IAV monitoring and surveillance efforts in other contexts which have revealed limited transmission in small-scale swine production settings (Chauhan and Gordon, 2022; Perera et al., 2013; Trevennec et al., 2012) and high prevalence in sow herds compared to fattening herds (Er et al., 2016).

In this study, the short time by which breeding farms and BSP became ever infected highlights these actors as potential targets for IAV surveillance aimed at the early detection and isolation of novel IAV subtypes. The practical viability of virological surveillance in BSP may however be limited given the low virological prevalence throughout the course of the epidemic predicted here, and their small herd sizes (median of 5 pigs; range 1-30; Chapter 3) meaning that outbreaks in a BSP herd are also likely to be short in duration. Pigs in breeding farms, contrastingly, are likely to be suitable target populations for both the early detection novel IAVs and, given their high herd-level prevalence predicted here, during endemic phases. Indeed, previous studies in neighbouring countries have found isolation rates to be highest in weaners and fatteners between 3 weeks and 4.5 months (Takemae et al., 2016, 2011). However, the feasibility of this approach for national surveillance may be limited by a lack of strong data and sample sharing mechanisms between the private and public sectors (Delabouglise et al., 2015; Perez et al., 2019). Pigs originating from the producer types highlighted here could therefore instead be sampled at slaughterhouses so long as their production origins can be established. Slaughterhouse surveillance has indeed been highlighted as a sustainable option in low-resource settings (Baudon et al., 2018; Siengsanan-Lamont et al., 2022).

This study predicted that large commercial farms have a high potential for infection and for seeding large epidemics, contrasting sharply with non-BSP smallholders. While these results may imply that smallholders have limited importance in IAV epidemiology, this study focused on IAV transmission among swine populations and did not consider interspecies transmission. Importantly, smallholder swine production sectors are well-recognised as hotspots for interspecies contact, creating opportunities for viral reassortment (Chea et al., 2020; Osbjer et al., 2017; Vincent et al., 2014). Therefore, even low levels of transmission within this sector could result in major consequences, such as the generation of viruses with pandemic potential. A valuable direction for future research would therefore be to extend the model framework to include a component of zoonotic IAV transmission, an area that has received limited attention to date (Dorjee et al., 2016, 2013).

This model is an abstraction of influenza transmission within the Cambodian swine trade network and therefore made a number of necessary assumptions. The epidemiological unit is the actor meaning that heterogeneity in virological and serological prevalence within herds was not accounted for. This may be justified at the initial stages of an epidemic, since the introduction of a novel subtype into a herd has been shown to infect a large proportion of a herd (Er et al., 2016; Howden et al., 2009; Pasma and Joseph, 2010; Rose et al., 2013). However, approaching the endemic phases, greater heterogeneity in immunity within a herd due to the presence of pig types of variable ages (e.g. sows, boars, piglets), and presence of maternally-derived antibodies in piglets, may influence the transmission process in ways which are not accounted for in this model. Indeed, at endemic phases, virological prevalence may be much lower (Pitzer et al., 2016). The pairing of this between-herd model with a within-herd model could be used to explore such processes and would be an interesting subject of future research.

In the current study, it was not possible to model the effect of geographical distance on edge formation due to a large amount of missing data on the locations of the contacts of commercial farms (84% missing; Chapter 3). ERGM analyses of smallholder swine sectors in other settings have found that geographical mixing influences the organisation of these networks (Relun et al., 2017), however, these effects may be less pronounced in commercial sectors which operate over large spatial scales. This meant the ABNM was not spatially explicit. Descriptive analyses however revealed that smallholders had a tendency to trade with geographically local partners but sometimes traded over long distances (chapter 3). Accounting for such features in the infectious disease models could increase local network clustering, and result in a reduced speed of initial infection growth due to greater depletion of local susceptible nodes.

In our analyses, 'breeding farms' included those raising market pigs as well as those raising replacement gilts. This reflected a shortcoming of our sampling design in that gilt distributor farms (n=2) were not sampled separately and were grouped with breeding farms. Therefore, the role of gilt distributor farms, which would be expected to be upstream of breeding farms in the production system, and likely being smaller in number, could not be quantified. Future surveys should sufficiently sample the full distribution of farm types in order to quantify the importance of these nodes in transmission.

We accounted for transmission via direct pig movements and indirect contact via shared intermediary nodes, or fomites assumed to occur from a recipient to a supplier. However, other forms of indirect contact, such as other on-farm visitors like animal health workers, may be relevant for IAV transmission which were unaccounted for here. The egocentric ERGM methods applied here, however, are well-suited for generating indirect contact networks from diary-based data on such contacts, such as has been descriptively analysed in prior studies (Bates et al., 2001; Brennan et al., 2008; Nöremark et al., 2013).

The egocentric-ERGM method also carried some limitations. Importantly, current specifications limited the simulation of unweighted and undirected networks, however, this is an area under development (Krivitsky and Morris, 2017; Statnet, 2023). Such features are however, important feature of empirical livestock trade networks. In this study, limited reciprocity among different actor types permitted directionality to be added to simulated networks which informed the infectious disease models, but the broader utility of egocentric ERGMs for modelling livestock trade networks may remain limited until progress on this front can be made.

The duration of immunity for growing farms (i.e. 1 production cycle) implies that growing farms are susceptible to infection upon restocking. In reality, beyond the initial stages of an epidemic, growing farms' immune status will depend on that of the breeding farms supplying them (e.g. Poljak et al., 2008a). Growing farms may therefore play an even more limited role in transmission than was predicted.

4.6 Conclusion

In conclusion, this study demonstrates how livestock trade networks can be inferred from relatively simple star-egocentric survey data, and used to study the potential transmission of diseases through livestock value chains. In this study, questionnaires were quite long and complex as they served the dual purpose of updating the characterisation of value chain actors and the network survey. However, the key information required for egocentric-ERGM analysis (i.e. variables of interest for alters, and equivalent data on egos) comprised a much smaller subset of these questions. Therefore, the collection of network data in pre-existing studies using these methods, need not be overly burdensome. These methods could be adopted to other pathogens and livestock types and are well suited to address challenges associated with limited network data availability - especially in resource-constrained settings (Chaters et al., 2019; Lanzas and Chen, 2015), and the application of egocentric data to network-based infectious disease models (Eames et al., 2015). Results from this study further provide useful initial insights into swine influenza transmission dynamics on pig value chain networks, including heterogeneities in the susceptibility of different node types and their relative contributions to transmission.

5 General discussion

In this thesis, through three related studies, I aimed to quantitatively characterise the live pig trade network in Cambodia to identify key points of vulnerability for pathogen introduction and dissemination, with a particular focus on swine IAVs. In so doing, I also aimed to explore and demonstrate how model-based approaches can be applied to simulate epidemiologically-relevant livestock contact networks in data-scarce settings.

This chapter presents an integrated discussion of the findings from this thesis structured around three main areas. First, I summarise the preceding chapters in this thesis. Next, I synthesise the evidence and findings across these chapters to discuss opportunities for targeted disease-control interventions within the Cambodian swine production sector. I then address the limitations of this thesis and discuss potential avenues for future research, focusing on the application of network simulation models to simulate livestock contact networks in data-scarce settings.

5.1 Summary of key findings

I set out to achieve the aims of this thesis via three related studies. In chapter 2, I systematically reviewed the literature on empirically informed, model-based approaches of network (re)-construction or inference in relation to generating epidemiologically relevant contacts among livestock populations. This chapter served to guide the analytical approaches used in this thesis. In chapter 3, I presented the results of an egocentric network analysis of the live pig trade network in south-central Cambodia. An updated typology of value chain actors was presented and their epidemiological relevance was assessed. I then characterised the roles and positions actors within the value chain actors on the basis of their egocentric network statistics. This data was further analysed in chapter 4 using a recently described subclass of ERGMs estimable from the type of star-egocentric data collected in chapter 3 (Krivitsky and Morris, 2017). This analysis revealed relevant factors influencing the organisation of the observed swine trade network and allowed for the simulation of sociocentric networks, calibrated to the egocentric data, which I used to explore the potential transmission dynamics of IAVs, and to inform possible strategies of IAV surveillance in pigs.

5.2 Opportunities for targeted disease control interventions

Livestock movements are commonly studied due to their broad relevance for pathogen transmission (Fèvre et al., 2006). An understanding of network structure is needed for targeted disease management strategies.

For example, many empirical networks, including livestock movement networks, exhibit large heterogeneity in the degree distribution of nodes, with a small set of nodes accounting for a large proportion of contacts (Barabási and Albert, 1999; Keeling and Eames, 2005; Liljeros et al., 2001; Shirley and Rushton, 2005; Woolhouse et al., 2005). Targeting such nodes can therefore be an efficient and cost-effective strategy for disease control in livestock populations (Fournie et al., 2013; Kiss et al., 2006; Marquetoux et al., 2016). Targeting highly connected nodes with non-specific preventative disease-control measures offers the potential to reduce the overall potential for pathogen dissemination through the trade network. Such measures may function to limit transmission via highly connected nodes, or to alter the network towards configurations that limit disease spread (e.g. Gates and Woolhouse, 2015; Tago et al., 2016). In this thesis, descriptive network analysis in chapter 3 demonstrated that the value chain of swine movements was hierarchically organised and that some actors, especially BSP and, to a lesser extent, middlemen had high in- and out-degree compared to others. In chapter 4, I demonstrated that the global degree distribution of the network was right tailed.

These finding highlight opportunities for targeted disease control interventions in the Cambodian swine sector. Limiting transmission via brokers such as BSP, middlemen, and breeding farms, could be achieved by improving biosecurity and biocontainment practices in these nodes and/or nodes in contact with them. In chapter 3, the characterisation of actors revealed considerable scope for improvement of biosecurity. For example, I found that middlemen commonly entered pig holding areas, collected and delivered pigs to multiple sites in a single trip, and kept traded pigs from multiple sources for several days before resale. Similarly, smallholders and BSP had low rates of implementation of biosecurity measures, including the restriction of visitors' access to pig pens, consistent findings from other studies of Cambodian smallholders (Chea et al., 2020; Young et al., 2017) .

Despite such opportunities, financial and resource constraints pose considerable barriers to enhancing biosecurity in smallholder production systems (e.g. Chenais et al., 2017; S. Costard et al., 2009). Moreover, multiple studies have demonstrated that increased knowledge and awareness of preventative disease control measures does not always translate into behavioural change (Agrawal et al., 2023; Brennan and Christley, 2013; Durrance-Bagale et al., 2021; Kiambi et al., 2021). Despite these potential challenges, in Cambodia and Laos, long-term knowledge-based interventions have been shown to effectively improve biosecurity practices among smallholders (MacPhillamy et al., 2022). Targeting high-risk brokers with such interventions could therefore be an efficient allocation of scarce-resources.

The promotion of artificial insemination (AI) could be an effective strategy in the context of targeted disease-control measures which function to alter the network towards inherently disease-limiting configurations. Findings from chapter 3 demonstrated that smallholders commonly hired boars for breeding, consistent with observations in other Cambodian provinces (Chea et al., 2020). Notably, BSP comprised the majority of contacts reported by breeding-orientated smallholders. In chapter 4, based on the assumptions made in the network rewiring strategy, visits by BSP and other intermediary nodes generated highly clustered networks. Therefore, eliminating connections made by BSP, who had the highest degree of any actor type, could limit the potential for disease transmission removing a large number of BSP-associated edges and fragmenting the network. Indeed, AI has been associated with improved disease management in pig production in Europe and the USA (Leiding, 2000), and been shown to be feasible in smallholder pig production settings where it can improve the productivity and the profitability of pig enterprises (Am-in et al., 2010; Sharma et al., 2020; Singh et al., 2022). In the Philippines, when boar lending among farms was prohibited to limit transmission of ASF and COVID-19, AI generated a source of income for BSP (Pena et al., 2023). AI requires investment in training, equipment, and necessitates an availability of disease-free boar centres and superior germplasm (Kadirvel et al., 2013; Sharma et al., 2020). However, in the wake of the ongoing ASF epidemics in Cambodia and across SEA – due to multiple factors such as the potential for ASF transmission via boar lending (Kalenzi Atuhaire et al., 2013; Nantima et al., 2015), the high vulnerability of smallholder pigs to infection, their purported role in ASF epidemiology in SEA (Dixon et al., 2020; Kedkovid et al., 2020; Normile, 2019), and the limited financial resilience of smallholders (Mason-D'Croz et al., 2022) – such investment may be necessary for the sustainability of smallholder production and for ASF-control in the region more broadly.

Understanding network structure provides valuable insights into the general disease spreading processes, but the actual transmission dynamics of an infectious agent, and consequently the effectiveness of targeted interventions, are of course influenced by other factors such as infectivity, speed of transmission, and related – the suitable timeframe for aggregating contacts in the network (Craft, 2015; Cross et al., 2005; Kao et al., 2007). Further work is needed to establish the potential benefits of such targeted interventions for specific diseases. Some avenues for future research on this front are discussed in section 5.4 below.

5.3 Limitations

This thesis quantitatively characterised swine trade networks in Cambodia, and applied ERGMs to reconstruct complete swine trade networks which were used to explore the potential dynamics of IAVs within the swine sector. Collectively, this work identified actors at a high risk of disease introduction and dissemination, predicted possible targets for IAV surveillance, and presented novel tools relevant to livestock network characterisation in data-scarce settings. However, these results need to be considered in light of a number of limitations.

Network surveys were conducted over multiple years during a period of considerable disruption due to concurrent ASF and COVID-19 pandemics. Therefore, the representativeness of this data, e.g. beyond these periods of disruption, remains uncertain. Additionally, the swine sector in Cambodia has been undergoing rapid intensification over the past decade (Asian Development Bank, 2022) meaning the data captured in this thesis may become quickly outdated. The rapidly changing landscape underscores the need for continued updating of network data to accurately assess evolving disease risks. Despite these limitations, the methods applied in this thesis may be well suited to such challenges, as is discussed in the section 5.4 .

In this thesis, I characterised the types of actor in the Cambodian swine trade network, and the interactions between them. However, while the study site was chosen for its high pig density and diversity of pig production types represented, sampling of egos was geographically limited to 4 provinces. Moreover, a large amount of missing data on the locations of farm's alters precluded a comprehensive analysis of spatial pig movements. Given the international nature of pig value chains, and the risk posed by transboundary animal diseases such as FMD, ASF, and IAVs in Cambodia (Asian Development Bank, 2022), there is a critical need for quantitative characterisation of pig movements across large spatial scales. In countries where livestock movement permits are systematically recorded, such data has been used to empirically describe livestock trade networks (e.g. Wiratsudakul et al., 2022) or to support model-based approaches for inferring networks from this data (e.g. Chaters et al., 2019; Lindström et al., 2013; Sellman et al., 2022b; Chapter 2). In Cambodia, although livestock movements across provincial boundaries officially require health certificates, enforcement is weak (ACIAR, 2012; Borin and Henrichs, 2012). Considering these challenges, engaging the commercial sector is crucial to comprehensively capture the spatial flows of pigs. During network surveys, we faced significant obstacles in accessing this information as farm workers had limited knowledge of intra-company pig movements. Therefore, there is a need to identify key stakeholders within the commercial sector who hold such information.

Finally, in chapter 4, I conducted limited model validation. Specifically, some internal validation of ERGMs was conducted based on comparison between the global- and actor stratified- degree distribution of empirical and simulated networks. However, it remains unclear if simulated networks are a good fit to other unobserved higher-order structures which may be relevant for disease transmission dynamics. Nonetheless, ABNM predictions achieved some degree of external-validation based on qualitative comparison between predicted herd-level IAV prevalence between smallholders and commercial farms, and observed seroprevalence and infection prevalence of pigs sampled in slaughterhouses in the same study area (Hidano et al., In prep.). More robust external validation based on quantitative comparison to herd-level virological and/or serological prevalence in smallholder and commercial farming systems would be a valuable step forward on this front.

5.4 Future research and directions

Findings from Chapter 2 reveal a geographical bias in the distribution of countries where network simulation models have been developed, suggesting significant potential for broader application in regions currently under-served by such tools. Notably, the majority of these models have been implemented in the USA, where livestock trade data are not centrally recorded due to data privacy and commercial concerns. Various model-based approaches, including the US Animal Movement Model (USAMM), have been developed to simulate national-scale livestock movements, predict the spread of major livestock diseases, and support decision-making for optimal disease management strategies (Brommesson et al., 2021; Buhnerkempe et al., 2014, 2013; Gilbertson et al., 2022, 2022; Gorsich et al., 2018, 2016; Lindström et al., 2013; Tsao et al., 2020).

These types of large-scale modelling approaches could prove invaluable in regions with limited livestock movement data and where livestock and poultry production are rapidly growing and intensifying, and the landscape of disease risk evolving. A recent ABM-based innovation, 'EPINEST' (Pinotti et al., 2024), simulates poultry production and distribution networks based on data from cross-sectional network surveys in Bangladesh. This model facilitates the simulation of pathogen transmission on these networks, addressing gaps in our understanding of livestock disease dynamics in rapidly changing agricultural settings, and helping to redress these geographical disparities in the application of such models.

The ability to apply ERGMs to simple, star-egocentric data opens interesting opportunities in the context of livestock network characterisation, despite outstanding limitations (discussed in chapter 4). For example, the ability to infer complete networks from a single wave of sampling could facilitate the collection of temporal network data by repeatedly surveying the same nodes. Such methods could be applied to quantify temporal network evolution, for example as livestock sectors transform, or to capture seasonally. Moreover, such methods could be used to explore how actors, and consequently network structure, respond to external factors such as market conditions, disease outbreaks, and/or disease control interventions like movement restrictions.

In this thesis, network surveys were conducted using mobile devices and digitised questionnaires. With adequate training and incentives, this data could be self-entered by interviewees using mobile devices, or entered by village animal health workers. Previous research in Cambodia has highlighted the potential to leverage adaptive mobile phone-based solutions to enhance the collection and sharing of animal health data in resource constrained settings (Goutard et al., 2015). In Cambodia, mobile-based participatory systems of disease surveillance have received recent attention, including through a mobile-based malaria reporting systems for village animal health workers (Ngor et al., 2018), and partially automated contact tracing during the COVID-19 pandemic (Lan et al., 2022). Mobile-based solutions to animal health surveillance have also been adopted in Indonesia marking this as an interesting and feasible opportunity to bridge important data gaps related to livestock contact networks (Fadillah et al., 2019).

The agent-based network modelling framework developed in this thesis accounts for the structure of the Cambodian swine trade network and allows for adjustments in the aggregation period of contacts. This makes it a useful tool for exploring disease management scenarios. For example, this framework could be repurposed to explore the role of BSP in ASF transmission. In chapter 4, I found that BSP had a limited propensity to initiate sustained IAV transmission, and so interventions mentioned previously, such as the promotion of AI, may have limited beneficial impacts to the swine sector directly. However, for diseases with longer node-level infectious durations, e.g. extended herd-level persistence or a prolonged period for transmission via fomites, the role of BSP could be more significant. Given the high potential for interspecies contact and interspecies IAV transmission in smallholder swine settings (Chea et al., 2020; Osbjer et al., 2017; Vincent et al., 2014), another valuable direction for future research would be to extend the model framework presented here to include a component of zoonotic IAV transmission – an area of research that has so far received limited attention (e.g. Dorjee et al., 2016, 2013).

6 Conclusions

Limited routine systems of recording livestock movements in many countries presents a challenge to effective disease control and underscores the need to develop solutions to address these data gaps. This thesis quantitatively characterised, for the first time, the live pig trade network in Cambodia and explored methods of network sampling and simulation which can be applied to address these challenges.

This work identified breeding farms, BSP, and middlemen as actors at a high risk of disease introduction and dissemination through the network on account of the large number of in- and out-going connections they made with producers. Breeding farms, were found to have a particularly high potential for pathogen dissemination, including for IAVs, as they supplied pigs to all other producer types.

Recent advances in ERGMs enable the inference of complete networks from egocentric data. This approach offers an informative and efficient method for livestock network characterisation, particularly valuable in resource-limited or data-constrained settings. Additionally, these methods are well suited to repeated network data capture and could be applied to monitor evolving trade network and associated disease risks. More broadly, model-based approaches of network simulation and inference are valuable tools for filling existing data gaps within livestock trade networks. Future research should aim to refine these models and develop robust methods for their validation, thereby enhancing their utility in supporting effective disease management strategies in settings with limited data.

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8 Supplementary information

8.1 Supplementary: Chapter 2

Table S 8.1. ***Systematic review search strategy.*** *Search terms and subject headings used for database queries for Medline, Embase, Web of Science, and Scopus. The number of papers found via each of these searces is also shown.*

DATABASE	1. Livestock	2. Network	3. Model	4. Disease	# papers (topics 1-4)
MEDLINE Subject headings:	livestock/ or poultry/ or ruminants/ or cattle/ or goats/ or sheep/ or exp swine/ or ducks/ or geese/ or exp Galliformes/ or Horses/ OR		exp Models, Statistical/ or exp Artificial Intelligence/ OR	□ exp "diseases (non mesh)"/ or exp disease eradication/ or exp disease outbreaks/ or exp disease reservoirs/ or exp disease transmission, infectious/ or exp endemic diseases/ or exp Public Health Surveillance/ OR	
MEDLINE key words:	((live adj3 animal*) OR livestock OR cattle OR cow* OR calf* OR heifer* OR bovine OR bovid* OR swine OR pig* OR porcine OR boar* OR poultry OR avian OR bird* OR chicken* OR duck* OR fowl OR goose OR geese OR waterfowl OR broiler* OR sheep OR ovine OR ewe OR ewes OR herder* OR goat* OR caprine OR horse* OR equine* OR ruminant* OR camel* OR llama* OR alpaca* or *deer).mp. AND	((network* or "graph theory" or (random adj3 graph*)).mp. or (*directed/ adj3 graph*.mp.) or (*weighted/ adj3 graph*.mp.) or "adjacency matri*".mp. or "contact matri*".mp. or sociogram*.mp.) AND	((network adj4 simul*) or (Erd#s adj2 R#nyi) or small-world or (watts adj2 strogatz) or (Barab#si adj2 Albert) or preferential-attachment or ERGM* or p1 model* or p2 model* or stochastic-block or network-block or blockmodel* or block-model* or agent-based or individual-based or Multiple regression quadratic assignment or MRQAP or Stochastic actor oriented or SAOM or latent-space or latent-network or latent-variable or gravity model* or radiation model or random forest or machine learning or (markov adj4 model) or (network adj3 model) or model* or simulat*).mp. AND	(disease* OR infect* OR contagio* OR zoono* OR epidemi* OR endemic* OR pandemic* OR *zootic OR outbreak OR transmiss* OR transmit* OR pathogen* OR fomite* OR *virus* OR *viral* or bacteri* OR virulen* OR surveillance).mp.	3,660
EMBASE: Subject headings:	exp livestock/ or exp bovine/ or exp pig breed/ or exp pig/ or exp pig farming/ or exp poultry farming/ or exp poultry/ or exp poultry egg/ or exp chicken/ or exp chicken breed/ or exp duck/ or exp domestic fowl/ or exp fowl/ or exp sheep/ or exp goat/ or exp equus/ or exp camel/ OR		exp statistical model/ or exp artificial intelligence/ or disease model/ or exp disease simulation/ or exp mathematical model/ OR	exp animal disease/ or exp disease control/	
EMBASE key words:	((live adj3 animal*) OR livestock OR cattle OR cow* OR calf* OR heifer* OR bovine OR bovid* OR swine OR pig* OR porcine OR boar* OR poultry OR avian OR bird* OR chicken* OR duck* OR fowl OR goose OR geese OR waterfowl OR broiler* OR sheep OR ovine OR ewe OR ewes OR herder* OR goat* OR caprine OR horse* OR equine* OR ruminant* OR camel* OR llama* OR alpaca* or *deer).mp. AND	((network* or "graph theory" or (random adj3 graph*)).mp. or (*directed/ adj3 graph*.mp.) or (*weighted/ adj3 graph*.mp.) or "adjacency matri*".mp. or "contact matri*".mp. or sociogram*.mp.) AND	((network adj4 simul*) or (Erd#s adj2 R#nyi) or small-world or (watts adj2 strogatz) or (Barab#si adj2 Albert) or preferential-attachment or ERGM* or p1 model* or p2 model* or stochastic-block or network-block or blockmodel* or block-model* or agent-based or individual-based or Multiple regression quadratic assignment or MRQAP or Stochastic actor oriented or SAOM or latent-space or latent-network or latent-variable or gravity model* or radiation model or random forest or machine learning or (markov adj4 model) or (network adj3 model) or model* or simulat*).mp. AND	(disease* OR infect* OR contagio* OR zoono* OR epidemi* OR endemic* OR pandemic* OR *zootic OR outbreak OR transmiss* OR transmit* OR pathogen* OR fomite* OR *virus* OR *viral* or bacteri* OR virulen* OR surveillance).mp.	3,605
Web of Science:	(live NEAR/2 animal* OR livestock OR cattle OR cow* OR calf* OR heifer* OR bovine OR bovid* OR swine OR pig* OR porcine OR boar* OR poultry OR avian OR bird* OR chicken* OR duck* OR fowl OR goose OR geese OR waterfowl OR broiler* OR sheep OR ovine OR ewe OR ewes OR herder* OR goat* OR caprine OR horse* OR equine* OR ruminant* OR camel* OR llama* OR alpaca* or *deer) AND	(network* or "graph theory" OR random NEAR/2 graph* OR *directed NEAR/2 graph* OR *weighted NEAR/2 graph* OR "adjacency matri*" OR "contact matri*" OR sociogram*) AND	(network NEAR/3 simul* OR Erd?s NEAR/1 R?nyi OR small-world OR watts NEAR/1 strogatz OR Barab?si NEAR/1 Albert OR preferential-attachment OR ERGM* OR "p1 model*" OR "p2 model*" OR stochastic-block OR network-block OR blockmodel* OR block-model* OR agent-based OR individual-based OR "Multiple regression quadratic assignment" OR MRQAP OR "Stochastic actor oriented" OR "SAOM" OR latent space OR latent-network OR latent-variable OR "gravity model*" OR "radiation model*" OR "random forest" OR "machine learning" OR markov NEAR/3 model OR model* or simulat*) AND	(disease* OR infect* OR contagio* OR zoono* OR epidemi* OR endemic* OR pandemic* OR *zootic OR outbreak OR transmiss* OR transmit* OR pathogen* OR fomite* OR *virus* OR *viral* or bacteri* OR virulen* OR surveillance)	4,540
Scopus:	((live w/2 animal*) OR livestock OR cattle OR cow* OR calf* OR heifer* OR bovine OR bovid* OR swine OR pig* OR porcine OR boar* OR poultry OR avian OR bird* OR chicken* OR duck* OR fowl OR goose OR geese OR waterfowl OR broiler* OR sheep OR ovine OR ewe OR ewes OR herder* OR goat* OR caprine OR horse* OR equine* OR ruminant* OR camel* OR llama* OR alpaca* or *deer) AND	(network* OR "graph theory" OR (random w/2 graph*) OR (*directed w/2 graph*) OR (*weighted w/2 graph*) OR "adjacency matri*" OR "contact matri*" OR sociogram*) AND	((network w/3 simul*) OR (Erd?s w/1 R?nyi) OR small-world OR (watts w/1 strogatz) OR (Barab?si w/1 Albert) OR preferential-attachment OR ERGM* OR "p1 model*" OR "p2 model*" OR stochastic-block OR network-block OR blockmodel* OR block-model* OR agent-based OR individual-based OR "Multiple regression quadratic assignment" OR MRQAP OR "Stochastic actor oriented" OR "SAOM" OR latent space OR latent-network OR latent-variable OR "gravity model*" OR "radiation model*" OR "random forest" OR "machine learning" OR (markov w/3 model) OR model* or simulat*) AND	(disease* OR infect* OR contagio* OR zoono* OR epidemi* OR endemic* OR pandemic* OR *zootic OR outbreak OR transmiss* OR transmit* OR pathogen* OR fomite* OR *virus* OR *viral* or bacteri* OR virulen* OR surveillance)	421
					12,226

8.2 Supplementary: Chapter 3

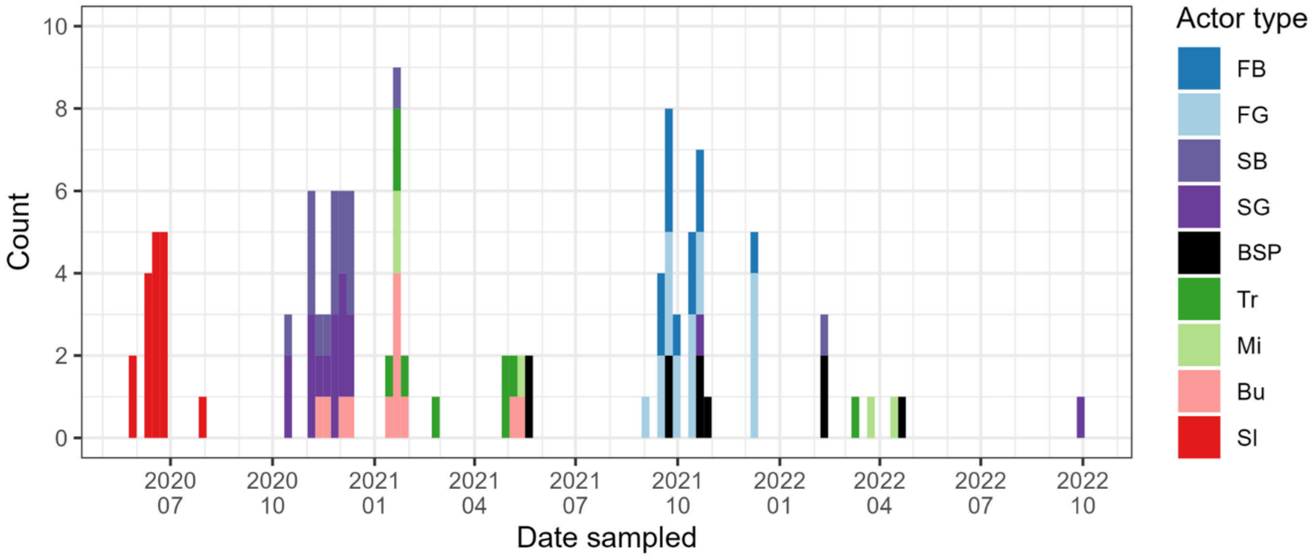

*Figure S 8.1. **Interview dates:** Actor types show breeding farms (FB), growing farms (FG), breeding smallholders (SB), growing smallholders (SG), boar service providers (BSP), traders (Tr), Middlemen (Mi), butchers (Bu) and slaughterhouses (Sl).*

*Table S 8.2. **Biosecurity measures.** On-site biosecurity measures asked about within the producer surveys*

Biosecurity measure
Vehicle wheel washes at site entrance
Boot dip stations at site entrance
Boot dip stations at pig house entrances
Disposable shoe covers used when entering pig pens/houses
Staff PPE (clothing and footwear) is used, and kept on site
Visitor PPE (clothing and footwear) is used, and kept on site
Site is contained within a livestock-proof (not including poultry) perimeter fence
Use of mosquito nets
Restrict visitors' access to pig pens
Restrict access to people who have contacted other pigs
Don't know
Other
None of the above

*Table S 8.3. **Variables used for producer typology generation:** Variable types could be quantitative (quant) or categorical (cat). Active variables contributed to the construction of the FAMD dimensions in contrast to supplementary (Supp) variables which were used to describe the dimensions.*

Variable	Type	Active / Supp	Notes
Site information			
Years operating	quant	Supp	Number of years this producer has kept pigs
Ownership	cat	Active	Type of ownership this farm/site has
Pigs present			
Total pigs	quant	Active	Total pigs on site at the time of visit
Sows present	cat	Supp	Pig type present/absent (binary variable)
Boars present	cat	Supp	Pig type present/absent (binary variable)
Piglets present	cat	Supp	Pig type present/absent (binary variable)
Weaners present	cat	Supp	Pig type present/absent (binary variable)
Growers/finishers present	cat	Supp	Pig type present/absent (binary variable)
Sows	quant	Active	Number on site at the time of visit
Boars	quant	Active	Number on site at the time of visit
Piglets	quant	Supp	Number on site at the time of visit
Weaners	quant	Active	Number on site at the time of visit
Growers/finishers	quant	Active	Number on site at the time of visit
Breeds present	cat	Active	Breeds raised in the past 6 months
Herd management			
Pigs per pen	quant	Active	Number of pigs are kept together in a pen
All in all out	cat	Active	All in all out type: barns/rooms/pens/none (i.e. where different batches of pigs are kept in separate and do not mix)
Pig housing: group, same types	cat	Active	Pig housing type (binary variable)
Pig housing: group, mixed types	cat	Active	Pig housing type (binary variable)
Pig housing: individual	cat	Active	Pig housing type (binary variable)
Pig housing: tethered / free-range	cat	Active	Pig housing type (binary variable)
Disinfects pig pens: between batches	cat	Active	Frequency of disinfection (binary variable)
Disinfects pig pens: never	cat	Active	Frequency of disinfection (binary variable)
Disinfects pig pens: after illness	cat	Supp	Frequency of disinfection (binary variable)
Disinfects pig pens: weekly	cat	Active	Frequency of disinfection (binary variable)
Disinfects pig pens: >weekly	cat	Active	Frequency of disinfection (binary variable)
Pig feed: Rice grain / agri. by-product	cat	Active	Pig feed types used (binary variable)
Pig feed: commercial feed	cat	Active	Pig feed types used (binary variable)
Pig feed: swill	cat	Active	Pig feed types used (binary variable)
Pig feed: forage / graze	cat	Active	Pig feed types used (binary variable)
Vaccinates pigs	cat	Active	(self-explanatory)
Clinical exam for pig introductions	cat	Active	(self-explanatory)
Purchases and sales			
Receives from producers	cat	Active	(self-explanatory)
Receives from pig-exchangers	cat	Active	(self-explanatory)
Receives from companies	cat	Active	(self-explanatory)
Receives from BSP	cat	Active	(self-explanatory)
Receives sows	cat	Active	(self-explanatory)

Receives growers/finishers	cat	Active	(self-explanatory)
Receives weaners	cat	Active	(self-explanatory)
Receives boars (hired)	cat	Active	(self-explanatory)
Receives A.I. doses	cat	Active	(self-explanatory)
Sends to producers	cat	Active	(self-explanatory)
Sends to pig-exchangers	cat	Active	(self-explanatory)
Sends to companies	cat	Active	(self-explanatory)
Sends sows	cat	Active	(self-explanatory)
Sends growers/finishers	cat	Active	(self-explanatory)
Sends weaners	cat	Active	(self-explanatory)
Sends boars (lent)	cat	Active	(self-explanatory)
Biosecurity measures			
Mosquito nets over pig pens	cat	Active	(self-explanatory)
Restricts site access to contacts of pigs	cat	Active	(self-explanatory)
Restrict visitors' access to pig pens	cat	Active	(self-explanatory)
Vehicle wheel washes at site entrance	cat	Active	(self-explanatory)
Livestock-proof perimeter fence	cat	Active	(self-explanatory)
Use of boot dip stations	cat	Active	(self-explanatory)
Use of staff / visitor PPE	cat	Active	(self-explanatory)
Restricts wild birds' access to pigs	cat	Active	(self-explanatory)
Restricts farmed birds' access to pigs	cat	Active	(self-explanatory)
Restricts wild birds' access to pig feed	cat	Active	(self-explanatory)
Restricts farmed birds' access to pig feed	cat	Active	(self-explanatory)
No biosecurity measures	cat	Active	(self-explanatory)

*Table S 8.4. **Variables used for pig exchanger typology generation:** Variable types could be quantitative (quant) or categorical (cat). Active variables contributed to the construction of the FAMD dimensions in contrast to supplementary (Supp) variables which were used to describe the dimensions.*

Variable	Type	Active / Supp	Notes
General information			
Years working as a pig-exchanger	quant	Supp	(self-explanatory)
License held	cat	Supp	Trading, selling meat, or none
Raises their own pigs	quant	Supp	(self-explanatory)
Purchases and sales			
Receives from smallholders	cat	Active	(self-explanatory)
Receives from companies	cat	Active	(self-explanatory)
Receives from pig-exchangers	cat	Active	(self-explanatory)
Receives from farms	cat	Active	(self-explanatory)
Number of suppliers	quant	Active	Total suppliers in the past 14 days
Receives sows	cat	Active	(self-explanatory)
Receives weaners	cat	Active	(self-explanatory)
Receives finishers	cat	Active	(self-explanatory)
Number of live pigs purchased	quant	Active	Total pigs purchased in the past 14 days
Sends to smallholders	cat	Active	(self-explanatory)
Sends to pig-exchangers	cat	Active	(self-explanatory)
Sends to slaughter points	cat	Active	(self-explanatory)
Sends to markets	cat	Active	(self-explanatory)
Number of recipients	quant	Active	Total recipients in the past 14 days
Sends sows	cat	Active	(self-explanatory)
Sends weaners	cat	Active	(self-explanatory)
Sends finishers	cat	Active	(self-explanatory)
Number of live pigs sold	quant	Active	Total pigs sold in the past 14 days
Catchment area (no. districts)	quant	Active	Number of districts most of their trading activity is conducted in
Trade practices		Active	
Days actively trading (in past 14 days)	quant	Active	(self-explanatory)
Pigs kept in intermediary location	cat	Active	In the past 14 days, whether purchased pigs were kept at an intermediary location for any length of time before sale/slaughter, OR kept at the place of slaughter for over 24 hours before they were killed
Location pigs are kept	cat	Supp	If pigs were kept at an intermediary location, the location pigs were kept (e.g. at home, at slaughterhouse)
Duration pigs are kept (hours)	quant	Supp	If pigs were kept at an intermediary location, the average duration they were kept in that location
Pigs from different origins can contact each other	cat	Supp	If pigs were kept at an intermediary location, whether pigs from different origins were able to come into direct contact with each other
Transports pigs	cat	Active	(self-explanatory)
Vehicles used	cat	Supp	If they transported pigs, the vehicle types used to transport pigs

No. pigs transported in one trip	quant	Supp	If they transported pigs, the vehicle types used to transport pigs?
Collects pigs from multiple sites in one trip	cat	Supp	(self-explanatory)
Delivers pigs to multiple sites in one trip	cat	Supp	(self-explanatory)
Enters pig holding areas	cat	Supp	Whether they ever enter pig pens/housing when collecting/delivering pigs

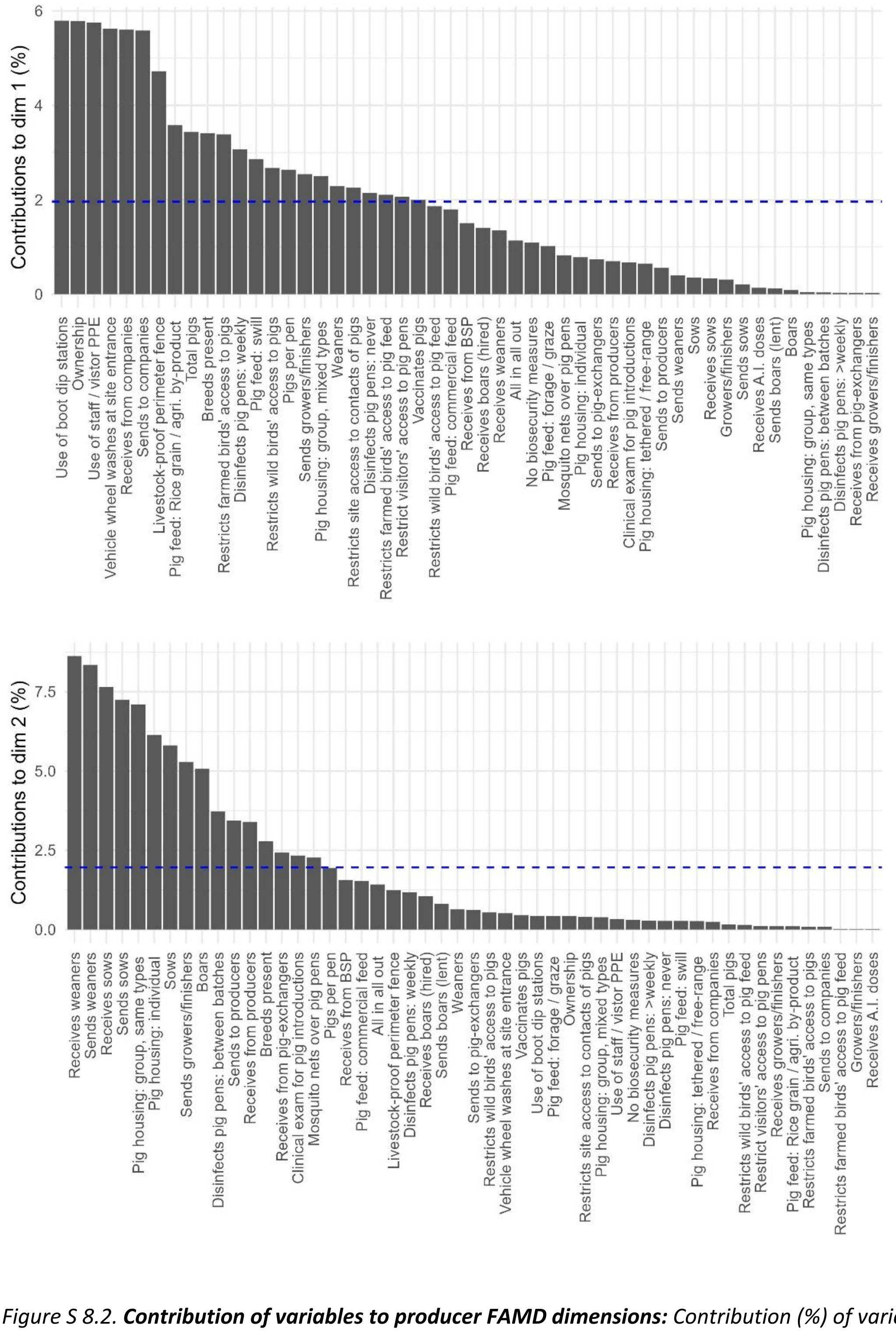

Figure S 8.2. ***Contribution of variables to producer FAMD dimensions:*** *Contribution (%) of variables to the formation of FAMD dimensions 1 to 2 – arranged from the highest contributing variables to the least. Dashed line shows the expected contribution of variables if they contributed uniformly to the dimensions (e.g. 100/number of active variables).*

Table S 8.5. ***Summary of producer types:*** *Description of producer clusters generated by FAMD and HCA.*

Variable	FB (N=21)	FG (N=68)	BSP (N=19)	SB (N=104)	SG (N=77)	Overall (N=289)
SITE INFORMATION						
Year operating*	10.0 [0.600, 19.0]	5.00 [1.00, 23.0]	10.0 [1.00, 30.0]	20.0 [0.300, 40.0]	10.0 [0.500, 40.0]	10.0 [0.300, 40.0]
Ownership						
company	1 (4.8%)	2 (2.9%)	0 (0%)	0 (0%)	0 (0%)	3 (1.0%)
contacted to a company	17 (81.0%)	65 (95.6%)	0 (0%)	0 (0%)	0 (0%)	82 (28.4%)
cooperative	0 (0%)	1 (1.5%)	0 (0%)	0 (0%)	0 (0%)	1 (0.3%)
single person / family	3 (14.3%)	0 (0%)	19 (100%)	104 (100%)	77 (100%)	203 (70.2%)
PIGS PRESENT						
Total pigs	884 [175, 13000]	2700 [25.0, 12000]	5.00 [1.00, 30.0]	2.00 [1.00, 71.0]	10.0 [1.00, 180]	11.0 [1.00, 13000]
Sows present*	21 (100%)	0 (0%)	11 (57.9%)	100 (96.2%)	42 (54.5%)	174 (60.2%)
Boars present*	13 (61.9%)	0 (0%)	19 (100%)	5 (4.8%)	2 (2.6%)	39 (13.5%)
Piglets present*	8 (38.1%)	0 (0%)	6 (31.6%)	11 (10.6%)	6 (7.8%)	31 (10.7%)
Weaners present*	3 (14.3%)	61 (89.7%)	1 (5.3%)	13 (12.5%)	14 (18.2%)	92 (31.8%)
Growers/finishers present*	0 (0%)	8 (11.8%)	2 (10.5%)	15 (14.4%)	60 (77.9%)	85 (29.4%)
Sows	737 [0, 6500]	0 [0, 0]	2.00 [0, 15.0]	2.00 [0, 13.0]	1.00 [0, 17.0]	1.00 [0, 6500]
Boars	3.00 [0, 35.0]	0 [0, 0]	2.00 [1.00, 10.0]	0 [0, 3.00]	0 [0, 2.00]	0 [0, 35.0]
Piglets*	0 [0, 6500]	0 [0, 0]	0 [0, 20.0]	0 [0, 22.0]	0 [0, 14.0]	0 [0, 6500]
Weaners	0 [0, 1400]	2050 [0, 12000]	0 [0, 5.00]	0 [0, 20.0]	0 [0, 60.0]	0 [0, 12000]
Growers/finishers	0 [0, 0]	0 [0, 4200]	0 [0, 7.00]	0 [0, 30.0]	8.00 [0, 120]	0 [0, 4200]
Breeds present						
cross-breed	2 (9.5%)	25 (36.8%)	18 (94.7%)	84 (80.8%)	76 (98.7%)	205 (70.9%)
exotic breed - imported	2 (9.5%)	5 (7.4%)	0 (0%)	0 (0%)	0 (0%)	7 (2.4%)
exotic breed - locally raised	17 (81.0%)	38 (55.9%)	1 (5.3%)	7 (6.7%)	0 (0%)	63 (21.8%)
local	0 (0%)	0 (0%)	0 (0%)	13 (12.5%)	1 (1.3%)	14 (4.8%)
HERD MANAGEMENT						
Pigs per pen	1.00 [1.00, 18.0]	28.0 [20.0, 500]	1.00 [1.00, 6.00]	1.00 [1.00, 30.0]	7.00 [1.00, 20.0]	2.00 [1.00, 500]
All in all out						
by barn	3 (14.3%)	3 (4.4%)	0 (0%)	2 (1.9%)	1 (1.3%)	9 (3.1%)
by room	18 (85.7%)	62 (91.2%)	13 (68.4%)	48 (46.2%)	37 (48.1%)	178 (61.6%)
by pen	0 (0%)	2 (2.9%)	4 (21.1%)	28 (26.9%)	19 (24.7%)	53 (18.3%)
no	0 (0%)	1 (1.5%)	2 (10.5%)	26 (25.0%)	11 (14.3%)	40 (13.8%)
unknown	0 (0%)	0 (0%)	0 (0%)	0 (0%)	9 (11.7%)	9 (3.1%)
Pig housing: group, same types	1 (4.8%)	23 (33.8%)	2 (10.5%)	22 (21.2%)	55 (71.4%)	103 (35.6%)
Pig housing: group, mixed types	2 (9.5%)	45 (66.2%)	1 (5.3%)	4 (3.8%)	6 (7.8%)	58 (20.1%)
Pig housing: individual	18 (85.7%)	0 (0%)	16 (84.2%)	66 (63.5%)	25 (32.5%)	125 (43.3%)
Pig housing: tethered / free-range	0 (0%)	0 (0%)	0 (0%)	29 (27.9%)	4 (5.2%)	33 (11.4%)
Disinfects pig pens: between batches	0 (0%)	6 (8.8%)	2 (10.5%)	6 (5.8%)	30 (39.0%)	44 (15.2%)
Disinfects pig pens: never	0 (0%)	0 (0%)	1 (5.3%)	76 (73.1%)	21 (27.3%)	98 (33.9%)
Disinfects pig pens: after illness*	0 (0%)	1 (1.5%)	0 (0%)	1 (1.0%)	0 (0%)	2 (0.7%)
Disinfects pig pens: weekly	20 (95.2%)	56 (82.4%)	12 (63.2%)	9 (8.7%)	12 (15.6%)	109 (37.7%)
Disinfects pig pens: >weekly	1 (4.8%)	6 (8.8%)	3 (15.8%)	11 (10.6%)	16 (20.8%)	37 (12.8%)
Pig feed: Rice grain / agri. by-product	0 (0%)	0 (0%)	8 (42.1%)	93 (89.4%)	53 (68.8%)	154 (53.3%)
Pig feed: commercial feed	21 (100%)	68 (100%)	13 (68.4%)	39 (37.5%)	73 (94.8%)	214 (74.0%)
Pig feed: swill	0 (0%)	0 (0%)	9 (47.4%)	85 (81.7%)	30 (39.0%)	124 (42.9%)
Pig feed: forage / graze	0 (0%)	0 (0%)	7 (36.8%)	37 (35.6%)	10 (13.0%)	54 (18.7%)
Vaccinates pigs						
yes	21 (100%)	66 (97.1%)	18 (94.7%)	32 (30.8%)	53 (68.8%)	190 (65.7%)
unsure	0 (0%)	2 (2.9%)	0 (0%)	0 (0%)	4 (5.2%)	6 (2.1%)
no	0 (0%)	0 (0%)	1 (5.3%)	72 (69.2%)	20 (26.0%)	93 (32.2%)
Clinical exam for pig introductions						
always	16 (76.2%)	63 (92.6%)	7 (36.8%)	59 (56.7%)	59 (76.6%)	204 (70.6%)
sometimes	0 (0%)	2 (2.9%)	0 (0%)	0 (0%)	5 (6.5%)	7 (2.4%)
never	2 (9.5%)	3 (4.4%)	0 (0%)	26 (25.0%)	4 (5.2%)	35 (12.1%)
unsure	1 (4.8%)	0 (0%)	0 (0%)	6 (5.8%)	3 (3.9%)	10 (3.5%)
NA (did not purchase pigs)	2 (9.5%)	0 (0%)	12 (63.2%)	13 (12.5%)	6 (7.8%)	33 (11.4%)
Routinely quarantines purchased pigs*						
always	8 (38.1%)	1 (1.5%)	0 (0%)	0 (0%)	2 (2.6%)	11 (3.8%)
sometimes	0 (0%)	0 (0%)	0 (0%)	0 (0%)	2 (2.6%)	2 (0.7%)
never	9 (42.9%)	50 (73.5%)	7 (36.8%)	90 (86.5%)	62 (80.5%)	218 (75.4%)
unsure	1 (4.8%)	16 (23.5%)	0 (0%)	1 (1.0%)	4 (5.2%)	22 (7.6%)
NA (did not purchase pigs)	2 (9.5%)	0 (0%)	12 (63.2%)	13 (12.5%)	6 (7.8%)	33 (11.4%)
missing	1 (4.8%)	1 (1.5%)	0 (0%)	0 (0%)	1 (1.3%)	3 (1.0%)

Variable	FB (N=21)	FG (N=68)	BSP (N=19)	SB (N=104)	SG (N=77)	Overall (N=289)
PURCHASES AND SALES						
Receives from producers	0 (0%)	0 (0%)	2 (10.5%)	26 (25.0%)	51 (66.2%)	79 (27.3%)
Receives from pig-exchangers	0 (0%)	0 (0%)	0 (0%)	0 (0%)	12 (15.6%)	12 (4.2%)
Receives from companies	18 (85.7%)	68 (100%)	1 (5.3%)	1 (1.0%)	1 (1.3%)	89 (30.8%)
Receives from BSP	0 (0%)	0 (0%)	0 (0%)	64 (61.5%)	10 (13.0%)	74 (25.6%)
Receives sows	19 (90.5%)	0 (0%)	3 (15.8%)	4 (3.8%)	2 (2.6%)	28 (9.7%)
Receives growers/finishers	0 (0%)	4 (5.9%)	0 (0%)	2 (1.9%)	5 (6.5%)	11 (3.8%)
Receives weaners	0 (0%)	64 (94.1%)	0 (0%)	15 (14.4%)	46 (59.7%)	125 (43.3%)
Receives boars (hired)	0 (0%)	0 (0%)	0 (0%)	60 (57.7%)	12 (15.6%)	72 (24.9%)
Receives A.I. doses	0 (0%)	0 (0%)	0 (0%)	10 (9.6%)	5 (6.5%)	15 (5.2%)
Sends to producers	3 (14.3%)	0 (0%)	19 (100%)	34 (32.7%)	1 (1.3%)	57 (19.7%)
Sends to pig-exchangers	0 (0%)	1 (1.5%)	1 (5.3%)	32 (30.8%)	34 (44.2%)	68 (23.5%)
Sends to companies	16 (76.2%)	67 (98.5%)	0 (0%)	0 (0%)	0 (0%)	83 (28.7%)
Sends sows	13 (61.9%)	0 (0%)	1 (5.3%)	4 (3.8%)	0 (0%)	18 (6.2%)
Sends growers/finishers	0 (0%)	68 (100%)	0 (0%)	6 (5.8%)	34 (44.2%)	108 (37.4%)
Sends weaners	16 (76.2%)	0 (0%)	5 (26.3%)	54 (51.9%)	2 (2.6%)	77 (26.6%)
Sends boars (lent)	0 (0%)	0 (0%)	19 (100%)	0 (0%)	0 (0%)	19 (6.6%)
BIOSECURITY MEASURES						
Mosquito nets over pig pens	1 (4.8%)	16 (23.5%)	16 (84.2%)	53 (51.0%)	60 (77.9%)	146 (50.5%)
Restricts site access to contacts of pigs	21 (100%)	67 (98.5%)	6 (31.6%)	33 (31.7%)	48 (62.3%)	175 (60.6%)
Restrict visitors' access to pig pens	21 (100%)	68 (100%)	8 (42.1%)	39 (37.5%)	45 (58.4%)	181 (62.6%)
Vehicle wheel washes at site entrance	21 (100%)	67 (98.5%)	2 (10.5%)	0 (0%)	1 (1.3%)	91 (31.5%)
Livestock-proof perimeter fence	19 (90.5%)	54 (79.4%)	1 (5.3%)	0 (0%)	0 (0%)	74 (25.6%)
Use of boot dip stations	21 (100%)	68 (100%)	1 (5.3%)	0 (0%)	2 (2.6%)	92 (31.8%)
Use of staff / vistor PPE	21 (100%)	67 (98.5%)	0 (0%)	0 (0%)	3 (3.9%)	91 (31.5%)
Restricts wild birds' access to pigs	21 (100%)	66 (97.1%)	3 (15.8%)	33 (31.7%)	22 (28.6%)	145 (50.2%)
Restricts farmed birds' access to pigs	20 (95.2%)	67 (98.5%)	4 (21.1%)	19 (18.3%)	26 (33.8%)	136 (47.1%)
Restricts wild birds' access to pig feed	21 (100%)	67 (98.5%)	4 (21.1%)	50 (48.1%)	38 (49.4%)	180 (62.3%)
Restricts farmed birds' access to pig feed	21 (100%)	68 (100%)	6 (31.6%)	44 (42.3%)	40 (51.9%)	179 (61.9%)
No biosecurity measures	0 (0%)	0 (0%)	0 (0%)	42 (40.4%)	8 (10.4%)	50 (17.3%)

*supplementary variable

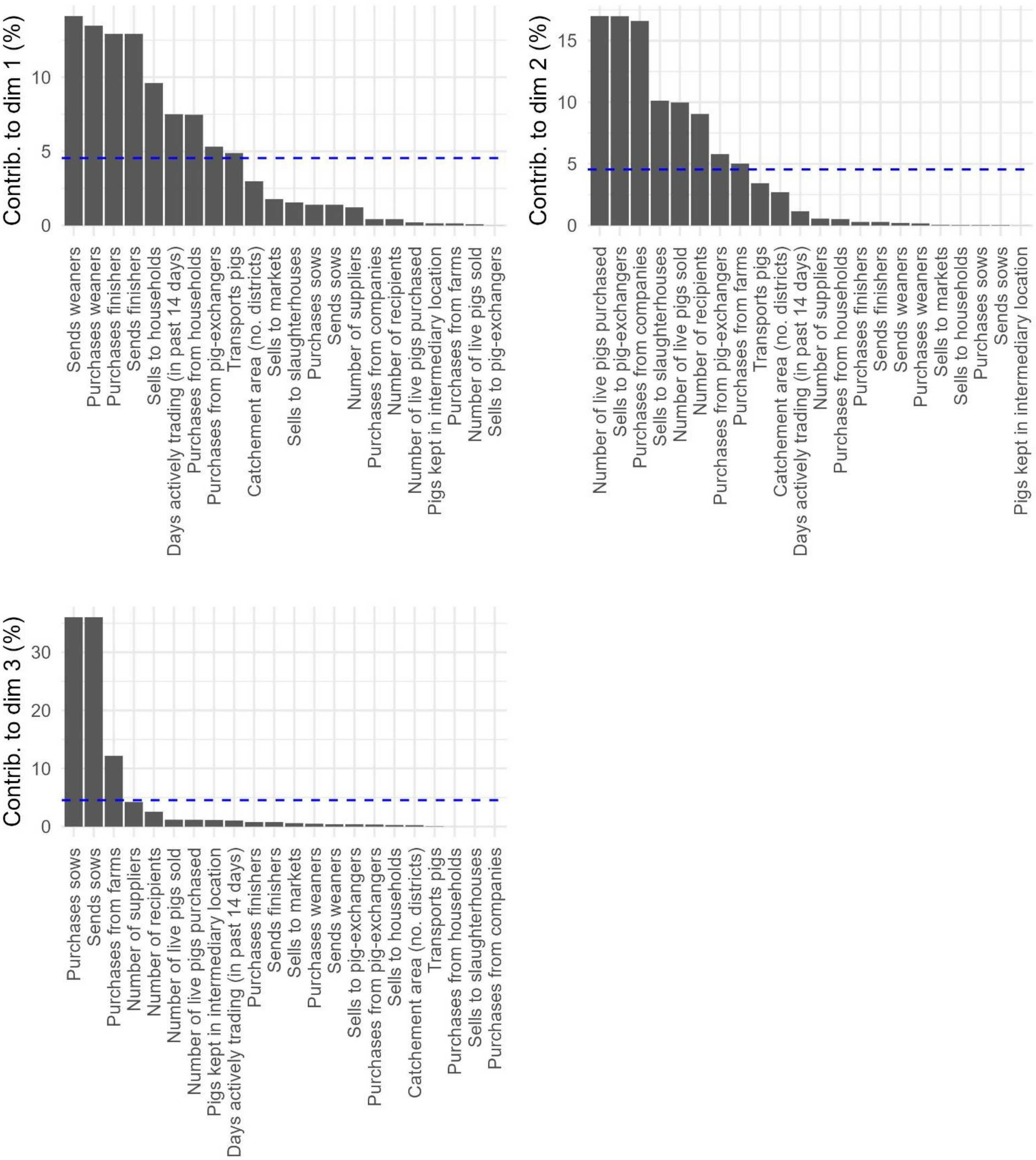

*Figure S 8.3. **Contribution of variables to pig exchanger FAMD dimensions:** Pig exchanger FAMD: % contribution of (active) variables to the formation of FAMD dimensions 1 to 3 – arranged from the highest contributing variables to the least. Dashed line shows the expected contribution of variables if they contributed uniformly to the dimensions (e.g. 100/number of active variables).*

Table S 8.6. ***Summary of pig exchanger types:*** *Description of pig exchanger clusters generated by FAMD and HCA.*

Variables	Mi (N=12)	Tr (N=11)	Bu (N=51)	Overall (N=74)
GENERAL INFORMATION				
Years working as a pig-exchanger*	20.0 [5.00, 30.0]	13.0 [5.00, 21.0]	12.0 [3.00, 40.0]	13.0 [3.00, 40.0]
License held*				
pig transporting	5 (41.7%)	4 (36.4%)	0 (0%)	9 (12.2%)
meat selling	0 (0%)	3 (27.3%)	49 (96.1%)	52 (70.3%)
both of the above	0 (0%)	4 (36.4%)	1 (2.0%)	5 (6.8%)
none	7 (58.3%)	0 (0%)	1 (2.0%)	8 (10.8%)
Raises their own pigs*	2 (16.7%)	0 (0%)	4 (7.8%)	6 (8.1%)
PURCHASES AND SALES				
Receives from smallholders	11 (91.7%)	1 (9.1%)	13 (25.5%)	25 (33.8%)
Receives from companies	0 (0%)	11 (100%)	6 (11.8%)	17 (23.0%)
Receives from pig-exchangers	1 (8.3%)	1 (9.1%)	33 (64.7%)	35 (47.3%)
Receives from farms	0 (0%)	1 (9.1%)	0 (0%)	1 (1.4%)
Number of suppliers	2.00 [0, 4.00]	2.00 [1.00, 3.00]	1.00 [0, 4.00]	1.00 [0, 4.00]
Receives sows	0 (0%)	2 (18.2%)	9 (17.6%)	11 (14.9%)
Receives weaners	11 (91.7%)	0 (0%)	0 (0%)	11 (14.9%)
Receives finishers	0 (0%)	11 (100%)	47 (92.2%)	58 (78.4%)
Number of live pigs purchased	22.0 [0, 50.0]	120 [14.0, 600]	14.0 [0, 350]	15.0 [0, 600]
Sends to smallholders	8 (66.7%)	0 (0%)	0 (0%)	8 (10.8%)
Sends to pig-exchangers	2 (16.7%)	11 (100%)	2 (3.9%)	15 (20.3%)
Sends to slaughter points	7 (58.3%)	0 (0%)	0 (0%)	7 (9.5%)
Sends to markets	1 (8.3%)	0 (0%)	0 (0%)	1 (1.4%)
Number of recipients	1.50 [1.00, 4.00]	3.00 [1.00, 13.0]	0 [0, 1.00]	0 [0, 13.0]
Sends sows	0 (0%)	2 (18.2%)	0 (0%)	2 (2.7%)
Sends weaners	12 (100%)	0 (0%)	0 (0%)	12 (16.2%)
Sends finishers	0 (0%)	11 (100%)	2 (3.9%)	13 (17.6%)
Number of live pigs sold	25.5 [6.00, 58.0]	56.0 [25.0, 199]	0 [0, 14.0]	0 [0, 199]
Catchement area (no. districts)	2.00 [1.00, 13.0]	1.00 [1.00, 12.0]	1.00 [0, 3.00]	1.00 [0, 13.0]
TRADE PRACTICES				
Days actively trading (in past 14 days)	6.00 [1.00, 14.0]	14.0 [14.0, 14.0]	14.0 [0, 14.0]	14.0 [0, 14.0]
Pigs kept in intermediary location	11 (91.7%)	9 (81.8%)	41 (80.4%)	61 (82.4%)
Location pigs are kept*				
home	11 (91.7%)	0 (0%)	12 (23.5%)	23 (31.1%)
slaughter location	0 (0%)	9 (81.8%)	26 (51.0%)	35 (47.3%)
home and/or slaughter location	0 (0%)	0 (0%)	3 (5.9%)	3 (4.1%)
NA (does not keep pigs)	1 (8.3%)	2 (18.2%)	10 (19.6%)	13 (17.6%)
Duration pigs are kept (hours) Median [Min, Max]				
Average:	36.0 [4.00, 48.0]	10.0 [7.00, 14.0]	10.0 [6.00, 48.0]	10.0 [4.00, 48.0]
Minimum:	24.0 [3.00, 24.0]	4.00 [2.00, 11.0]	7.00 [1.00, 20.0]	7.00 [1.00, 24.0]
Maximum:	120 [48.0, 168]	18.0 [9.00, 72.0]	48.0 [8.00, 240]	48.0 [8.00, 240]
Pigs from different origins can contact each other*				
yes	9 (75.0%)	4 (36.4%)	21 (41.2%)	34 (45.9%)
no	2 (16.7%)	4 (36.4%)	19 (37.3%)	25 (33.8%)
unsure	0 (0%)	1 (9.1%)	1 (2.0%)	2 (2.7%)
NA (does not keep pigs)	1 (8.3%)	2 (18.2%)	10 (19.6%)	13 (17.6%)

Variables	Mi (N=12)	Tr (N=11)	Bu (N=51)	Overall (N=74)
Transports pigs	12 (100%)	10 (90.9%)	26 (51.0%)	48 (64.9%)
Vehicles used*				
moped/motorbike	10 (83.3%)	0 (0%)	4 (7.8%)	14 (18.9%)
moped/motorbike with cart	0 (0%)	0 (0%)	8 (15.7%)	8 (10.9%)
4 wheeled vehicle	0 (0%)	9 (81.8%)	11 (21.6%)	20 (27.0%)
moped/motorbike & 4 wheeled vehicle	2 (16.7%)	0 (0%)	3 (5.9%)	5 (6.8%)
lorry	0 (0%)	1 (9.1%)	0 (0%)	1 (1.4%)
NA (does not transport pigs)	0 (0%)	1 (9.1%)	25 (49.0%)	26 (35.1%)
No. pigs transported in one trip*	10.0 [1.00, 22.0]	25.0 [6.00, 50.0]	5.00 [1.00, 50.0]	10.0 [1.00, 50.0]
Collects pigs from multiple sites in one trip*				
always	4 (33.3%)	0 (0%)	0 (0%)	4 (5.4%)
mostly	1 (8.3%)	0 (0%)	1 (2.0%)	2 (2.7%)
sometimes	5 (41.7%)	2 (18.2%)	8 (15.7%)	15 (20.3%)
never	2 (16.7%)	9 (81.8%)	35 (68.6%)	46 (62.2%)
unsure	0 (0%)	0 (0%)	7 (13.7%)	7 (9.5%)
Delivers pigs to multiple sites in one trip*				
always	5 (41.7%)	2 (18.2%)	2 (3.9%)	9 (12.2%)
mostly	1 (8.3%)	0 (0%)	0 (0%)	1 (1.4%)
sometimes	1 (8.3%)	1 (9.1%)	4 (7.8%)	6 (8.1%)
never	5 (41.7%)	8 (72.7%)	41 (80.4%)	54 (73.0%)
unsure	0 (0%)	0 (0%)	4 (7.8%)	4 (5.4%)
Enters pig holding areas*				
always	4 (33.3%)	4 (36.4%)	18 (35.3%)	26 (35.1%)
mostly	6 (50.0%)	0 (0%)	4 (7.8%)	10 (13.5%)
sometimes	1 (8.3%)	1 (9.1%)	1 (2.0%)	3 (4.1%)
never	1 (8.3%)	6 (54.5%)	26 (51.0%)	33 (44.6%)
unsure	0 (0%)	0 (0%)	2 (3.9%)	2 (2.7%)

*supplementary variable

Table S 8.7. ***Actor mixing patterns:*** *For each ego type in aggregate, the total number of alters they traded with and the total number pigs they purchased from, or sold to them (with % breakdown by ego type). Ego types show breeding farms (FB), growing farms (FG), breeding smallholders (SB), growing smallholders (SG), boar service provider (BSP), traders (Tr), Middlemen (Mi), butchers (Bu) and slaughterhouses (Sl). Alter types additionally show smallholders (Sm; incudes both breeding-orientated and growing-orientated as it was not possible to differentiate smallholder alters along these boundaries) and Killing points (KP). N.B. different recall periods are associated with actors: FB, FG, SB, SG (6 months); BSP, Tr, Mi Bu (14 days), Sl (7 days).*

Purchases (in)			
Ego	**Alter**	**Number of alters (%)**	**Pigs (%)**
Producers			
FB	FB	19 (100)	8806 (100)
FG	FB	64 (94.12)	203980 (95.95)
FG	FG	4 (5.88)	8600 (4.05)
SB	FB	1 (0.93)	2 (1.23)
SB	Sm	22 (20.56)	64 (39.26)
SB	BSP	84 (78.5)	97 (59.51)
SG	FB	1 (1.02)	3 (0.43)
SG	Sm	66 (67.35)	489 (70.56)
SG	BSP	18 (18.37)	43 (6.2)
SG	Mi	13 (13.27)	158 (22.8)
BSP	FB	2 (0.27)	2 (0.27)
BSP	Sm	739 (99.73)	750 (99.73)
Pig exchangers			
Tr	FB	4 (19.05)	608 (31.6)
Tr	FG	15 (71.43)	1290 (67.05)
Tr	Sm	1 (4.76)	20 (1.04)
Tr	Tr	1 (4.76)	6 (0.31)
Mi	Sm	25 (96.15)	262 (96.32)
Mi	Mi	1 (3.85)	10 (3.68)
Bu	FB	2 (2.7)	28 (2.03)
Bu	FG	4 (5.41)	421 (30.49)
Bu	Sm	26 (35.14)	177 (12.82)
Bu	Tr	34 (45.95)	636 (46.05)
Bu	Bu	8 (10.81)	119 (8.62)
Slaughterhouses			
Sl	Sm	1 (0.98)	6 (0.38)
Sl	Tr	65 (63.73)	1366 (85.8)
Sl	Bu	36 (35.29)	220 (13.82)

Sales (out)			
Ego	**Alter**	**Number of alters (%)**	**Pigs (%)**
Producers			
FB	FB	13 (30.95)	80855 (76.73)
FB	FG	4 (9.52)	23300 (22.11)
FB	Sm	25 (59.52)	1225 (1.16)
FG	Tr	2 (2.9)	1100 (0.53)
FG	Sl	67 (97.1)	205516 (99.47)
SB	Sm	48 (15.29)	547 (44.65)
SB	BSP	219 (69.75)	288 (23.51)
SB	Mi	39 (12.42)	341 (27.84)
SB	Bu	7 (2.23)	44 (3.59)
SB	KP	1 (0.32)	5 (0.41)
SG	Sm	6 (7.14)	34 (4.92)
SG	BSP	33 (39.29)	126 (18.23)
SG	Mi	6 (7.14)	81 (11.72)
SG	Bu	38 (45.24)	440 (63.68)
SG	KP	1 (1.19)	10 (1.45)
BSP	Sm	253 (99.22)	350 (94.59)
BSP	Mi	1 (0.39)	15 (4.05)
BSP	Bu	1 (0.39)	5 (1.35)
Pig exchangers			
Tr	Tr	1 (2.44)	120 (16.35)
Tr	Bu	40 (97.56)	614 (83.65)
Mi	Sm	14 (58.33)	96 (29.91)
Mi	Mi	2 (8.33)	60 (18.69)
Mi	Sl	3 (12.5)	71 (22.12)
Mi	KP	4 (16.67)	88 (27.41)
Bu	Bu	2 (100)	21 (100)
Slaughterhouses			
Sl	Tr	4 (100)	56 (100)

Table S 8.8. ***Transaction frequencies and repeatability:*** *Values show proportions of egos' trades occurring at a frequency less than or equal to the defined time period (e.g. 1 week = "at least every week"). For each ego (row), increasing proportions are shaded darker.*

	In	1 day	2 days	3 days	1 week	2 weeks	1 month	3 months	6 months	1 year	2 years	First time
Ego	FB	0	0	0	0.21	0.21	0.37	0.21	0	0	0	0
	FG	0	0	0	0	0	0	0.1	0.88	0.01	0	0
	SB	0	0	0	0	0	0.01	0.07	0.49	0.08	0.01	0.35
	SG	0	0	0	0	0	0	0.05	0.21	0.08	0.01	0.64
	BSP	0	0	0	0	0	0.02	0.09	0.58	0.07	0	0.24
	Tr	0.33	0.29	0.14	0	0.05	0	0.1	0	0	0	0.1
	Mi	0	0	0.08	0	0	0	0.54	0.23	0	0	0.15
	Bu	0.38	0.15	0.14	0.01	0	0	0.07	0.08	0.08	0	0.09
	Sl	0.95	0.01	0	0	0	0	0.01	0	0	0	0.03

	Out	1 day	2 days	3 days	1 week	2 weeks	1 month	3 months	6 months	1 year	2 years	First time
Ego	FB	0	0	0	0.12	0.14	0.12	0.38	0.1	0	0	0.14
	FG	0	0	0	0	0	0	0.12	0.88	0	0	0
	SB	0	0	0	0	0	0.01	0.06	0.39	0.06	0.01	0.48
	SG	0	0	0	0	0	0.02	0.1	0.47	0.08	0	0.33
	BSP	0	0	0	0	0	0.02	0.09	0.59	0.05	0	0.24
	Tr	0.98	0.02	0	0	0	0	0	0	0	0	0
	Mi	0.12	0.21	0	0.08	0	0	0.12	0.17	0	0	0.29
	Bu	0.5	0	0.5	0	0	0	0	0	0	0	0
	Sl	0.75	0.25	0	0	0	0	0	0	0	0	0

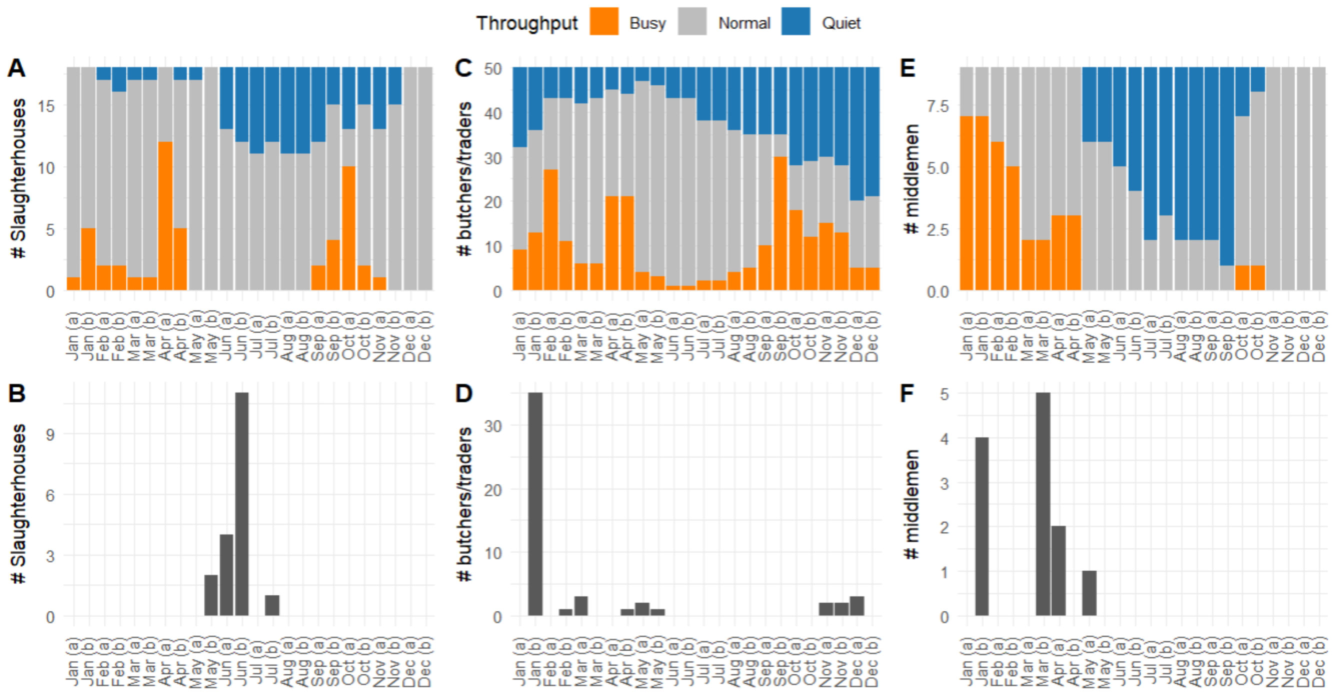

Figure S 8.4. ***Temporal variation in activity:*** *Temporal variation in volumes of pigs killed in slaughterhouses (A-B), or traded by butchers and traders (C-D), and middlemen (E-F). This is displayed as (A, C, E) the frequencies of slaughterhouses or pig exchangers reporting that this was a 'busy', 'quiet', or otherwise, 'normal' time-period (A, C, E; i.e. ~2 weeks indicating the first [a] and second half [b] of each month) in terms of throughput or trade activity; and the number of actors sampled in each time-period (B, D, F).*

8.2.1 Ego recruitment

Farms: Sampling frames for farms included information on farm types (e.g. breeding/growing) and company affiliations (e.g. contracted, directly owned, or none). No farms were present in Phnom Penh, and few farms were present in Kandal and refused to participate (n=5). Therefore, two additional districts were purposively selected from Kampong Speu and Takeo based on the diversity of farm types within them. Farms were then purposively selected from districts to sample the diversity of farm types while facilitating logistical feasibility.

Smallholders: To permit logistical feasibility when sampling from the large number of smallholders present in the study area, two villages (tertiary sampling units) were selected from each district with probability proportional to the number of smallholders. All households keeping pigs within these villages were recruited into the study. During visits to study villages, we were able to identify only a third (34%) of the number of smallholders officially listed (Ministry of Agriculture Forestry and Fisheries, 2019). During initial scoping of the study villages, we found that the number of smallholders, out of 471 smallholders officially recorded, only 161 (34% of this total) were identified.

Boar service providers (BSP): The smallholder sampling scheme detailed above recruited only one BSP but revealed that they were an important supplier/recipient of smallholders. Due to a lack of official records of BSP, BSP were recruited via two methods. BSP were recruited at province level to increase the sample size of this hard to reach population. Most BSP were recruited based on government vets' knowledge of BSP operating within study provinces (n=14). A minority were identified via the contact lists from smallholder surveys i.e. via link trace sampling. We attempted to recruit all BSP for whom contact details were provided. Of 7 BSP for whom contact details were available, 4 (57% of these) were interviewed.

Pig exchangers (registered): We attempted to recruit all registered pig exchangers (Table 3.1) identified in study districts. Out of 83 identified actors, 57 (69%) were recruited, 3 refused to participate (3.6%), and 23 (28%) were not available for interview.

Pig exchangers (un-registered): Un-registered pig exchangers were recruited by a combination of link-trace sampling (n=4) and on an opportunistic basis during informal interviews with smallholders, butchers, and meat sellers at markets (n=4).

Slaughterhouses: All registered slaughterhouses in selected districts (n=14) were recruited, but two refused or were unable to answer about pig trading activity so were excluded from this study. Additional slaughterhouses were also recruited; in study districts where no slaughterhouses were in operation, a slaughterhouse in a neighbouring district was substituted (Takeo n=1; Phnom Penh n=3). An additional high throughput slaughterhouse located outside our target districts in Phnom Penh was recruited to increase our sample size for pig surveillance (Zeller et al., 2023) as most slaughterhouses were low throughput.

8.2.2 Alter re-classification

To use the more nuanced (FAMD and HCA generated) actor types when comparing mixing patterns among egos and alter types, alter types were harmonised for consistency with ego types. Due to the limited set of variables available for alters, it was not possible to use FAMD and HCA here. Instead, the characteristics of ego types (Table S 8.5 and Table S 8.6) were used to inform alter classifications according to the types of pigs traded, and the actors they traded with.

Pig exchanger alters were simply reclassified as middlemen when they purchased or sold weaners. Farms were reclassified as breeding or growing farms: Since they clearly diverged on the basis of the types of pigs they traded, these alters could be clearly categorised. Specifically, only breeding farms received or sent sows/gilts while only growing farms received growers/finishers and weaners (Table S 8.5; table section: purchases and sales). Smallholders were less clearly diverged according to their trading activities. The only clearly defining feature was between BSP and other types of smallholder (i.e. breeding or growing orientated smallholders) (Table S 8.5). For this reason, smallholder alters were simply reclassified as BSP or smallholders - i.e. not differentiating between breeding or growing orientated smallholders.

8.2.3 Egocentric network rescaling: description and pseudocode

Re-scaling egocentric networks up to longer recall periods was carried out as follows:

1. When an ego made multiple transactions with an alter during the survey (i.e. transaction frequency < recall period), the ego was expected to trade with this alter in each unsampled time period. Therefore, the total expected number of pigs traded with this alter was simply adjusted by weighing the observed number of traded pigs by the ratio between the target (e.g. 6 months) and the recall period.
2. When an ego made only one transaction with an alter during the recall period (i.e. transaction frequency ≥ recall period), we imputed additional alters for the unsampled time period(s). In practice, this was simply achieved by imputing additional alters with identical features to the sampled set of alters within each unsampled time period.
    a. If only one transaction was *also* expected in the target period, the number of alters to impute was simply based on the ratio between the length of the target and recall periods. i.e. a new alter was imputed for each time period.
    b. If more than one transaction would be expected in the target period, it was necessary to account for the repeatability of that alter in this time period. The number of alters to impute was therefore based on the ratio between the transaction frequency and the recall period. Then the same adjustment was then made to correct the number of pigs traded with each alter as in adjustment 1.

To rescale to a shorter recall periods, we determined whether an interviewed ego would have reported each alter if a shorter target period had been used. We assumed that multiple transactions with an alter occurred at equal frequencies.

1. Where the transaction frequency was such that a maximum of one transaction could be expected in the target period (i.e. transaction frequency >= target), an alter was sampled with a defined probability to see if they would be 'selected' in the shorter target recall period.
    a. When a single transaction occurred in the survey (transaction frequency >= survey recall), the alter was simply sampled with a probability equal to target/ recall.

b. When multiple transactions occurred in the survey (transaction frequency < survey recall), the alter was instead sampled with a probability target recall/transaction frequency to account for the greater chance of ‘sampling’ this alter in the new target recall period.

2. Where multiple transactions would be expected between an ego and an alter within the target period (i.e. transaction frequency < target), no adjustment was applied as the probability of ‘sampling’ this alter in the target period was 1.

Table S 8.9. ***Egocentric network rescaling procedure.*** *Pseudocode for rescaling egocentric networks to different recall periods. Target = the desired target recall period, recall = the recall period used in the network survey for a given actor type, freq = the transaction frequency with which egos traded with their alters.*

```
# Imputing number of alters or pigs when target > recall:
IF(target > recall) AND
    IF(freq < recall)
      → pigs (in target) = pigs (in recall period) * (target/recall)
    IF(freq >= recall & freq >= target)
      → repeat alter * (target/recall)
    IF(freq >= recall & freq <  target)
      → repeat alter * (freq/recall) AND
        pigs (in target) = pigs (in recall period) * (target/recall)

# Sampling alters when target < recall
IF(target < recall) AND
   IF(freq >= recall & freq >= target)
     → sample with probability (target/recall)
   IF(target < recall & freq < recall & freq >= target)
     → sample with probability (target/freq)
   IF(target < recall & freq < target)
     → sample with probability of 1 (i.e. do nothing)

# Do nothing when target = recall
IF(target = recall)
     → do nothing
```

8.3 Supplementary: Chapter 4

8.3.1 Study population calculations

Smallholders: Official records reported the number of pigs in smallholdings for each province (292,515 in our study area; Ministry of Agriculture Forestry and Fisheries, 2019). To estimate the number of smallholders in the study area, we divided this value by the mean number of pigs kept by smallholders (9 pigs; Chapter 3). We previously found that this value had considerably reduced i.e. field visits conducted in 2020-21 identified only a third of smallholders than were officially listed (Ministry of Agriculture Forestry and Fisheries, 2019). These large reductions in smallholder numbers in our study area are consistent with the national picture, with the number of pigs in smallholders reportedly reducing, on average, 7.9% each year between 2016 and 2021 (Asian Development Bank, 2022, p. 6). Therefore, assuming that this reduction had occurred across the whole smallholder sector in the study area, we reduced the number of smallholders calculated in the study area by two thirds (292,515 pigs ÷ 9 pigs per household x 0.333 factor reduction = 10,804 smallholders).

BSP: The number of BSP was not available from official records or sampling frames. Therefore, we calculated the number of BSP required to serve all smallholders in the study area. First, we calculated the number of smallholders requiring a BSP: in the 6 months surveyed, 40.8% of smallholders hired boars for breeding (Chapter 3) (10,804 smallholders x 0.408 = 4,417 customers). This was considered to represent all smallholders likely to require a BSP in the study area, given smallholders had a median of 2 farrowing cycles per year (Chapter 3). Next, the number of BSP required to serve these smallholders was calculated. Since the number of customers BSP had was non-normally distributed, we calculated the proportional increase in BSP needed to serve these customers in 6 months (i.e. the usual frequency of visits of BSP reported by smallholders) (4,417 customers ÷ 245 customers in 6 months by 19 BSP [= proportional increase in BSP needed] x 19 BSP = 29 BSP). This calculation implicitly assumed that the distribution of the number of customers BSP had was representative of all BSP in the study area.

We performed two cross-checks of this value to check this value was within a reasonable range. First, we approximated the maximal serviceable geographic area of BSP by finding the area of the circle whose radius was equal to the mean of the maximum distances they travelled. We then calculated the minimum number of BSP required to cover the study area by dividing the study area by the mean serviceable area. This generated a similar value (=31 BSP) to the method above. Next, based on the fact that one BSP was sampled out of 181 smallholders, we calculated the number of BSP while assuming that the proportion of BSP here was equal to the proportion of BSP in the study area (1 ÷ 181 x 10,804 smallholders = 60 BSP).

Middlemen: An equivalent method was used to estimate the number of middlemen in the study population. In the 6 months surveyed, 26.6% of smallholders used a middleman (10,804 smallholders x 0.266 = 2,854 customers). This again, was considered to represent all smallholders who would use a middleman, given that middlemen sold or purchased weaners from smallholders who had a median of 2 farrowing, and 2 fattening cycles per year (Chapter 3). The proportional increase in middlemen needed to serve all smallholder customers was calculated as previously (2,854 customers ÷ 387 customers in 6 months by 12 middlemen [= proportional increase in middlemen needed] x 12 middlemen = 89 middlemen).

Cross-checking based on maximal serviceable geographic area found that the minimum number of middlemen required to cover the study area was 25 middlemen.

Farms: The total number of farms in the study area was informed directly by census data (Ministry of Agriculture Forestry and Fisheries, 2019). In contrast to smallholder surveys, we did not observe a difference in the number of farms reported in 2019 vs those observed during field visits. The number of farms of different production types was however not available at province level. Therefore, we assumed that the proportion of breeding and growing farms in Kampong Speu - the only province for which the proportion of breeding and growing farms were known.

Traders and butchers: We had information on the number of traders and butchers in study districts (as reported by government veterinarian offices). This was scaled up to the number expected in the whole study area (i.e. for unsampled districts in the study provinces). We simply assumed that the number of butchers or traders in a district was proportional to the human population in that district (which itself, is correlated with swine population [(Ly, 2016)]). Human population was informed by (National Institute of Statistics and Ministry of Agriculture, Forestry and Fisheries, 2019). In study districts, we calculated that 1 in 13,254 people in the general population were butchers, while 1 in 52,853 were traders. These values were scaled up to the total human population in the study provinces.

Slaughterhouses: The number of slaughterhouses was directly informed by sampling frames collated by government veterinary offices.

8.3.2 Transmission process

1. Define index case
2. For current time step, randomly select an ERGM-simulated network without replacement
3. Identify potentially infectious edges (i.e. dyads involving an infectious and susceptible node)
4. Calculate the total transmission probability incident on each susceptible node based on the number of direct and indirect contacts with infected nodes they have, and the defined probabilities of transmission from direct and indirect contact (pT_{direct} and $pT_{indirect}$):
   i. The probability that a node becomes infected from at least one direct contact:

      $D = 1-(1 - pT_{direct})^{n\_direct}$

   ii. The probability that a node becomes infected from at least one indirect contact:

      $I = 1-(1 - pT_{indirect})^{n\_indirect}$

   iii. The union of D or I:

      $P(D \cup I) = P(D)+P(I)-P(D) \cdot P(I)$

5. Determine which susceptible nodes become infected (S→I) based on a Bernoulli trial using $P(D \cup I)$
6. Update the disease state of newly recovered nodes when infection duration of a node >= duration of infectiousness (I → R)
7. Update the disease state of newly susceptible nodes when immunity duration of a node >= duration of immunity (R→S)
8. Repeat steps 2-7 for subsequent time steps

8.3.3 Table S1: Edge direction between nodes

Table S 8.10. ***Edge direction rules for each pair of actor types for nodes i and j in a dyad****: 1 = i→ j, 2 = j→ i, 3=randomise edge direction with Bernoulli trial and a probability of (0.5), NA=non-existent edge type. Rules are based off of empirical mixing patterns.*

		j							
		f_breed	f_grow	s_general	s_boar	trader	middleman	butcher	slaughterhouse
i	f_breed	3	1	1	1	1	NA	1	NA
	f_grow	2	3	1	NA	1	NA	1	NA
	s_general	2	2	3	2	NA	3	1	1
	s_boar	2	NA	1	3	NA	1	1	NA
	trader	2	2	NA	NA	3	NA	1	1
	middleman	NA	NA	3	3	NA	3	NA	1
	butcher	2	2	2	2	2	NA	3	1
	slaughterhouse	NA	2	2	NA	2	2	2	NA

Table S 8.11. ***ERGM goodness of fit: model terms****. The values of modelled statistics observed (obs) in the egocentric sample after scaling up to the population size, the distribution (min, mean, max) of corresponding statistics from 100 networks simulated from the fitted ERGM, and the proportion of statistics from simulated networks that are at least as extreme as the observed value (MC p-value; smaller p-values indicate increasing differences between observed and simulated networks for a given statistic, here shaded grey if below 0.05). Rows show statistics explicitly modelled as a term in the ERGM for models 1-4.*

		Model 1				Model 2				Model 3				Model 4			
model term	**obs**	**min**	**mean**	**max**	**MC p-value**	**min**	**mean**	**max**	**MC p-value**	**min**	**mean**	**max**	**MC p-value**	**min**	**mean**	**max**	**MC p-value**
edges	**0.18**	0.17	0.18	0.2	0.94	0.17	0.18	0.19	0.92	0.17	0.18	0.2	0.92	0.17	0.18	0.2	0.9
nodefactor.actor.butcher	**0.073**					0.066	0.073	0.08	0.78	0.062	0.073	0.081	0.9	0.065	0.073	0.082	0.98
nodefactor.actor.f_breed	**0.016**					0.014	0.016	0.019	0.84	0.011	0.016	0.022	0.9	0.012	0.017	0.021	0.88
nodefactor.actor.f_grow	**0.01**					0.0072	0.01	0.014	0.96	0.0064	0.0099	0.013	1	0.0073	0.0099	0.013	0.82
nodefactor.actor.middleman	**0.023**					0.018	0.023	0.027	0.92	0.019	0.023	0.026	0.88	0.017	0.022	0.028	0.96
nodefactor.actor.s_boar	**0.035**					0.032	0.035	0.042	0.92	0.03	0.035	0.041	0.94	0.03	0.035	0.039	0.82
nodefactor.actor.slaughterhouse	**0.036**					0.029	0.036	0.041	0.98	0.031	0.036	0.043	0.86	0.03	0.036	0.041	0.88
nodefactor.actor.trader	**0.047**					0.041	0.047	0.052	1	0.04	0.047	0.054	0.92	0.04	0.047	0.055	1
mix.actor.butcher.butcher	**0.0033**									0.0012	0.0034	0.0058	0.84	0.002	0.0032	0.0049	1
mix.actor.f_breed.f_breed	**0.0057**									0.0037	0.0057	0.0093	0.94	0.0038	0.0058	0.0077	0.74
mix.actor.butcher.middleman	**0**									0	0	0	1	0	0	0	1
mix.actor.f_breed.middleman	**0**									0	0	0	1	0	0	0	1
mix.actor.f_grow.middleman	**0**									0	0	0	1	0	0	0	1
mix.actor.f_grow.s_boar	**0**									0	0	0	1	0	0	0	1
mix.actor.s_boar.s_boar	**0**									0	0	0	1	0	0	0	1
mix.actor.butcher.s_general	**0.016**									0.012	0.016	0.019	0.98	0.013	0.016	0.019	0.92
mix.actor.f_grow.s_general	**0**									0	0	0	1	0	0	0	1
mix.actor.middleman.s_general	**0.02**									0.015	0.02	0.024	0.82	0.015	0.02	0.025	0.88
mix.actor.s_boar.s_general	**0.035**									0.03	0.035	0.04	0.9	0.03	0.034	0.039	0.88
mix.actor.s_general.s_general	**0.028**									0.023	0.028	0.033	0.78	0.023	0.028	0.034	0.92
mix.actor.butcher.slaughterhouse	**0.022**									0.018	0.022	0.027	0.96	0.018	0.022	0.025	0.98
mix.actor.f_breed.slaughterhouse	**0**									0	0	0	1	0	0	0	1
mix.actor.s_boar.slaughterhouse	**0**									0	0	0	1	0	0	0	1
mix.actor.slaughterhouse.slaughterhouse	**0**									0	0	0	1	0	0	0	1
mix.actor.butcher.trader	**0.026**									0.022	0.027	0.031	0.86	0.023	0.027	0.032	0.92
mix.actor.f_grow.trader	**0.0057**									0.0036	0.0057	0.0081	0.82	0.004	0.0057	0.0077	0.96
mix.actor.middleman.trader	**0**									0	0	0	1	0	0	0	1
mix.actor.s_boar.trader	**0**									0	0	0	1	0	0	0	1
mix.actor.s_general.trader	**0**									0	0	0	1	0	0	0	1
mix.actor.slaughterhouse.trader	**0.012**									0.0089	0.012	0.015	1	0.0085	0.012	0.015	0.94
nodematch.company	**0.0073**													0.0053	0.0074	0.01	0.92

Table S 8.12. ***ERGM goodness of fit: degree.*** *The values of observed (obs) degree statistics in the egocentric sample after scaling up to the population size, the distribution (min, mean, max) of corresponding statistics from 100 networks simulated from the fitted ERGM, and the proportion of statistics from simulated networks that are at least as extreme as the observed value (MC p-value; shaded grey if below 0.05). Rows show degree values for models 1-4.*

		Model 1				Model 2				Model 3				Model 4				
degree	**obs**	**min**	**mean**	**max**	**MC p-value**	**min**	**mean**	**max**	**MC p-value**	**min**	**mean**	**max**	**MC p-value**	**min**	**mean**	**max**	**MC p-value**	**degree**
0	**0.81**	0.66	0.69	0.71	0	0.8	0.81	0.82	0.76	0.8	0.81	0.82	0.78	0.8	0.81	0.82	0.78	**0**
1	**0.13**	0.24	0.25	0.28	0	0.12	0.13	0.14	0.76	0.12	0.13	0.14	0.74	0.12	0.13	0.14	0.66	**1**
2	**0.027**	0.04	0.047	0.054	0	0.018	0.024	0.028	0.12	0.021	0.024	0.029	0.1	0.019	0.023	0.027	0	**2**
3	**0.0091**	0.0032	0.0055	0.0074	0	0.009	0.012	0.015	0.02	0.0093	0.012	0.015	0	0.0093	0.012	0.015	0	**3**
4	**0.011**	0	0.00059	0.0013	0	0.0056	0.0077	0.011	0	0.0048	0.0077	0.01	0	0.0048	0.0079	0.011	0	**4**
5	**0.0041**	0	0.000034	0.00027	0	0.0029	0.0049	0.0068	0.28	0.0033	0.005	0.0076	0.24	0.0028	0.005	0.007	0.2	**5**
6	**0.0023**	0	0.0000013	0.00013	0	0.0017	0.0033	0.005	0.1	0.0016	0.0033	0.0053	0.14	0.002	0.0035	0.0046	0.06	**6**
7	**0.0012**	0	0	0	0	0.00093	0.0022	0.0034	0.1	0.0011	0.0023	0.0034	0.04	0.0012	0.0023	0.0041	0.02	**7**
8	**0.00096**	0	0	0	0	0.00053	0.0015	0.0027	0.14	0.00027	0.0014	0.0029	0.36	0.00053	0.0015	0.0024	0.32	**8**
9	**0.0004**	0	0	0	0	0.00027	0.00097	0.0017	0.06	0.00013	0.00094	0.0016	0.04	0.00013	0.00087	0.0019	0.26	**9**
10	**0.0008**	0	0	0	0	0.00013	0.00057	0.0012	0.28	0	0.0006	0.0015	0.4	0.00013	0.00056	0.0012	0.22	**10**
11	**0.00013**	0	0	0	0	0	0.00043	0.0011	0.42	0	0.00042	0.0012	0.48	0	0.00045	0.0013	0.22	**11**
12	**0.00033**	0	0	0	0	0	0.00035	0.00093	0.92	0	0.0004	0.0013	0.86	0	0.00034	0.0011	0.94	**12**
13	**0**	0	0	0	1	0	0.00029	0.0011	0.14	0	0.00028	0.00093	0.24	0	0.00031	0.0008	0.14	**13**
14	**0.0011**	0	0	0	0	0	0.00029	0.0008	0	0	0.00032	0.0008	0	0	0.00025	0.0008	0	**14**
15	**0.00013**	0	0	0	0	0	0.00026	0.00066	0.82	0	0.00023	0.00066	0.94	0	0.00024	0.00093	0.9	**15**
16	**0.00013**	0	0	0	0	0	0.00025	0.0008	0.78	0	0.00023	0.0008	0.98	0	0.00023	0.00066	0.9	**16**
17	**0.00033**	0	0	0	0	0	0.00017	0.00053	0.24	0	0.00018	0.00066	0.26	0	0.00019	0.00053	0.44	**17**
18	**0**	0	0	0	1	0	0.00014	0.00066	0.7	0	0.00013	0.0004	0.76	0	0.00014	0.0008	0.76	**18**
19	**0**	0	0	0	1	0	0.000082	0.0004	1	0	0.0001	0.0004	0.8	0	0.00012	0.00053	0.84	**19**
20	**0.00027**	0	0	0	0	0	0.000068	0.00053	0.06	0	0.000064	0.0004	0.02	0	0.000066	0.0004	0.02	**20**
21	**0**	0	0	0	1	0	0.000037	0.00027	1	0	0.000049	0.0004	1	0	0.000056	0.00027	1	**21**
22	**0.00013**	0	0	0	0	0	0.000033	0.0004	0.04	0	0.000024	0.00027	0.04	0	0.00003	0.00027	0.06	**22**
23	**0**	0	0	0	1	0	0.000021	0.00027	1	0	0.000013	0.00027	1	0	0.000015	0.00027	1	**23**
24	**0**	0	0	0	1	0	0.0000053	0.00013	1	0	0.000013	0.00013	1	0	0.0000093	0.00013	1	**24**
25	**0**	0	0	0	1	0	0.0000066	0.00013	1	0	0.000008	0.00013	1	0	0.000004	0.00013	1	**25**
26	**0**	0	0	0	1	0	0.0000013	0.00013	1	0	0.000004	0.00013	1	0	0.000008	0.00013	1	**26**
27	**0**	0	0	0	1	0	0.0000013	0.00013	1	0	0	0	1	0	0.0000013	0.00013	1	**27**
28	**0**	0	0	0	1	0	0	0	1	0	0	0	1	0	0.0000013	0.00013	1	**28**
29	**0.00013**	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0000013	0.00013	0	**29**
30	**0.00027**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**30**

Table S 8.13. ***ERGM parameter coefficients as conditional log odds.*** *Actor types are breeding farms (FB), growing farms (FG), smallholders (Sm), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl). *Baseline is all pairwise actor combinations with 0<observations<10 (Bu-FB, Bu-FG, FB-FG, FG-FG, Mi-Mi, Bu-BSP, FB-BSP, Mi-BSP, FB-Sm, FG-Sl, Mi-Sl, Sm-Sl, FB-Tr, and Tr-Tr). Pairwise actor combinations with zero observations were not estimated by MCMC and had a fixed log odds of zero (these are not shown but included: Bu-Mi, FB-Mi, FG-Mi, FG-BSP, BSP-BSP, FG-Sm, FB-Sl, BSP-Sl, Sl-Sl, Mi-Tr, BSP-Tr, Sm-Tr). The coefficient for the offset in all models was equal to log(network size/pseudo-population size) = 0.45.*

	Model 1: Null		**Model 2: actor**		**Model 3: + actor mix.**		**Model 4: + company hom.**	
Model terms	**Coef (SE)**	**p-value**	**Coef (SE)**	**p-value**	**Coef (SE)**	**p-value**	**Coef (SE)**	**p-value**
Edges	-10.38 (0.1)	0.00E+00	-12.32 (0.24)	0.00E+00	-16.89 (1.7)	3.26E-23	-16.57 (1.88)	1.50E-18
Node factor effects: Actor								
Sm			Reference		Reference		Reference	
Bu			2.74 (0.2)	1.55E-43	3.53 (0.95)	2.01E-04	3.99 (1.12)	3.58E-04
FB			2.35 (0.29)	3.84E-16	5.01 (0.9)	2.25E-08	4.37 (0.97)	6.26E-06
FG			1.38 (0.28)	9.38E-07	4.39 (0.84)	1.51E-07	3.34 (0.92)	2.70E-04
Mi			3.02 (0.28)	1.87E-26	5.42 (0.84)	1.32E-10	5.21 (0.87)	2.36E-09
BSP			4.62 (0.24)	6.03E-80	3.72 (1.02)	2.68E-04	3.51 (1.13)	1.97E-03
Sl			3.71 (0.23)	1.00E-59	5.11 (1.13)	6.50E-06	5.16 (1.4)	2.31E-04
Tr			3.65 (0.24)	5.94E-51	5.26 (1.02)	2.89E-07	5.23 (1.1)	1.88E-06
Nodal mixing: Actor								
Other actor pairings*					Reference		Reference	
Bu-Bu					2.21 (0.93)	1.80E-02	0.96 (1.09)	3.81E-01
FB-FB					2.02 (0.67)	2.40E-03	1.32 (0.79)	9.58E-02
Bu-Sm					3.33 (1)	9.03E-04	2.55 (1.07)	1.75E-02
Mi-Sm					3.09 (0.95)	1.16E-03	2.98 (1.1)	6.93E-03
BSP-Sm					6.5 (0.97)	2.18E-11	6.4 (1.05)	1.18E-09
Sm-Sm					4.8 (1.73)	5.47E-03	4.48 (1.91)	1.89E-02
Bu-Sl					3.5 (0.57)	1.08E-09	2.67 (0.8)	8.96E-04
Bu-Tr					3.24 (0.65)	7.23E-07	2.47 (0.63)	7.95E-05
FG-Tr					1.47 (0.61)	1.64E-02	2.21 (0.64)	5.99E-04
Sl-Tr					2.55 (0.74)	5.81E-04	2.2 (0.79)	5.62E-03
Nodal homophily effects								
Different company							Reference	
Same company							2.5 (0.7)	3.63E-04

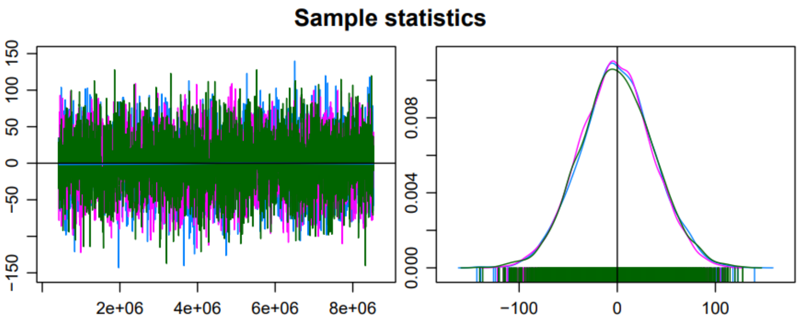

Figure S 8.5. ***MCMC diagnostics for ERGM model 1***

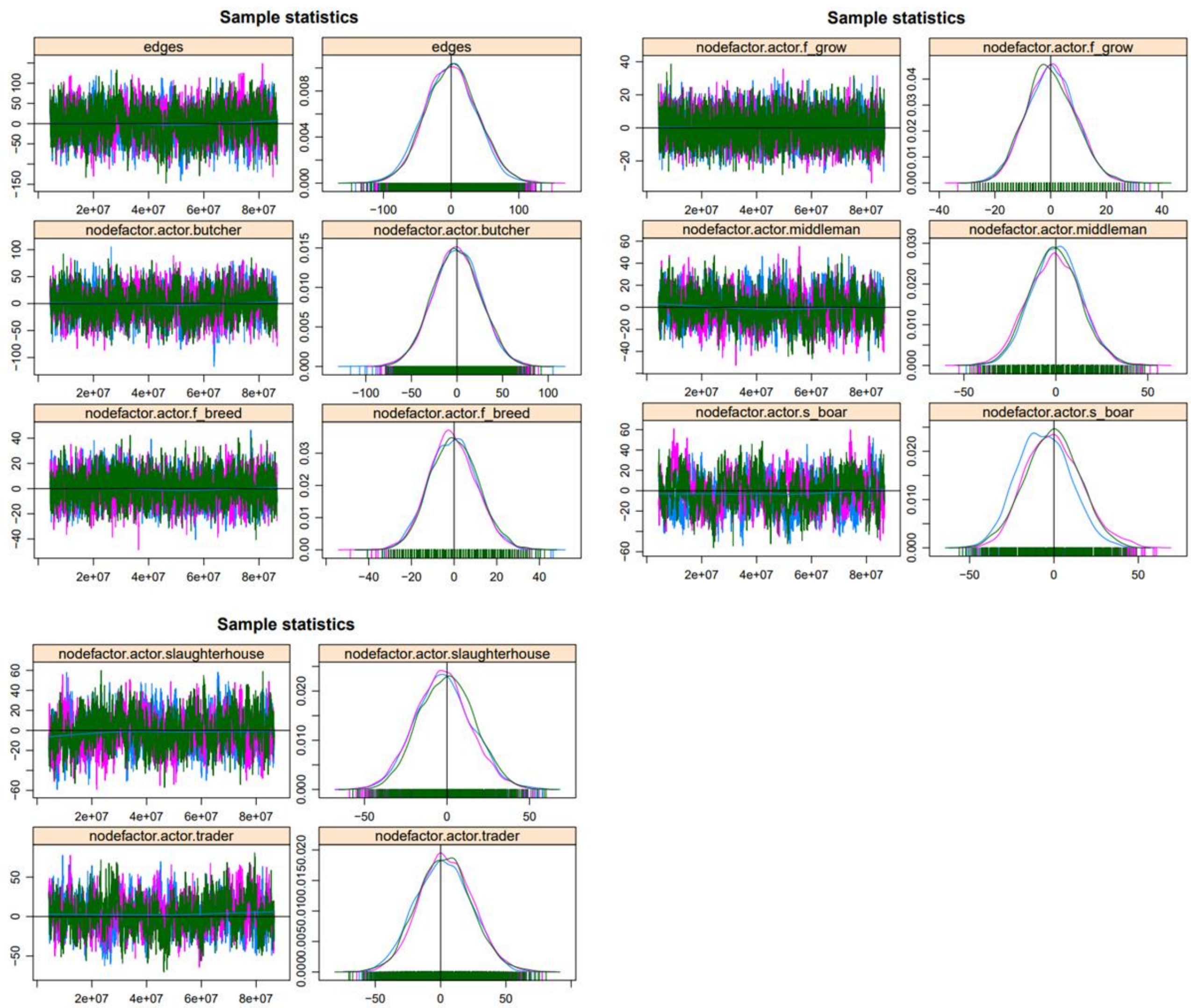

Figure S 8.6 ***MCMC diagnostics for ERGM model 2***

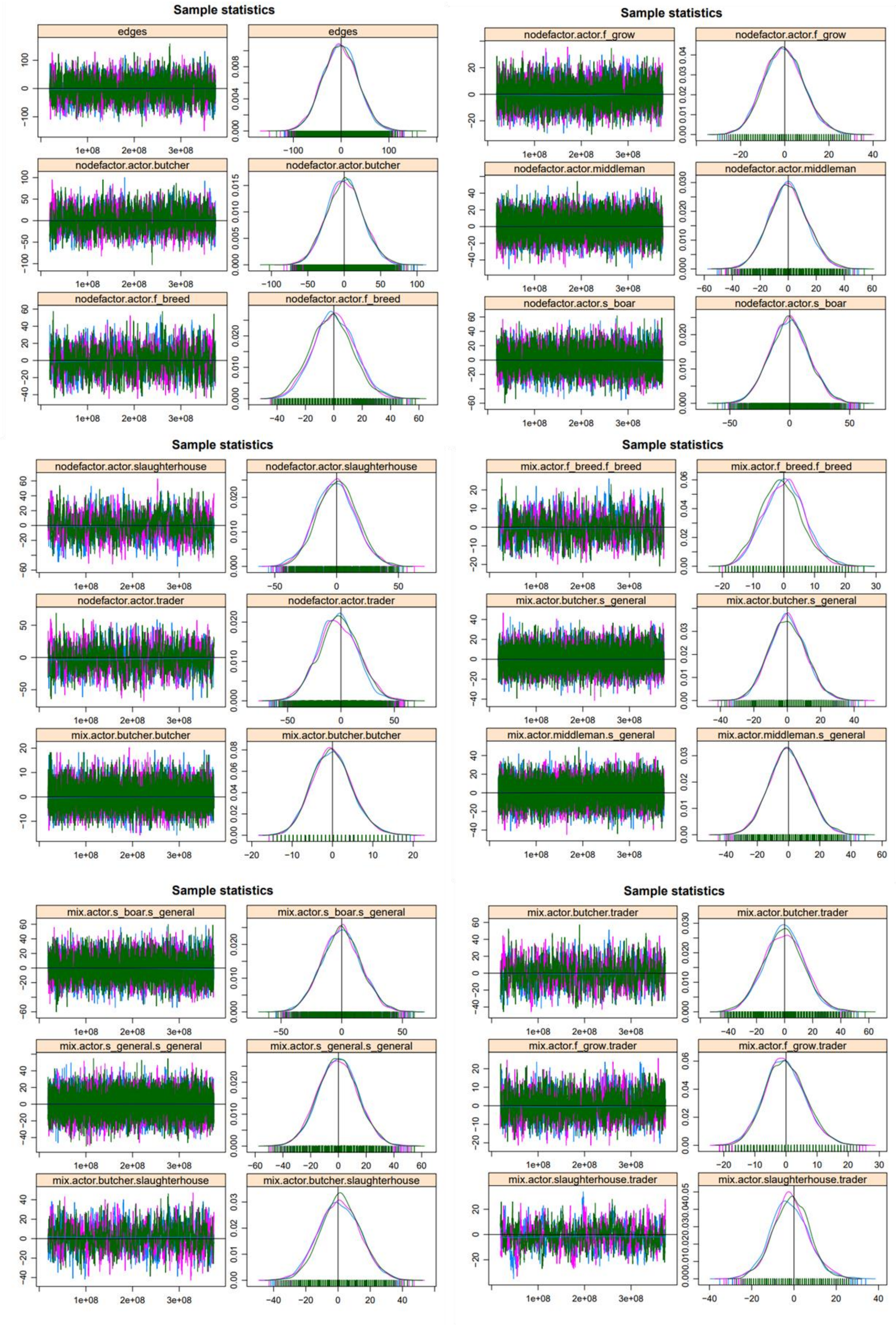

Figure S 8.7 ***MCMC diagnostics for ERGM model 3***

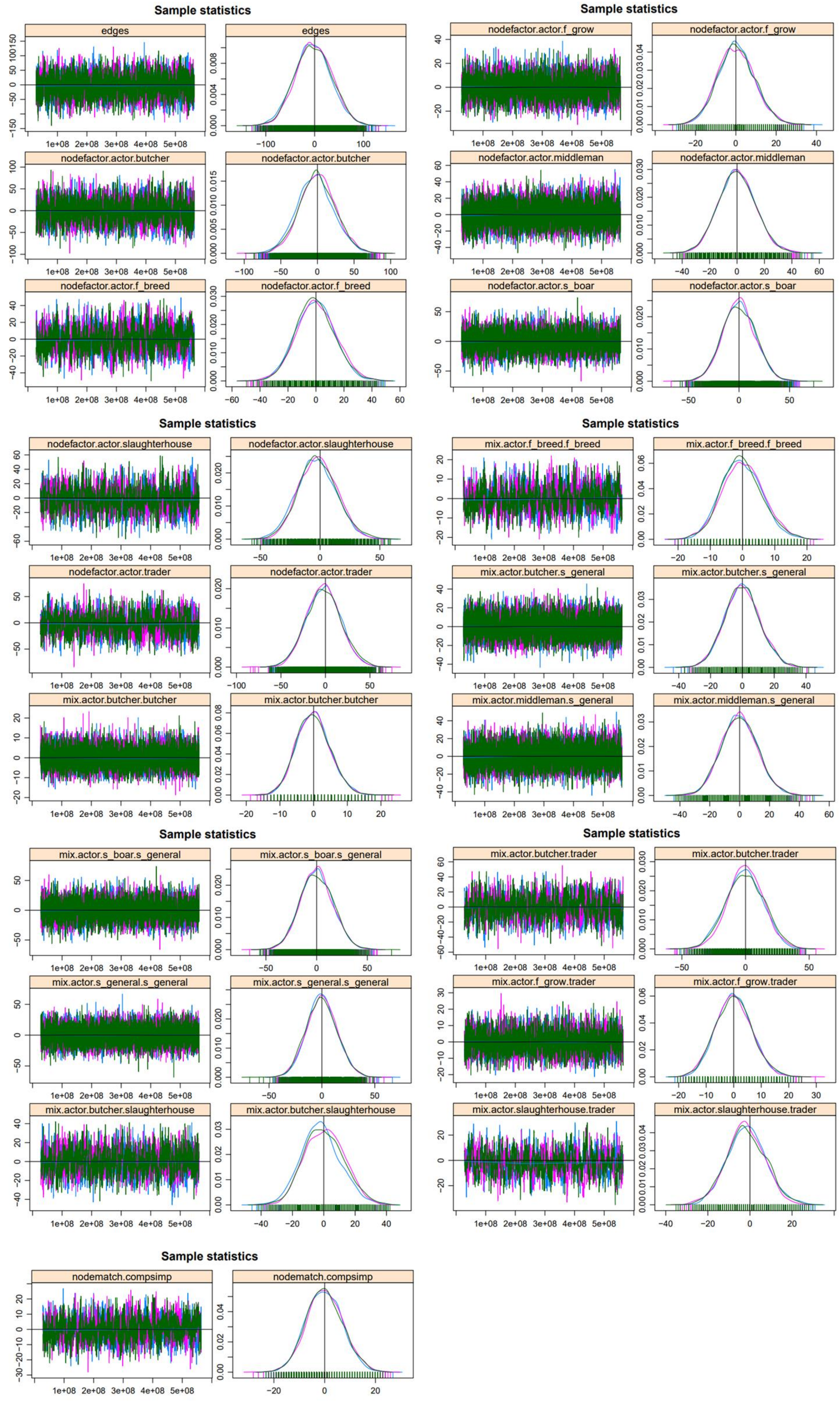

Figure S 8.8 ***MCMC diagnostics for ERGM model 4***

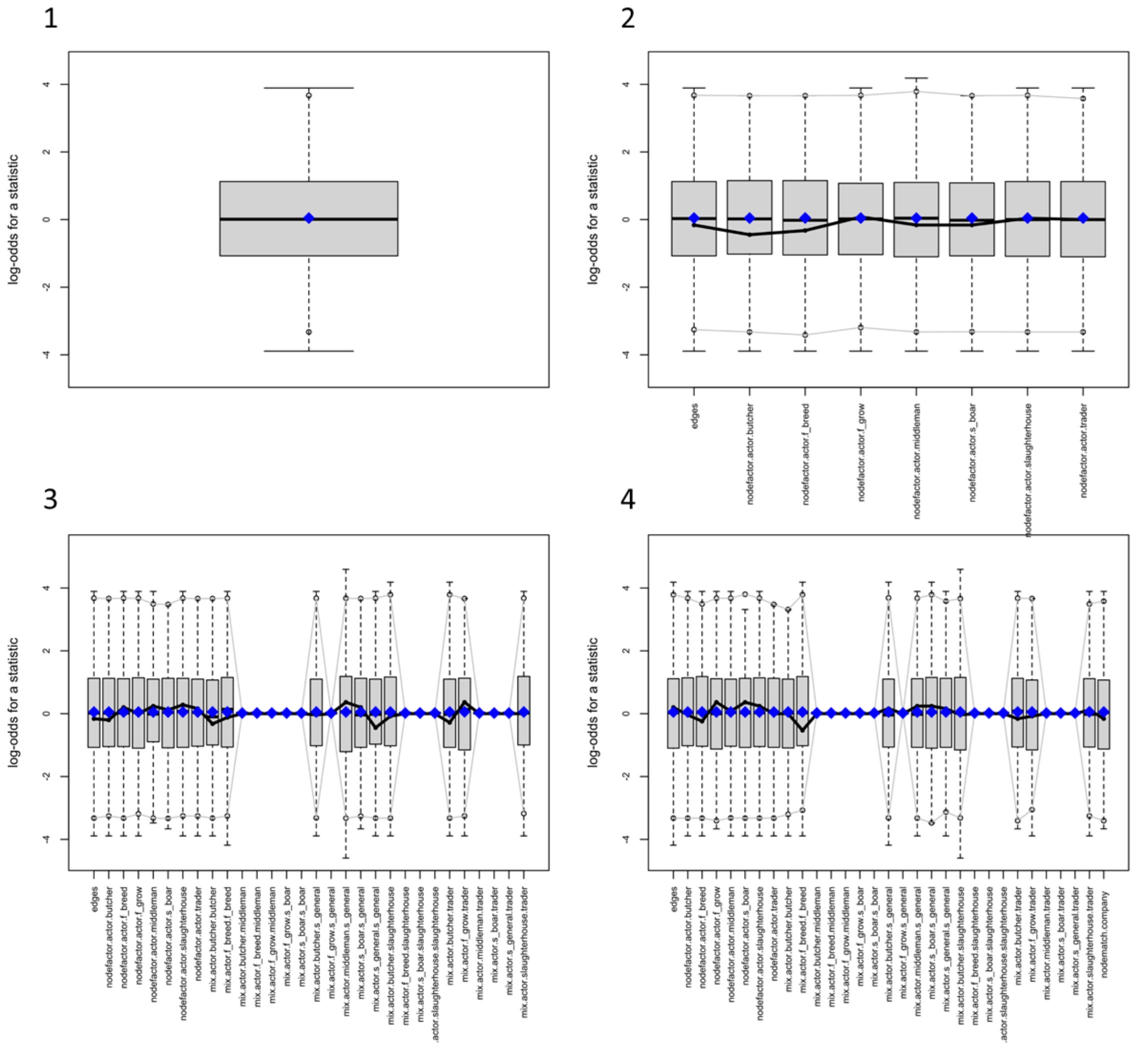

Figure S 8.9 ***ERGM goodness of fit (model statistics) for models 1-4****. Observed network statistics (black lines) relative to the normalised distribution of simulated network statistics (boxplots) centred at zero. Boxplots show model statistics from 100 simulated networks with mean values displayed as blue diamonds. Blank spaces denote model terms with no observations and which were fixed at an odds of zero.*

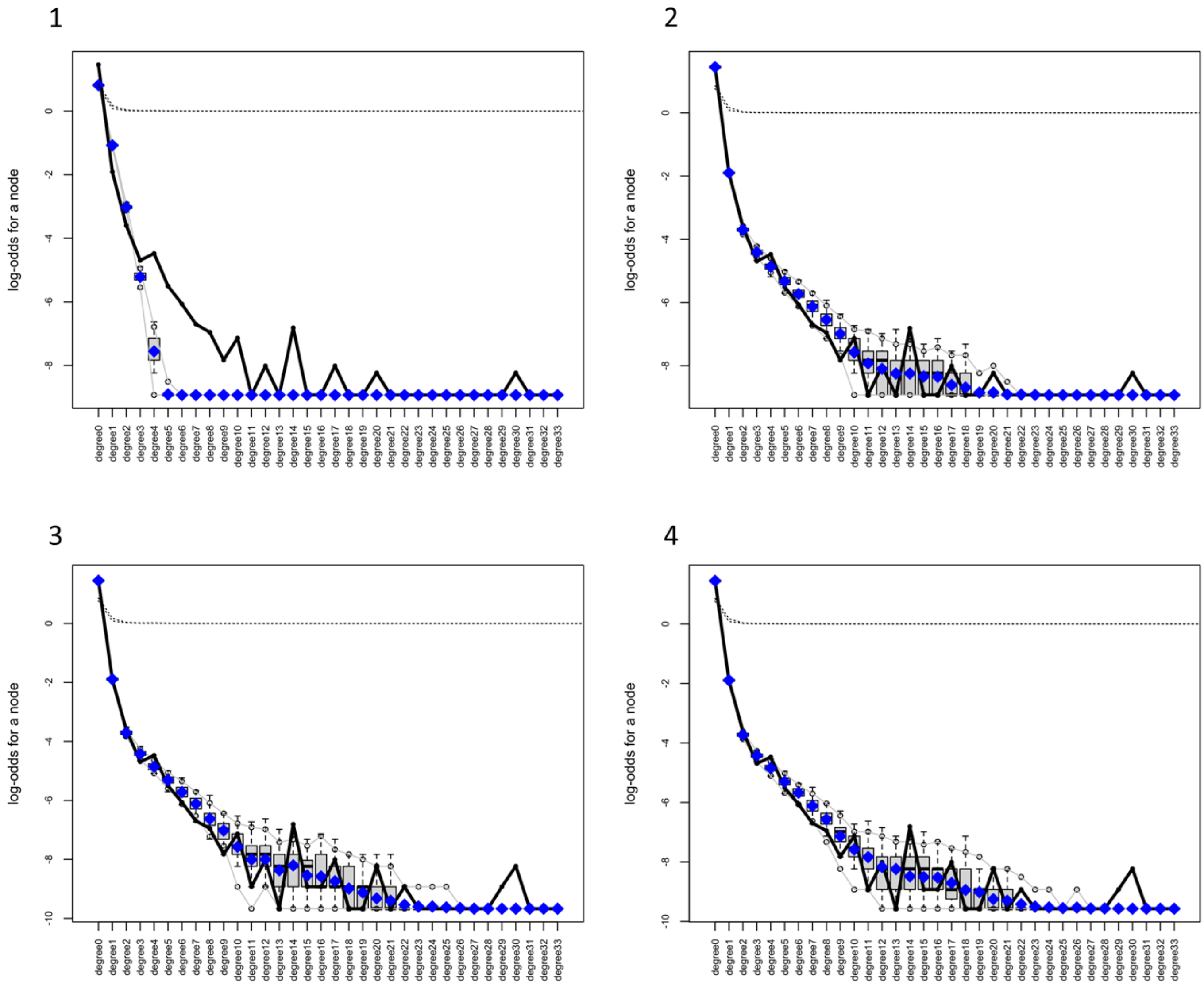

Figure S 8.10 ***ERGM goodness of fit: degree distribution for models 1-4****. Observed global degree distribution (black lines) relative to the degree distribution of simulated networks (boxplots). Boxplots show model statistics from 100 simulated networks with mean values displayed as blue diamonds.*

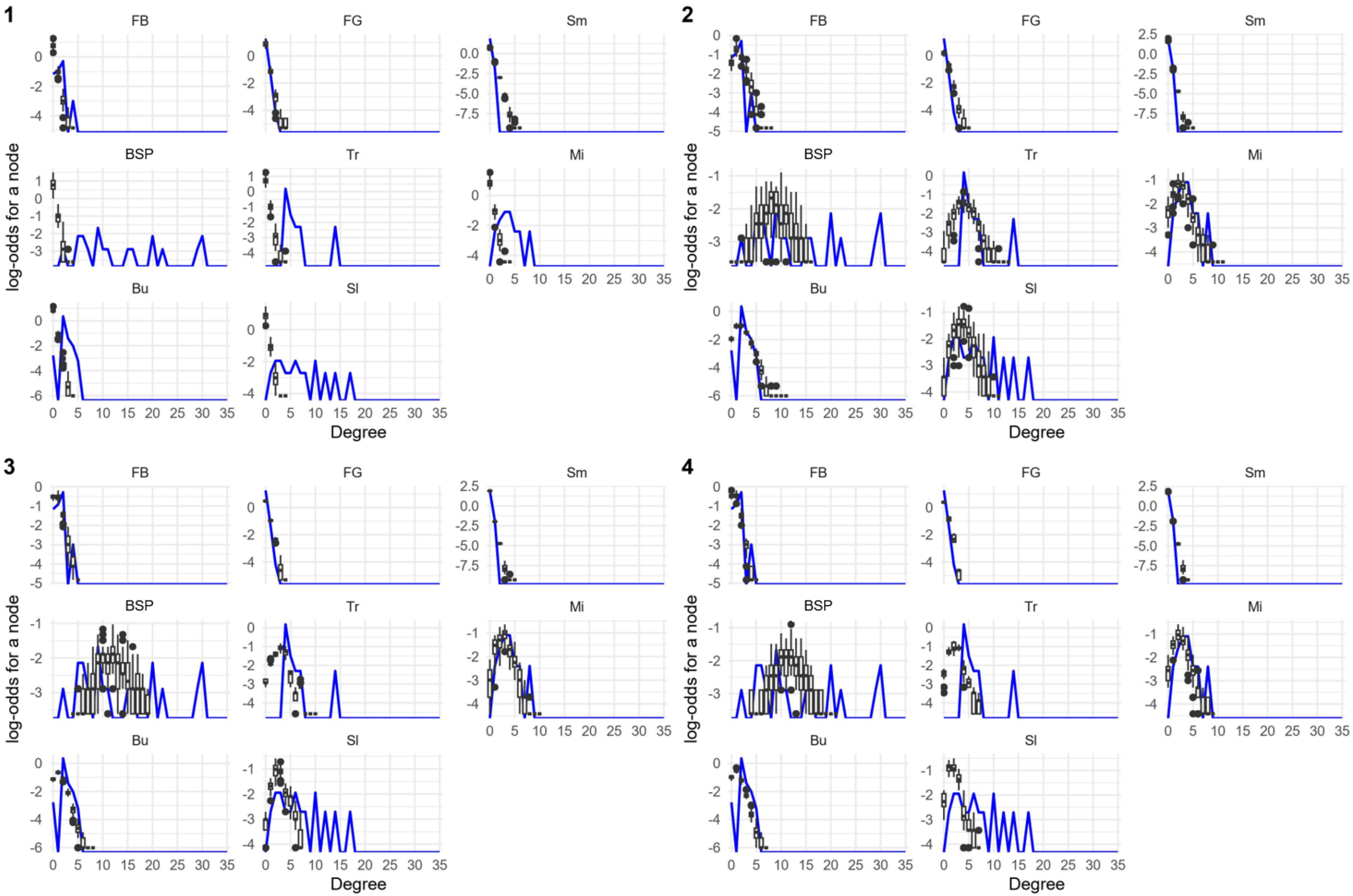

Figure S 8.11 ***ERGM goodness of fit: degree distribution by actor for models 1-4****. Observed actor-stratified degree distribution (blue lines) relative to the degree distribution of simulated networks (boxplots). Boxplots show model statistics from 100 simulated networks. Actor types are breeding farms (FB), growing farms (FG), smallholders (Sm), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl)*

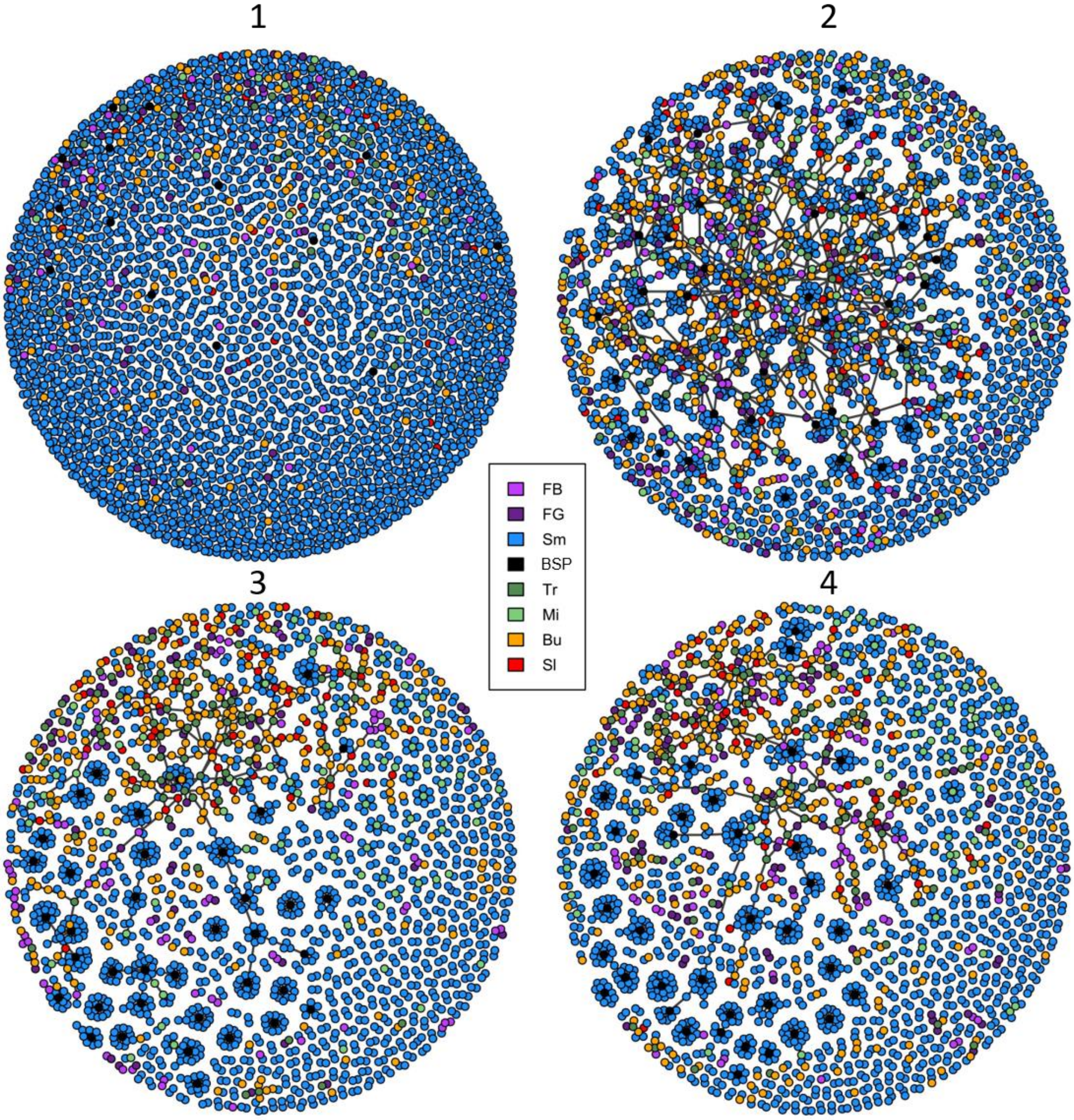

Figure S 8.12 ***Network plots.*** *Examples of networks simulated from models 1-4. Isolates have been removed for viewability. Nodes are arranged using the Fruchterman-Reingold algorithm and coloured by actor type: breeding farms (FB), growing farms (FG), smallholders (Sm), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl)*

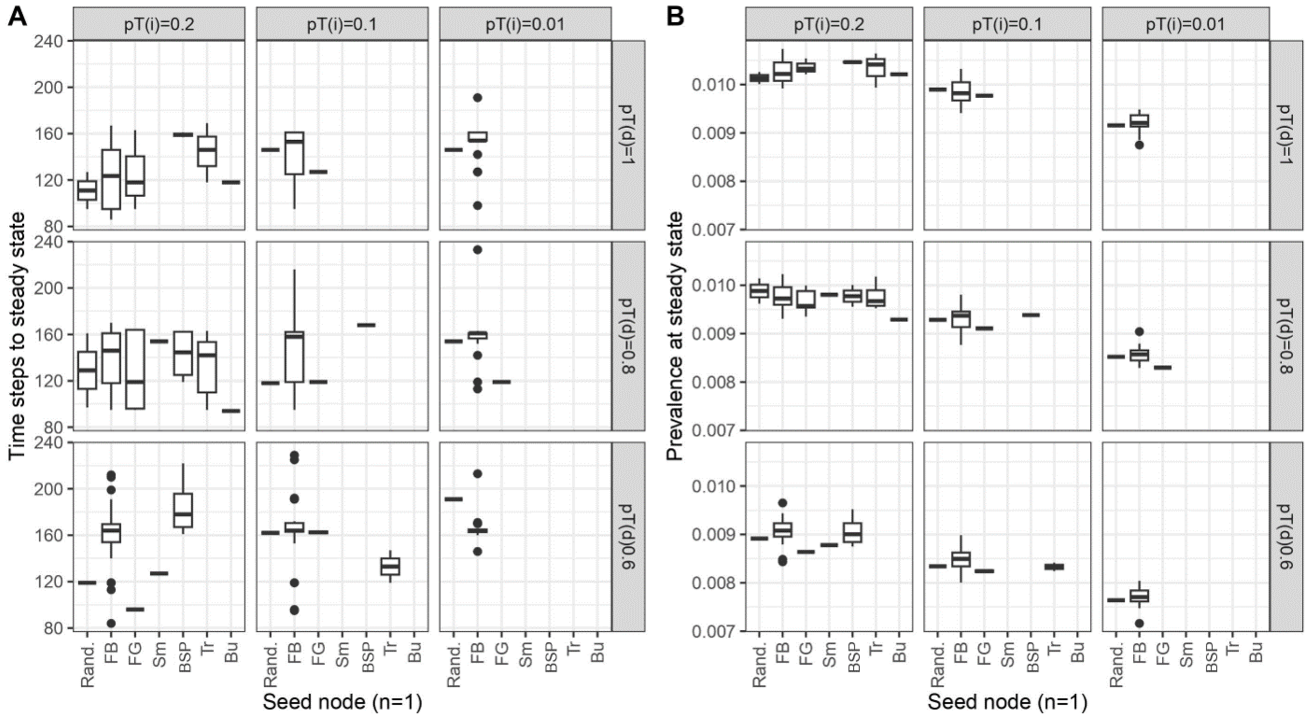

Figure S 8.8.13. ***Time to reach epidemic stationarity (A) and overall prevalence at epidemic stationarity (B)*** *after total random seeding (Rand.) and random actor seeding. Distributions show values for simulations generating an epidemic. Missing boxplots show seed node and transmissibility combinations that never generated an epidemic across simulations (n=100). Actor types are breeding farms (FB), growing farms (FG), smallholders (Sm), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl)*

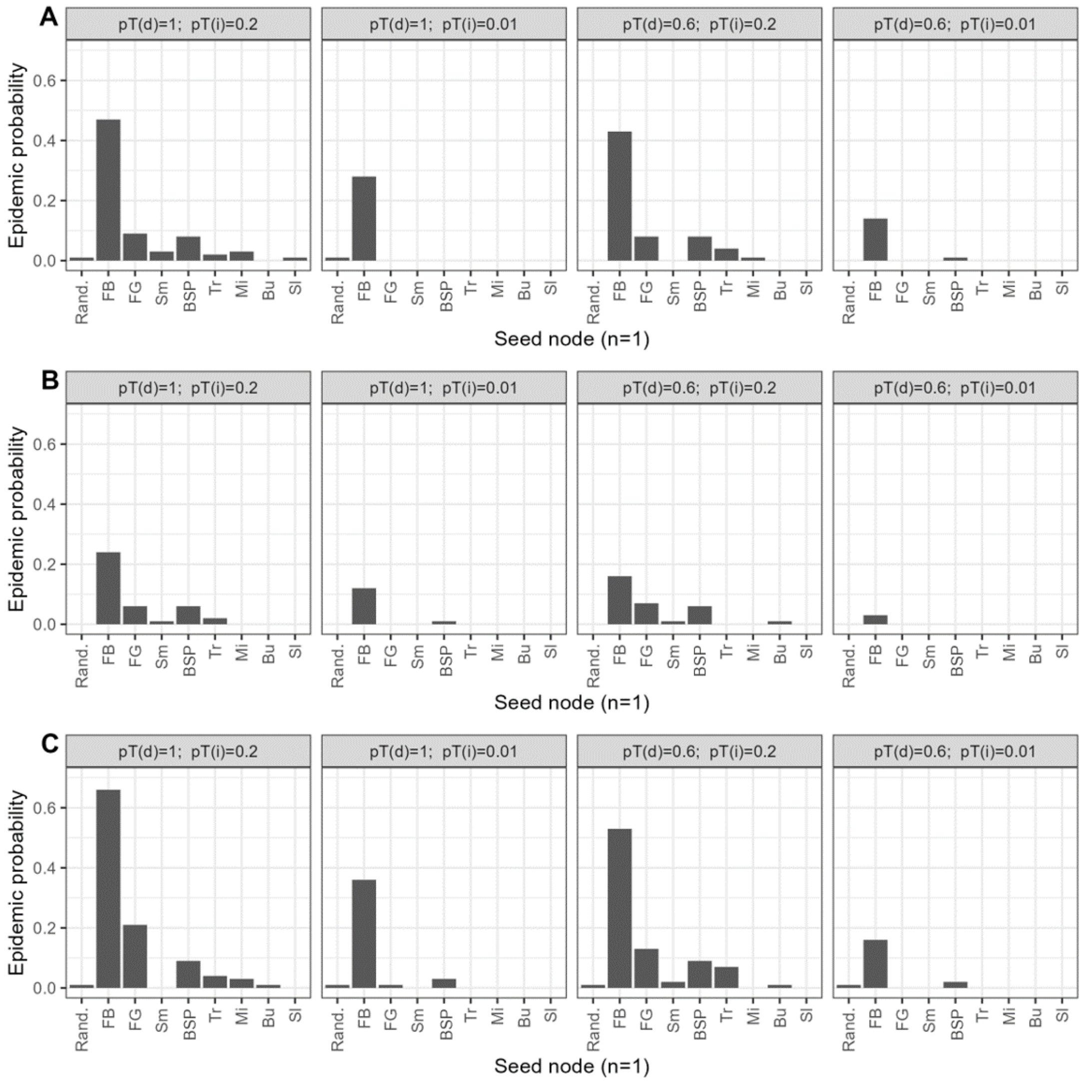

Figure S 8.14. ***Sensitivity of epidemic probability to infectious duration of breeding farms.*** *Values of 52 weeks (**A**), 22 weeks (**B**) and 78 weeks (**C**) are shown. Proportion of simulations (n=100) generating epidemics after total random seeding (Rand.) or random actor seeding. Different levels of direct (d) and indirect (i) transmission probabilities (pT) are shown. Actor types are breeding farms (FB), growing farms (FG), smallholders (Sm), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl)*

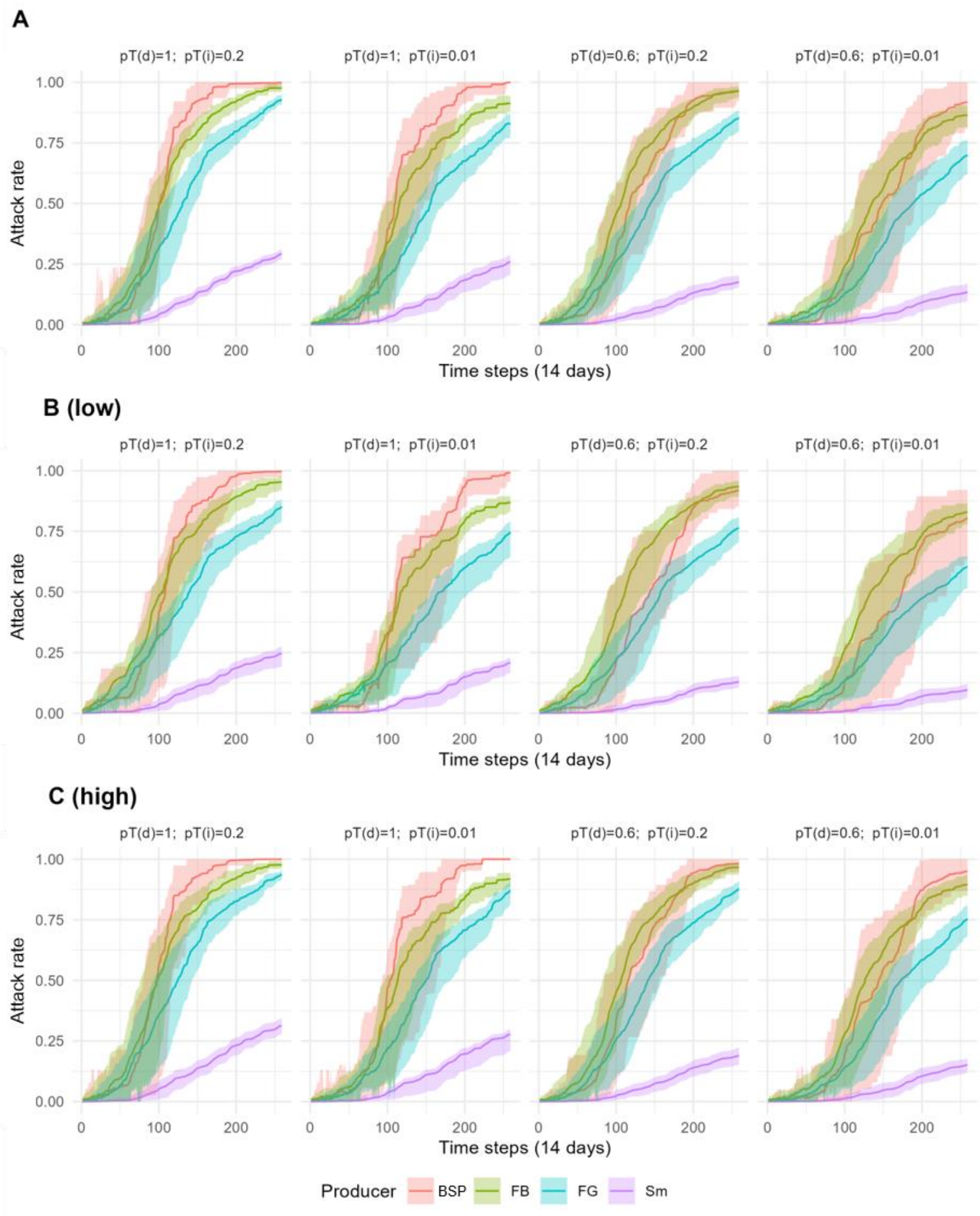

Figure S 8.15. ***Node's susceptibility to infection – sensitivity to breeding farm infectious duration.*** *Evolution of attack rate over time by actor type. Breeding farm (FB) infectious durations of 52 weeks (**A**), 22 weeks (**B**) and 78 weeks (**C**) are used. Seeding occurred in FB. Lines show means and shaded areas show the 5th and 95th percentiles of simulations (n=100). Different levels of direct (d) and indirect (i) transmission probabilities (pT) are shown. Actor types are boar service providers (BSP), breeding farms (FB), growing farms (FG), smallholders (Sm).*

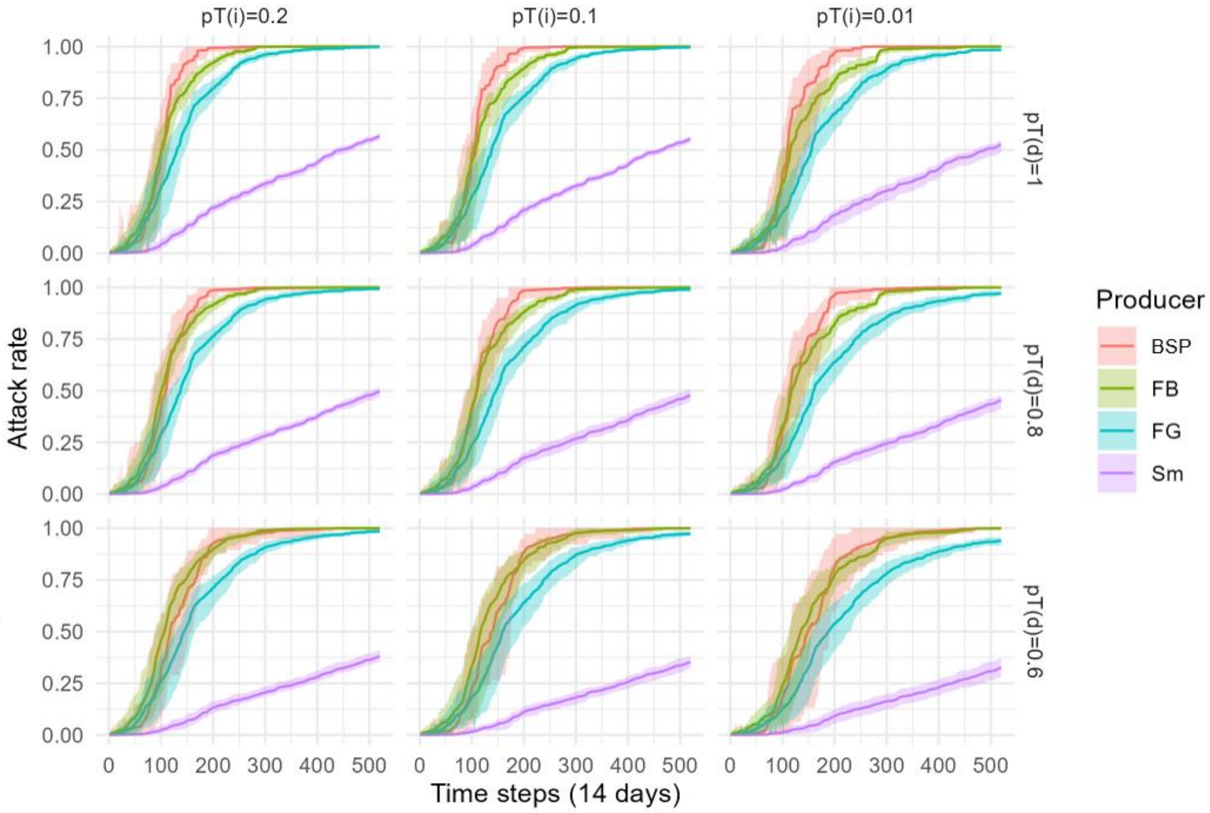

Figure S 8.16 ***Node's susceptibility to infection – all transmission probabilities.*** *Evolution of attack rate over time by actor type. Infections were seeded in breeding farms to ensure most simulations led to sustained transmission. Lines show means and shaded areas show the 5th and 95th percentiles of simulations (n=100). Different levels of direct (d) and indirect (i) transmission probabilities (pT) are shown. Actor types are boar service providers (BSP), breeding farms (FB), growing farms (FG), smallholders (Sm).*

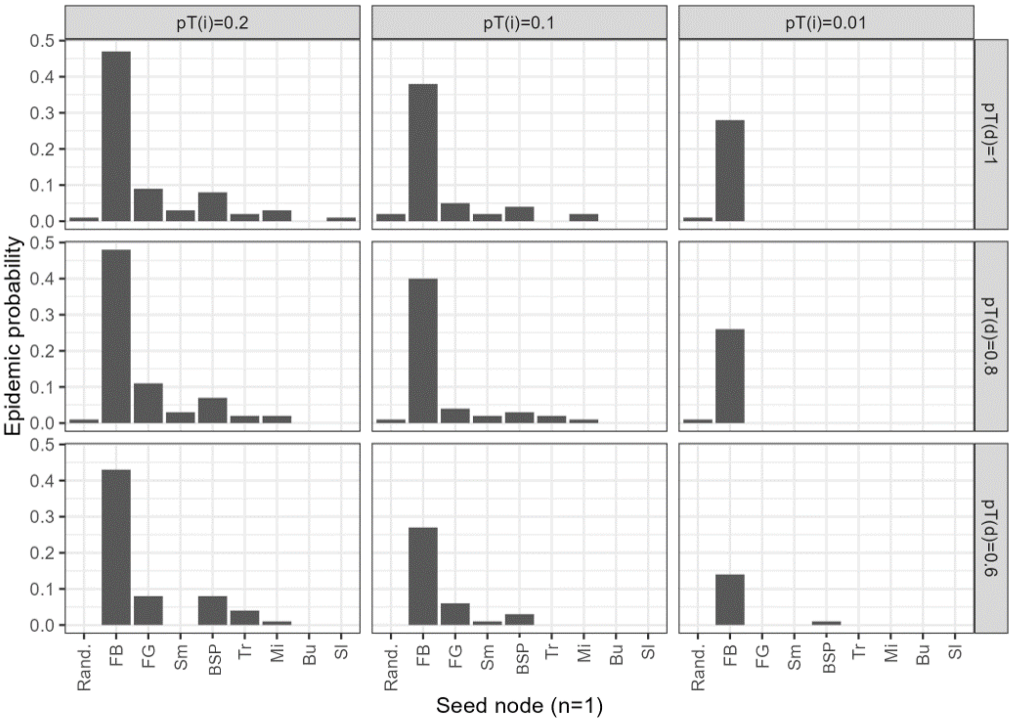

Figure S 8.17. ***Probability of an epidemic over all transmission probabilities tested.*** *Proportion of simulations (n=100) generating epidemics after total random seeding (Rand.) or random actor seeding. Different levels of direct (d) and indirect (i) transmission probabilities (pT) are shown. Actor types are breeding farms (FB), growing farms (FG), smallholders (Sm), boar service providers (BSP), traders (Tr), middlemen (Mi), butchers (Bu), and slaughterhouses (Sl).*

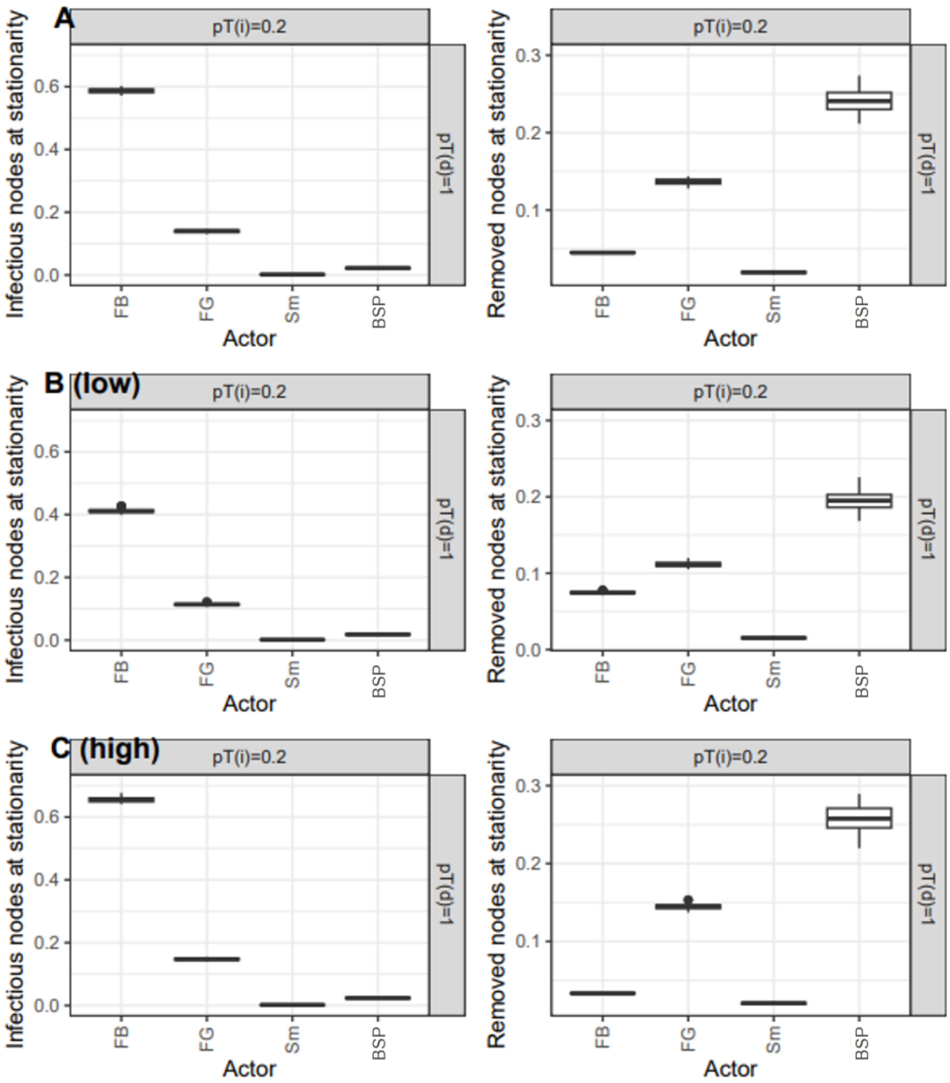

*Figure S 8.18. **Sensitivity analyses: epidemic outcomes at stationarity**. Sensitivity in the proportion of infectious (column 1) and recovered (column 2) nodes at epidemic stationarity for each actor type to infectious duration of breeding farms. Values of 52 weeks (**A**), 22 weeks (**B**) and 78 weeks (**C**) are shown. Plots show the mean proportion at stationarity averaged over simulations resulting in an epidemic. Results are shown here for model 4 and high direct and indirect transmission probabilities only after seeding in breeding farms (which generated the largest number of epidemics over which to average values). Actor types are boar service providers (BSP), breeding farms (FB), growing farms (FG), smallholders (Sm).*

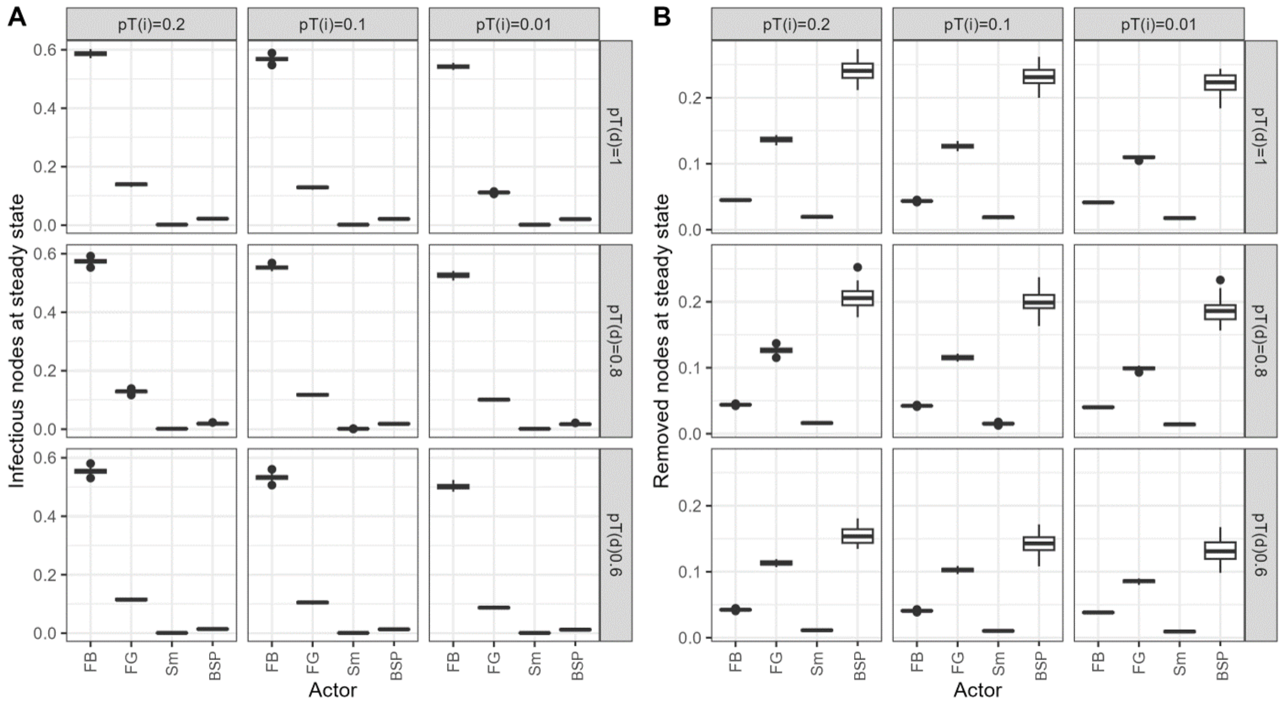

*Figure S 8.19. **Epidemic outcomes at stationarity.** The proportion of infectious (**A**) and recovered (**B**) nodes at epidemic stationarity for each actor type, and by transmissibility scenario. Results are shown here for model 4 only. Seeding in breeding farms is shown here as this generated the largest number of outbreaks over which to estimate values (seed actor type did not impact results). Actor types are boar service providers (BSP), breeding farms (FB), growing farms (FG), smallholders (Sm).*

9 Appendix

9.1 Published article (Chapter 2)

INTERFACE

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Review

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THE ROYAL SOCIETY PUBLISHING

Simulating contact networks for livestock disease epidemiology: a systematic review

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Contact structure among livestock populations influences the transmission of infectious agents among them. Models simulating realistic contact networks therefore have important applications for generating insights relevant to livestock diseases. This systematic review identifies and compares such models, their applications, data sources and how their validity was assessed. From 52 publications, 37 models were identified comprising seven model frameworks. These included mathematical models ($n = 8$; including generalized random graphs, scale-free, Watts–Strogatz and spatial models), agent-based models ($n = 8$), radiation models ($n = 1$) (collectively, considered 'mechanistic'), gravity models ($n = 4$), exponential random graph models ($n = 9$), other forms of statistical model ($n = 6$) (statistical) and random forests ($n = 1$) (machine learning). Overall, nearly half of the models were used as inputs for network-based epidemiological models. In all models, edges represented livestock movements, sometimes alongside other forms of contact. Statistical models were often applied to infer factors associated with network formation ($n = 12$). Mechanistic models were commonly applied to assess the interaction between network structure and disease dissemination ($n = 6$). Mechanistic, statistical and machine learning models were all applied to generate networks given limited data ($n = 13$). There was considerable variation in the approaches used for model validation. Finally, we discuss the relative strengths and weaknesses of model frameworks in different use cases.

1. Introduction

Livestock holdings may be epidemiologically connected through both direct and indirect contacts. Direct contact typically pertains to the movement of livestock between holdings, while mechanisms for indirect contact include the transfer of biological material, equipment or personnel [1]. These contact patterns can be conceptualized as networks in which nodes may represent livestock populations (given that livestock are often managed in groups or are otherwise spatially clustered) and edges represent the contact(s) of interest between those populations. It is well recognized that the structure of livestock contact networks has important implications for infectious disease transmission dynamics [2–6]. Characterizing the structure of these networks therefore plays a crucial role in understanding transmission patterns of infectious diseases in livestock and, consequently, for informing disease risk assessments and control strategies. This may involve the use of disease transmission models which explicitly account for contact network structure [3,7–11].

Insights about the epidemiological importance of livestock contact networks, especially livestock movement (e.g. trade) networks [1,12–15], have been generated by the analysis of routinely recorded livestock movement data collected via livestock identification and traceability systems (LITS) [14,16–19]. Where such routine data are unavailable (or insufficient), targeted network surveys can also be conducted [7,20–24].

Such empirical approaches are, however, associated with major challenges. In certain settings, LITS may not be implemented as data collection, and sharing may be restricted by commercial interests and related data privacy concerns [3,25–27]. The costs and infrastructure required to implement and sustain routine systems also constrains their feasibility, especially in low- and middle-income countries [28]. The analysis and utility of such data may be constrained by its vastness [28]. Moreover, a lack of updated or complete data may also limit its use for supporting decision making during disease outbreaks [28–30]. While network surveys have been used when such data are unavailable, these are usually targeted towards specific geographical locations and time periods. Indeed, both routine and non-routine network data capture activities are highly resource intensive and are therefore likely to be targeted towards livestock species or production types of particular interest from a national livestock disease-management perspective [28,31–33].

Model-based approaches are increasingly being used to help address some of these challenges. We therefore conducted a systematic review to provide an overview of the state-of-the-art in modelling livestock contact networks. Our objectives were to identify the main types of models and methods used, compare their applications and data requirements, and examine the extent to which such models have been validated. Based on the findings, we also discuss key challenges and opportunities for future research in this area. In this review, we focus on studies which have employed empirically informed, model-based approaches of network (re)-construction or inference, with a primary interest in epidemiologically relevant (i.e. potentially infectious) contacts between livestock populations.

2. Methods

2.1. Systematic search strategy

This systematic review followed the PRISMA 2020 guidelines for the reporting of systematic reviews [34]. Search terms were developed around four key topics: (i) livestock and poultry, (ii) networks, (iii) models, and (iv) disease. Four databases—Medline, Embase, Web of Science and Scopus—were queried using title, abstract and keyword searches on 22 January 2021 and no date limits. Database searches were repeated on 27 January 2023 to cover all records published up to this date. Relevant subject headings were applied to databases using subject heading indexing (i.e. Medline and Embase; electronic supplementary material, table S1). Search terms within the 'networks' topic were informed by previous reviews of the use of network simulation models in different contexts [35–39]. However, broad terms were also included to ensure identified records were not restricted to known model types. Within each search topic, Boolean 'OR' operators were used to combine search terms and subject headings, while different topics were combined using 'AND' operators (electronic supplementary material, table S1). Wildcards, truncations and adjacency searches were applied using the relevant syntax for each database. Peer-reviewed papers and conference proceedings were all eligible for inclusion. The screening process was expanded to include the reference lists of the included publications, as well as any papers that cited them. For full search terms see electronic supplementary material, table S1.

2.2. Inclusion and exclusion criteria

Inclusion and exclusion criteria were agreed by all authors. A single reviewer screened records but discussed any records for which inclusion was uncertain with the other authors. Screening was split into two stages:

Stage 1: Titles, abstracts and keywords were screened; records were rejected if any of the following statements were true: (i) there was no reference to livestock; (ii) there was no reference to contacts between livestock, contact networks or infectious disease dynamics on networks; (iii) the record was not peer-reviewed, and (iv) the record was not written in English.

Stage 2: Full texts were screened; records were retained if all following statements were true: (i) a model was used to simulate a network of epidemiologically relevant contacts between livestock subpopulations; (ii) the model attempted to reproduce structural properties of an empirical network and/or its underlying generating mechanisms, and (iii) these properties or mechanisms were informed empirically.

Hence, we did not review records which simulated theoretical networks (e.g. to be used as reference or null models) and/or which randomized some aspects of a network to make comparisons with empirical networks (e.g. [40,41]). We also excluded studies that solely reconstructed transmission networks, since these are subsets of the contact networks which are the focus of this review. Where multiple models were used in papers, each model was screened individually for inclusion.

2.3. Data extraction

Information from each study was systematically recorded in a data extraction table. This was designed to record information about: (i) the type of model used; (ii) the applications of models; (iii) characteristics of the empirical network under study (livestock type, geographical location and disease focus); (iv) definition of network nodes and edges; (v) data types and variables used for model fitting, and (vi) how the performance of models was assessed (table 2). Descriptive analyses and visualizations of the frequency of key study characteristics were conducted using R v. 4.2.0 [42].

2.4. Model classifications

Following exploratory scoping of the literature, particularly previous reviews on network simulation models in other disciplines [36–39], we classified models into three groups: mechanistic, statistical and machine learning. Though these categories are not mutually exclusive (e.g. mechanistic model parameters may be estimated using statistical methods), they are useful for describing the general characteristics of the reviewed models, as described below.

Mechanistic models are here defined as mathematical equations *or* an algorithmic set of rules, a 'mechanism', used to generate a set of edges between nodes, i.e. a network. We include in this grouping mechanistic models that span from (i) abstracted and intentionally simplified 'mathematical models' [38], such as scale-free and small-world models (and which include the 'probabilistic' and 'idealized' models/networks described by others) [37,39], to (ii) complex agent-based models (ABMs) explicitly modelling individual-level contact processes. Notably, across both of these subgroups, the generating mechanisms may simply serve as an arbitrary algorithmic tool used to generate networks exhibiting a certain topology, or else they may be configured to reproduce the emergent processes (assumed or otherwise) that generated the observed network, that is, based on 'first principles' [43,44].

Statistical models describe a network as a function of factors hypothesized to be associated with edge formation. They start

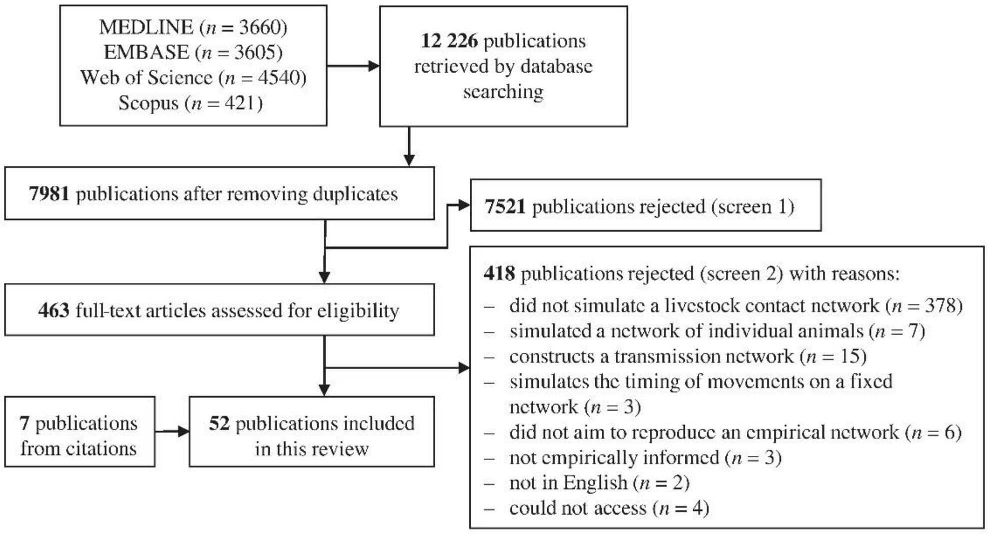

Figure 1. PRISMA flow diagram.

with observations of an empirical network and fit the parameters of a selected model framework to the data through formal statistical inference [36,38,39]. Within this group, we include standard statistical models (e.g. generalized linear models) which may be used to estimate the probability or strength of an edge between nodes given a set of covariates, in addition to network-specific statistical models which explicitly account for the dependencies inherent to network data [36,38,39].

Machine learning models learn patterns in the data without the model being specified by the user and commonly place an emphasis on predictive accuracy rather than causal inference [45,46]. These can be broadly categorized according to whether the model fitting is 'supervised', where the value of the dependent variable is known (i.e. data are 'labelled' in machine learning-terminology), or 'unsupervised', which use 'unlabelled' data and commonly include clustering algorithms [45]. In the context of network simulation, they may be used to solve classification and regression problems.

Table 1. Model frameworks applied to simulate livestock contact networks across 52 included studies. ABM = agent-based model; (T)ERGM = (temporal) exponential random graph model; GM = gravity model; RF = random forests.

category	model framework	number of models	number of publications
mechanistic	mathematical models	8	7
	ABMs	8	15
	radiation models	1	1
statistical	(T)ERGMs	9	7
	GMs	4	4
	other statistical models	6	17
machine learning	RF	1	1
total	-	37	52

3. Results

3.1. Screening process

Database searches retrieved 12 226 publications of which 7981 (65%) were unique. Title, abstract and keyword screening excluded 7521 (94%) unique records (figure 1). A further 418 (5%) were excluded after screening full texts, mostly because they did not simulate a livestock contact network but presented descriptive analyses of empirical networks or simulated infectious disease transmission on empirical networks (figure 1). Six additional publications were identified from the citations of included papers. A single additional publication citing these publications was then identified. Therefore, a total of 52 publications published between 2009 and 2022 were eligible for inclusion (see electronic supplementary material, table S2 for all exclusion reasons).

To identify the number of different models used across all included studies, we considered a model to be 'distinct' from others when a specific framework was applied to a particular dataset. Hence, analyses in 20 publications were based on previously published models (table 2), while two publications presented multiple models, applying different model types to a single setting [47], or the same model type to different settings [29]. Consequently, 37 distinct models (tables 1 and 2) were identified and reviewed across the 52 included publications. We refer to unique models using the first published instance.

Following the PRISMA checklist, we highlight nine studies that might appear to meet the inclusion criteria, but were excluded. Three studies rewired empirically observed networks without also attempting to simulate the empirical network [93–95]. Three studies simulated the timing or volume of livestock movements on a predefined (non-modelled) network [96–98]. Two used mechanistic models with entirely hypothetical parameter values [99,100]. One study applied random forests (RFs) to predict the timings of trading events, without using this information to simulate a network [101].

Table 2. Summary of key characteristics and applications of 37 identified models. ABM = agent-based model; GM = gravity model; RF = random forests; (T)ERGM = (temporal) exponential random graph model; LITS = livestock identification and traceability system; limited data = simulating a network from the available data, when empirical networks are incompletely characterized; network-generating processes = inference of factors associated with network (or edge) generation; structure and transmission = analytical exploration of the relationship between network structure and diffusion of phenomena (e.g. disease) on networks; SA disease control = scenario analysis related to assessing the impact of disease control strategies; SA altering network = comparing the impact of alternative network configuration scenarios on simulated disease transmission patterns; SA surveillance = exploring disease surveillance scenarios; behavioural response = modelling adaptive behaviour, e.g. farmers' response to disease on a network.

model ID		model classification			model purpose		network characteristics						data
no.	model [model name]; other papers using the model	year	model category	model framework	model applications	infectious disease model	livestock focus	setting	disease focus	nodes	edges	static / dynamic	data used for calibration
1	(Ferdousi *et al.* [48])	2019	mechanistic	generalized random graph	structure and transmission, limited data, SA: disease control	yes	pigs	USA	African swine fever	livestock holdings, markets	livestock movement	static	network survey
2	(Gates & Woolhouse [44])	2015	mechanistic	generalized random graph	SA: altering network	yes	cattle	Britain	hypothetical	livestock holdings	livestock movement	static	LITS
3	(Thakur *et al.* [47]) (A)	2015	mechanistic	Watts–Strogatz	structure and transmission, limited data	yes	pigs	Canada	porcine reproductive and respiratory syndrome	livestock holdings	livestock movement, vehicle	static	network survey
4	(Thakur *et al.* [47]) (B)	2015	mechanistic	scale-free	structure and transmission, limited data	yes	pigs	Canada	porcine reproductive and respiratory syndrome	livestock holdings	livestock movement, vehicle	static	network survey
5	(Tago *et al.* [49])	2016	mechanistic	scale-free	SA: disease control, behavioural response	yes	cattle	France	hypothetical	livestock holdings, markets, exchangers	livestock movement	static	LITS
6	(Lennartsson *et al.* [50]; [SpecNet])	2012	mechanistic	other mathematical	presents model	no	pigs	Sweden	non-specific	livestock holdings, slaughter point	livestock movement	static	LITS
7	(Rossi *et al.* [51])	2017	mechanistic	spatial	structure and transmission, limited data	yes	cattle	Italy	hypothetical highly contagious	livestock holdings	livestock movement, personnel	static	LITS
8	(Hu *et al.* [52])	2021	mechanistic	spatial	limited data	yes	pigs	China	African swine fever	livestock holdings, slaughter point	livestock movement	static	LITS
9	(Wiltshire [53]; [RUSHPNBM]) (Bucini *et al.* [54]; Koliba *et al.* [55]; Wiltshire *et al.* [27])	2018	mechanistic	ABM	SA: altering network, structure and transmission, behavioural response	yes	pigs	USA	porcine epidemic diarrhoea	livestock holdings, slaughter points, feed mills	livestock movement, feed, vehicle	dynamic	emergent
10	(Yang *et al.* [56]) (Yang *et al.* [57,58])	2019	mechanistic	ABM	SA: disease control, limited data, behavioural response	yes	cattle	USA	foot and mouth disease	livestock holdings, exchangers, markets	livestock movement, vehicle	dynamic	emergent

11	(Ross *et al.* [59])	2011	mechanistic	ABM	presents model	no	cattle	USA	bovine tuberculosis	livestock holdings, markets	livestock movement	dynamic	emergent
12	(Liu *et al.* [60]; [Epirur_Cattle])	2012	mechanistic	ABM	limited data	yes	cattle	USA	hypothetical direct contact	livestock holdings	livestock movement	dynamic	emergent
13	(Ansari *et al.* [61])	2021	mechanistic	ABM	presents model	no	pigs	Germany	non-specific	livestock holdings, exchangers	livestock movement	dynamic	LITS
14	(Brock *et al.* [62])	2021	mechanistic	ABM	SA: disease control	yes	cattle	Ireland	bovine herpesvirus type 1	livestock holdings	livestock movement	dynamic	emergent
15	(Knight *et al.* [63,64])	2021	mechanistic	ABM	structure and transmission, behavioural response	yes	cattle	Scotland	hypothetical slowly spreading	livestock holdings	livestock movement	dynamic	LITS
16	(Kim *et al.* [65]; Pomeroy *et al.* [66])	2016	mechanistic	ABM	structure and transmission	yes	cattle	Cameroon	foot and mouth disease	geo-locations	livestock movement	dynamic	network survey
17	(Kong *et al.* [67])	2022	mechanistic	radiation model	limited data	no	poultry	China	non-specific	geo-locations	livestock movement	static	emergent
18	(Valdes-Donoso *et al.* [68])	2017	machine learning	RF	limited data, network-generating processes	no	pigs	USA	porcine reproductive and respiratory syndrome	livestock holdings, markets	livestock movement	static	network survey
19	(Nicolas *et al.* [69])	2018	statistical	GM	network-generating processes, limited data	no	cattle, sheep/goats, camels	Mauritania	non-specific	geo-locations	livestock movement	static	network survey
20	(Chaters *et al.* [28])	2019	statistical	GM	limited data, network-generating processes	yes	cattle	Tanzania	non-specific	geo-locations	livestock movement	static	movement permits
21	(Qiqi Yang *et al.* [15]	2020	statistical	GM	limited data	no	poultry	China	avian influenza	geo-locations	livestock movement	static	network survey, emergent
22	(Blair and Lowe [70])	2022	statistical	GM	SA: disease control	no	pigs	USA	non-specific	geo-locations, slaughter point	livestock movement	static	network survey
23	(Ortiz-Pelaez *et al.* [71])	2012	statistical	ERGM	network-generating processes		sheep/goats	Ethiopia	non-specific	geo-locations	livestock movement	static	network survey
24	(Relun *et al.* [29]) (A)	2017	statistical	ERGM	network-generating processes	no	pigs	Bulgaria	non-specific	livestock holdings, exchangers	livestock movement	static	LITS
25	(Relun *et al.* [29]) (B)	2017	statistical	ERGM	network-generating processes	no	pigs	Spain	non-specific	livestock holdings, exchangers	livestock movement	static	LITS
26	(Relun *et al.* [29]) (C)	2017	statistical	ERGM	network-generating processes	no	pigs	France	non-specific	livestock holdings, exchangers	livestock movement	static	LITS
27	(Kukielka *et al.* [32])	2017	statistical	ERGM	network-generating processes	no	pigs	Georgia	African swine fever	geo-locations	livestock movement	static	network survey

(*Continued.*)

Table 2. (*Continued.*)

model ID		model classification			model purpose		network characteristics						data
no.	model [model name]; other papers using the model	year	model category	model framework	model applications	infectious disease model	livestock focus	setting	disease focus	nodes	edges	static / dynamic	data used for calibration
28	(Poolkhet *et al.* [72])	2018	statistical	ERGM	network-generating processes	no	poultry	Thailand	avian influenza	livestock holdings, exchangers, markets, slaughter point, other	livestock movement, other	static	network survey
29	(Belkhiria *et al.* [73])	2019	statistical	ERGM	network-generating processes	no	cattle, sheep/goats, donkeys	Senegal	Rift valley fever	geo-locations	livestock movement	static	network survey
30	(Hammami *et al.* [74])	2022	statistical	ERGM	network-generating processes	no	pigs	France	non-specific	livestock holdings, slaughter point	livestock movement	static	LITS
31	(Lee *et al.* [75])	2021	statistical	TERGM	structure and transmission, SA: disease control	yes	pigs	Vietnam	African swine fever	livestock holdings	livestock movement, indirect	dynamic	network survey
32	(Lindström *et al.* [25]; [USAMM]) (Brommesson *et al.* [76]; Buhnerkempe *et al.* [77,78]; Gilbertson *et al.* [79]; Gorsich *et al.* [80,81]; Kao *et al.* [82]; Sellman *et al.* [83]; Tsao *et al.* [84])	2013	statistical	statistical other	SA: disease control, limited data, SA: surveillance	yes	cattle	USA	non-specific, foot and mouth disease, bovine tuberculosis	geo-locations	livestock movement	static	movement permits, census
33	(Sellman *et al.* [85])	2022	statistical	statistical other	limited data	no	pigs	USA	porcine epidemic diarrhea	livestock holdings	livestock movement	static	movement permits, census
34	(Lindström *et al.* [86]) (Brommesson *et al.* [87]; (Lindström *et al.* [88–90])	2009	statistical	statistical other	network-generating processes, structure and transmission	yes	cattle, pigs	Sweden	non-specific, hypothetical	livestock holdings	livestock movement	static	LITS
35	(Xiao *et al.* [91]) (Pomeroy *et al.* [66])	2015	statistical	statistical other	network-generating processes	yes	cattle	Cameroon	foot and mouth disease	geo-locations	livestock movement	dynamic	network survey
36	(Moon *et al.* [26])	2019	statistical	statistical other	limited data	no	pigs	USA	non-specific	livestock holdings	livestock movement	static	census
37	(Schumm *et al.* [92])	2015	statistical	statistical other	limited data	no	cattle	USA	non-specific	geo-locations	livestock movement	static	census

3.2. General model characteristics

The identified models were applied to 20 countries in four continents; no eligible models were applied to Australia or South America. The USA was the most well-represented country, with 11 distinct models applied (figure 2*a*). Most models were applied to a single livestock type, including pigs ($n = 17$), cattle ($n = 13$) and poultry ($n = 3$). Three models were applied to multiple livestock types (figure 2*d*). All models were applied in a disease context, related to specific ($n = 18$), non-specific ($n = 13$) or hypothetical diseases with specific characteristics ($n = 6$). Infectious disease transmission was simulated on the networks generated by 18 models (13 mechanistic; 5 statistical; table 2).

In 25 models, nodes represented farms or herds, with 14 of these also accounting for other units such as markets, slaughterhouses and/or livestock traders. Nodes were livestock populations in given administrative areas (e.g. villages, provinces and counties) in the other 12 models. Edges represented livestock movements in all models: either movements of animals among populations ($n = 24$), or transhumant movements of whole livestock populations between geographical areas ($n = 3$). Seven models simulated multi-layer networks with additional sets of edges representing epidemiologically relevant contacts via vehicles, personnel or feed providers. A single model broadly defined an edge as any type of potentially infectious contact in the context of avian influenza without defining transmission routes specifically [72]. Most models ($n = 27$) generated static networks. However, the timing of trades on the simulated static network was sometimes time varying, e.g. based on a probability of trading [49]. Alternatively, nodes or edges were sometimes added or removed by copying empirical records exactly (i.e. without modelling these) [44,52]. Contrastingly, eight ABMs and two statistical models generated dynamically evolving networks.

Most models were statistical ($n = 19$), with the most common frameworks being exponential random graph models (ERGMs; $n = 9$), gravity models (GMs) ($n = 4$) and other statistical models ($n = 6$). Only one machine learning model, based on RFs, was identified. The mechanistic models ($n = 17$) included mathematical models ($n = 8$), ABMs ($n = 8$) and a radiation model ($n = 1$) (table 1). The first model was published in 2009, but most ($n = 31$; 84%) were published between 2015 and 2022 (figure 2*c*).

In the following sections, we first review the objectives addressed by the different model frameworks and the data sources used. We then introduce the key methodological characteristics of each modelling framework, including how they have been calibrated to data, and review the degree to which their performance was assessed.

3.3. Model applications

Network simulation models were used for a range of applications which varied according to the model type used (figure 3*a;* table 2). For 13 models, multiple applications were identified.

Approximately half of models (16/37) were used to generate networks based on limited data, for example where total network data was not available but descriptive statistics of that network were, or where models based on complete networks were used for prediction in other settings. These included all model frameworks described above, except ERGMs. A single study used artificially constrained data on indirect contacts among farms to explore how inferring these contacts using different levels of information and assumptions influenced the outputs of disease transmission models [51].

A third of models ($n = 13$), mostly statistical ($n = 12$), were applied to explore network-generating processes, specifically, the inference of factors associated with network (or edge) generation. For the RF model, the relative importance of predictors was assessed by comparing prediction accuracies of models with and without a given predictor. Nine models, mostly mechanistic ($n = 7$), were applied to analytically explore the relationship between network structure and diffusion of phenomena (e.g. disease) on networks.

Models were also applied to test scenarios related to (i) assessing the impact of disease control strategies ($n = 7$) such as targeted livestock movement restrictions, culling or vaccination; (ii) using simulated livestock movement patterns to inform optimal sites for directing disease surveillance activities ($n = 1$; [80]), and (iii) comparing the impact of alternative network configuration scenarios on simulated disease transmission patterns ($n = 2$; all mechanistic). These scenarios involved, for example, rewiring nodes [44] and changing the composition of the farm population [53]. Mechanistic models were applied to explore the interaction between agents' adaptive behaviour, and network formation or disease spread. Examples of such applications included modelling of farmers' decisions to implement biosecurity measures in response to disease risk [54], or trigger sales in anticipation of movement restrictions [49]. In Knight *et al.* [64], farmers' adaptive behaviour (i.e. anticipatory response to disease control interventions) influenced the formation of the network itself.

Three models were presented as a proof of principle to demonstrate their ability to reproduce structural features of an empirical livestock contact network, without further application [50,59,61]; these models were therefore omitted from figure 3*a*.

3.4. Data sources used

Different data sources were exploited for calibrating models, with some variation seen between model types (figure 3*b*). Most models ($n = 30$) were informed by empirical network data, including data from network surveys ($n = 13$), LITS ($n = 12$), censuses with some data on livestock trade, i.e. capturing total number of animals 'sold or moved' by actors in a given year ($n = 2$), and livestock movement permits which are used in some countries for recording and regulating movements, e.g. across administrative borders ($n = 1$; figure 3*b*). Contrastingly, mechanistic models sometimes did not use network data, but instead used data to parametrize model processes influencing edge formation (e.g. herd demographic processes ($n = 6$; table 2)).

While models sometimes exploited similar data types, the way that these data were used to calibrate models varied substantially according to model type as detailed in the next section (§3.5).

3.5. Model frameworks

3.5.1. Mechanistic

3.5.1.1. Mathematical models ($n = 8$)

3.5.1.1.1. Generalized random graphs. Random graphs generate edges between sets of nodes at random, either by assigning a

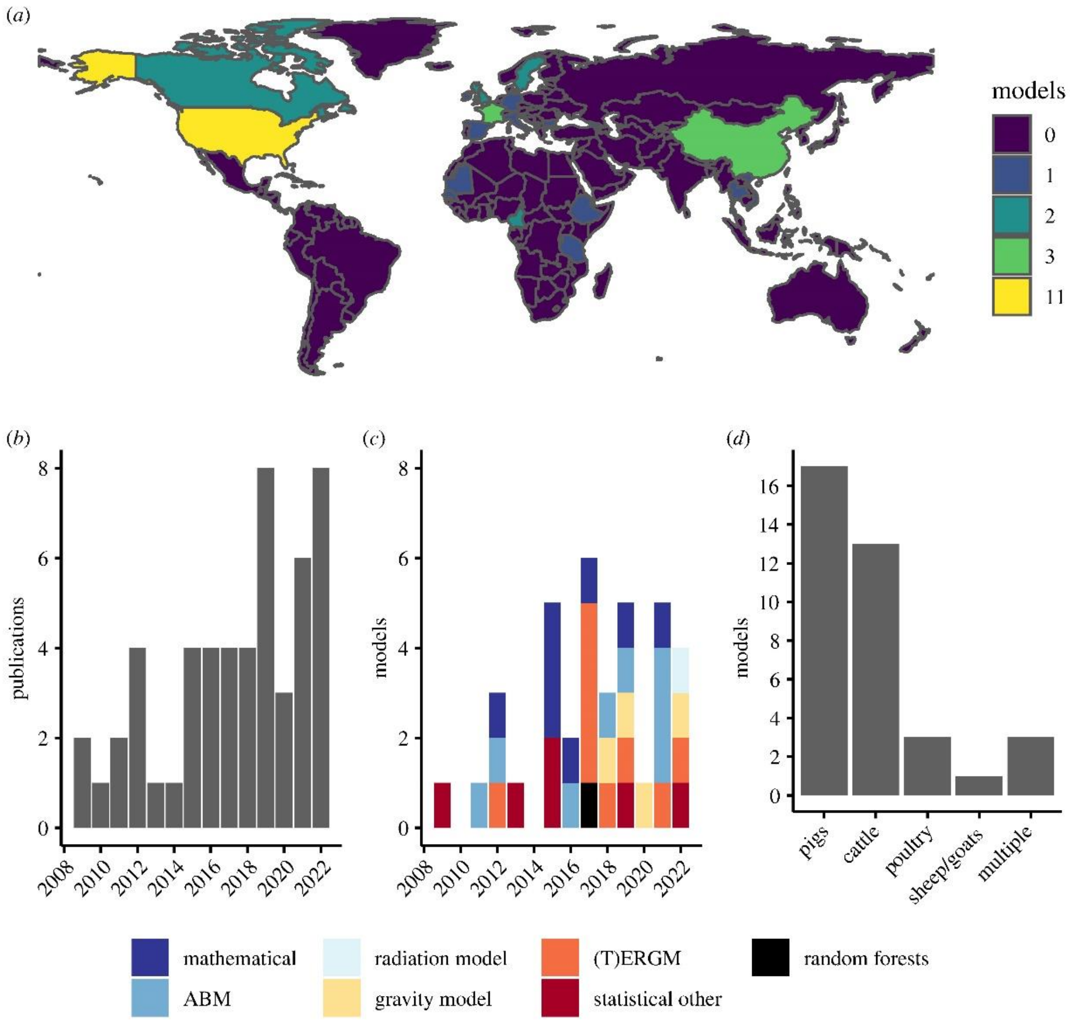

Figure 2. Scope of included papers and models: (*a*) map of countries models were applied to; (*b*) papers published by year; (*c*) models published by year according to model group (blue = mechanistic, red/orange = statistical, black = machine learning); (*d*) livestock types models were applied to.

fixed number of edges [102,103] or by assigning edges with a fixed uniform probability [104]. These models therefore control for network density alone, and the resulting networks fail to capture some important structural features of empirical networks, especially high clustering and a right-skewed degree distribution [38,105,106].

Generalizations may, however, be applied to control for other network structural features beyond density thus permitting the generation of more 'realistic' networks [38,106]. The configuration model, or matching algorithm [107,108], allows for degree distribution to be fixed by algorithmically assigning a number of incoming and outgoing connections (stubs) to nodes, while randomly matching in- and out-stubs between different nodes. Other structural features can be controlled for: for example, in the pig movement network generated in Ferdousi *et al.* [48], connections were only permitted between certain stub combinations, thus additionally controlling for selective mixing among nodes (assortativity). Gates & Woolhouse [44] also adopted a modified configuration algorithm to generate cattle trade networks, preserving farms' empirical daily amounts of purchases and sales, while selectively matching those reported to have exchanged cattle of the same type (dairy/beef) in the same market, on the same day.

3.5.1.1.2. Scale-free models. Other types of mathematical model seek to reproduce stylized topologies that are common in empirical networks. A key example is the scale-free property which results from the network degree distribution following a power law: $p_k \sim k^{-\gamma}$; where k denotes degree and γ the scaling parameter. The Barabasi & Albert [109] preferential-attachment model generates scale-free networks by progressively adding nodes to a network, with new nodes preferentially forming edges with high-degree nodes. This generates hub-like structures observed in many empirical networks, including those of livestock, where most nodes are poorly connected and a small number of nodes (e.g. markets and breeding farms) have a very high number of connections [105,110].

Thakur *et al.* [47] used the Barabasi–Albert model to simulate scale-free pig trade networks, fitting the model with a scaling parameter derived from empirical studies. The resulting network was altered in a second step by randomly

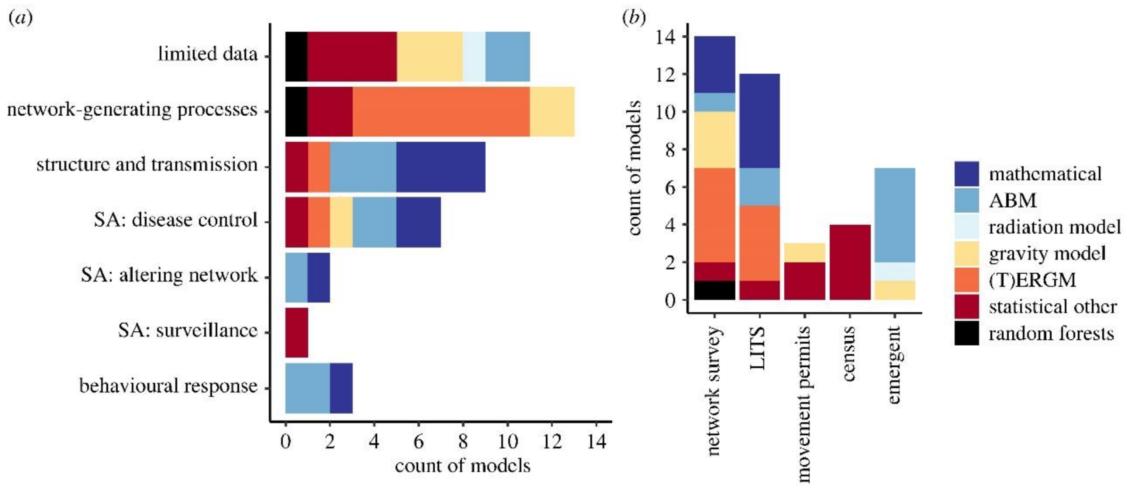

Figure 3. Model applications and data sources by model framework. (*a*) Model applications (multiple permitted): limited data = simulating a network from the available data, when empirical networks are incompletely characterized; network-generating processes = inference of factors associated with network (or edge) generation; structure and transmission = analytical exploration of the relationship between network structure and diffusion of phenomena (e.g. disease) on networks; SA disease control = scenario analysis related to assessing the impact of disease control strategies; SA altering network = comparing the impact of alternative network configuration scenarios on simulated disease transmission patterns; SA surveillance = exploring disease surveillance scenarios; behavioural response = modelling adaptive behaviour e.g. farmers' response to disease on a network. (*b*) Data sources used for model calibration. Blue = mechanistic; red/orange = statistical; black = machine learning. LITS = livestock identification and traceability systems; emergent = did not use network data but instead used data to parametrize model processes influencing edge formation.

rewiring edges connecting node types that were not connected in the empirical network, while preserving clustering coefficient and mean degree of the Barabasi–Albert model simulation. Tago *et al.* [49] generated a scale-free cattle trade network using an empirically derived scaling parameter and mimicked the real network by classifying nodes as markets, dealers or farms, based on the degree of these nodes determined empirically.

3.5.1.1.3. Watts–Strogatz model. The Watts–Strogatz model is another example of a model which reproduces particular features of empirical networks—in this case, 'small-world' properties. The latter refers to networks with short average path lengths, as observed in random graphs, but with higher clustering than is found in random graphs of equivalent size and the same mean degree [111].

This is achieved by taking a ring lattice network, which exhibits high clustering, and randomly rewiring a proportion of its edges such that average path length is reduced. The edge rewiring probability (p) is the single parameter by which the network can be interpolated between the highly clustered lattice and random graph [36,105]. Thakur *et al.* [47] used this model to generate pig trade networks, choosing a value for p to reproduce clustering coefficients observed in empirical networks.

3.5.1.1.4. Other mathematical models. Other network simulation model frameworks have been devised within different fields of study. Lennartsson *et al.* [50] describe an algorithm which generates spatially explicit networks of a defined number of nodes and mean degree which can then be tuned to target specified levels of degree-assortativity (selective mixing between nodes of similar degree), clustering coefficient, fragmentation index and spatial aggregation of nodes (random to aggregated). As a proof of principle, the authors generated networks matching values of these statistics as observed in an empirical swine transportation network.

3.5.1.1.5. Spatial models. With the models described above, the influence of nodes' spatial locations is irrelevant for edge formation. In reality, however, the probability of a connection between livestock populations is likely to be influenced by the geographical distance between them [51,86,112]. While distance may be a variable in other types of model, some of the simplest spatial models express the probability of an edge between nodes as a function of distance alone. For example, in Hu *et al.* [52], edges between nodes were simply assigned if the Euclidean distance was lower than an empirically informed threshold. In Rossi *et al.* [51], the probability of contacts between farms via veterinary staff visits was estimated by fitting a logistic regression with distance as the predictor variable.

3.5.1.2. Agent-based models ($n = 8$)

In ABMs, a set of autonomous agents interact with one another and their environment according to defined rules and processes [113,114]. A key feature of ABMs is that they allow complex phenomena to emerge from such processes [114]. Indeed, a livestock contact network can be considered to emerge from the multitude of economic, demographic, husbandry or other behavioural processes occurring at the level of individual agents operating in the system. This may be explicitly modelled within an ABM framework.

In six identified ABMs, network evolution was driven by herd demographic processes (e.g. livestock births, ageing/growth and deaths), and agent trade or partnership generation processes (e.g. selection of trade partners according to geographical distance, and compatibility in terms of industry role and current need to buy or sell) [53,56,57,59–62]. In these models, agents could be defined with distinct industry roles, holding capacities and geographical locations. In an additional model layer in Liu *et al.* [60], individual animal contacts during grazing were modelled using random walks. In Knight *et al.* [63,64], a dynamic trade network was generated from defined partnership rules—with the rate at which trade partnerships formed and dissolved, dependent on farms' in- and out-flow of animals (i.e. supply and demand). In the most recent paper, farm-level demand, and consequently farmers' edge forming and dissolving behaviours, were adaptive to market shocks such that farms with high-demand sought partnerships at a higher rate. Kim *et al.* [65] simulated a population of mobile pastoralist agents based on seasonal movement rules informed by field surveys. Edges (contact between herds via grazing) were then considered between agents setting up camp within a given distance from one another.

3.5.1.3. Radiation models ($n = 1$)

Radiation models, which were initially developed in the human mobility literature as an alternative to GMs ([115]; see next section), represent a mechanistic approach to predict human movements based on population distributions alone (i.e. distance is not used directly). This method takes analogy from radiation emission and absorption processes in physical sciences and was initially used to describe human commuting patterns, with commuters being 'emitted' from an origin and 'absorbed' by employment opportunities [115]. The model stipulates that the commuting flow (T_{ij}) between an origin (i) and destination (j) is a function of the size of their respective populations (m_i and n_j) and, notably, the 'intervening opportunities' between i and j (alternative employment sinks). The latter are represented by the population (s_{ij}) in the area of the circle with radius r_{ij}, centred at i (excluding m_i and n_j) (equation (3.1)). The variable, T_i represents the overall count of individuals starting their journey at location i $\left(T_i \equiv \sum_{j \neq i} T_{ij}\right)$, which is taken as a proportion of m_i.

$$\langle T_{ij} \rangle = T_i \frac{m_i n_j}{(m_i + s_{ij})(m_i + n_j + s_{ij})}. \quad (3.1)$$

Kong *et al.* [67] adapted the radiation model to predict country-scale poultry flows in China, with poultry population representing supply (m_i), and human populations representing demand (n_j) and 'intervening' demand (s_{ij}).

3.5.2. Statistical

3.5.2.1. Gravity models ($n = 4$)

GMs were initially developed to model the flow of commodities between pairs of discrete geographical areas (C_{ij}, from origin i to destination j) as a function of their distance (d_{ij}) and Gross National Products representing supply (push) at origin and demand (pull) at destination (p_i and p_j), with normalizing constant k and coefficients α, β and γ (equation (3.2)) [116,117]. The standard formulation of the flow of commodities from node i to j (C_{ij}) is

$$C_{ij} = k \frac{p_i^{\alpha} p_j^{\beta}}{d_{ij}^{\gamma}}. \quad (3.2)$$

This concept has been applied to model livestock trade as a function of livestock population at an origin (supply) and human population at a destination (demand) [15,28,69,70], with different functional relationships (e.g. exponential and power law) between distance and flows having been investigated [15]. Beyond the basic principles of mass and distance, the actual specification of GMs has been loosely defined [118]. GMs may be parametrized in equation (3.2) by fixing the coefficients α, β and γ; an approach which essentially represents a mechanistic parametrization. More often, however, these coefficients are estimated by statistical inference. For example, Qiqi Yang *et al.* [58] used both mechanistic and statistical GM parametrizations to model poultry movements. Equation (3.2) is commonly linearized by logarithmic transformation allowing additional covariates, hypothesized to be relevant for edge formation, to be included in the model (equation (3.3)).

$$\log(C_{ij}) = k + \alpha \log(p_i) + \beta \log(p_j) + \gamma \log(d_{ij}) + \ldots \quad (3.3)$$

The coefficients of such models may then be estimated by ordinary least-squares (OLS) regression (e.g. [28,69,70]).

3.5.2.2. Exponential random graph models ($n = 9$)

Under an ERGM formulation, the observed network is considered as just one realization of possible networks (configurations of edges given a set of nodes) with certain characteristics that result from an unknown stochastic process [119]. The ERGM defines a model of this network generation process and a probability distribution over all possible networks. Parameters are selected and estimated, such that the probability of the observed network being generated under the defined model is maximized. It may take a general form as in equation (3.4). Here, the dependent variable is the *whole network* (the probability of drawing the observed network y from the distribution Y), which is modelled as a function of covariates $z_k(y)$ hypothesized to be relevant for network formation. The covariates are weighted by coefficients θk, with c being a normalizing constant [119,120].

$$P_\theta(Y = y | n \text{ nodes}) = c e^{\theta_1 z_1(y) + \ldots - \theta_k z_k(y)}. \quad (3.4)$$

A model with a covariate for network density alone is equivalent to a random graph model [119]. However, additional covariates may describe attributes of edges, nodes or notably, local structural features, such as the tendency for reciprocated edges, or the tendency for triangles to form (i.e. where three nodes are completely connected) [121]. Network simulation is achieved by drawing from the probability distribution of possible network configurations given a set of nodes and their attributes. This is the basis for model fitting and assessment of goodness-of-fit: coefficients are fit and the model goodness-of-fit checked based on comparison between characteristics of the simulated and empirical networks [122]. ERGM output is analogous to a logistic regression making their interpretation straightforward [29,71].

ERGMs have been fitted to networks of livestock movements between aggregated spatial units [32,71,73], or actors such as livestock holdings [29,72,74]. These models have sometimes been applied to livestock networks of entire countries (e.g. [29,74]). The use of ERGMs in this context has allowed livestock contact networks to be modelled and simulated as a function of the tendency of farms to form (dis-)assortative trade partnerships with respect to farm size, type, management practices, company affiliation or location [29,74], in addition to local structural factors [29,32,71,73].

An extension of ERGMs, temporal exponential-family random graph models (TERGMs), enables the statistical modelling of tie dynamics [123]. Here, ERGMs are used to model both tie formation and dissolution, with potentially distinct models for each process. Separable-TERGMs (STERGMs) are used in the latter case. While these models were developed for the statistical modelling of empirical dynamic networks, model parameters may alternatively be defined without being inferred statistically i.e. similar to mechanistic modelling. Lee *et al.* [75] applied TERGMs in this way to simulate dynamic contact networks among pig farms according to a defined mean degree (overall and by node type) and the frequency of contacts.

3.5.2.3. Other statistical models ($n = 6$)

In a series of developments, [86–90] applied a hierarchical Bayesian model to Swedish pig and cattle movement networks incorporating data on between-holding distances, origin and destination production types, and the number of animals in each holding.

Building on these, the USAMM model [25], which has been applied and modified extensively [76–84], uses a Bayesian kernel approach to reconstruct the US cattle trade network. Similarly to GMs, movement probabilities were modelled as a function of the number of cattle premises at the origin and destination, and the distance between them, while also incorporating data on historical state-level cattle inflows. Sellman *et al.* [85] adapted these methods to reconstruct the national US pig movement network.

Xiao *et al.* [91] modelled pastoralists' movements by fitting statistical models to detailed movement survey data. Distinct seasonal movement trajectories were modelled according to different movement models. For example, origin-destination movements were modelled using a Brownian bridge motion model. This movement model was used to generate dynamic daily contact networks among mobile herds in a separate study [66], with 'contacts' between herds being considered when pastoralists set up camp within a given distance from one another on a given day—corresponding to grazing distances observed in field surveys.

Moon *et al.* [26] and Schumm *et al.* [92] used a statistical inferential method of maximum entropy (which is designed to estimate probability distributions from highly dimensional data) to estimate the movement probabilities of pigs within and between geographical units from census data. Based on the size and number of farms within each county, these movement probabilities were then used to simulate a farm-to-farm pig movement network.

3.5.3. Machine learning

3.5.3.1. Random forest ($n = 1$)

The probability or strength of an edge between two nodes can be treated, respectively, as a classification or regression problem which may be addressed using machine learning models such as classification or regression tree-based approaches. These models perform repeated partitions of the data based on the values of predictor variables, such that the observations in each partition are increasingly homogeneous with respect to the outcome of interest [124]. The values of observations in the resulting terminal tree-nodes are used as the basis of prediction. RF models combine multiple trees to reduce the variance of predictions and increase predictive performance [124,125]. Predictors may take the form of node or edge attributes. Valdes-Donoso *et al.* [68] used a RF to classify whether livestock movement occurred between pairs of nodes (farms or markets) as a function of geographical distance, node type mixing patterns (i.e. farm, market) and whether or not nodes were under shared ownership. This fitted model was then used to predict edges among nodes in the larger region, for which relevant node attributes were available.

3.6. Model validation

Adopting definitions by Porgo *et al.* [126], model validation (i.e. 'how well a model performs and how applicable the results are to a particular situation') was performed for around two-thirds (23/37) of models. We do not consider model calibration here (see §3.5). There was considerable variation in the methods by which model performance was assessed. This extended from the types of network properties considered, the methods of validation used, and the rigour to which this was carried out.

In terms of the types of validation used, 17 models were internally validated, while nine were externally validated. Approaches for external validation included splitting the data into training and validation sets (e.g. [68]), or through comparison with different datasets [15,56,65,67], such as for different time points [74,85,87]. A single GM was externally validated by assessing whether observed changes in livestock movements resulting from demand changes (i.e. closure of a terminal swine-processing facility) could be reproduced in the model [70]. Lastly, for two models, cross-validation was performed by comparing networks simulated by different models [65,91].

Regarding the types of network statistic considered, a third of models were validated by comparing structural network statistics of simulated and empirical networks ($n = 14$; electronic supplementary material, table S3). For example, model goodness-of-fit for ERGMs ($n = 9$) was assessed by comparing distributions of structural metrics not used for calibration such as in- and out-degree, geodesic distances, edgewise shared partnership and triad census.

Other models were internally validated at the level of the dyad ($n = 6$). Examples of approaches here included computing the predictive accuracy of binary or weighted edges based on, respectively, the area under the receiver operating characteristic curve, or correlation coefficients ([69] GM, [25] other statistical, [68] RF; Kong *et al.* [67] radiation model). Distributions of observed and predicted geographical distances between connected dyads were also sometimes compared ([86] other statistical, [68] RF, [56] ABM).

Alternatively, the outcomes of epidemics modelled on simulated networks were compared ($n = 4$) with either (i) epidemics modelled on empirical networks ([51] spatial), or (ii) empirical disease incidence. For example, the outputs of epidemics simulated on the pastoralist ABM by Kim *et al.* [65] were compared with annual disease incidence data. Meanwhile, Qiqi Yang *et al.* [58] assessed the statistical association between a GM-inferred poultry trade network and the geographical distribution of different avian influenza virus subtypes.

4. Discussion

In this systematic review, we present an overview of empirically informed, model-based approaches of network generation and inference that have been applied to simulate networks of contacts between livestock populations. We found 52 publications presenting 37 distinct models and seven model frameworks being used in this context. The increasing number of publications identified over the past decade illustrates the growing interest in this area. This reflects the considerable interest in applying network science to study the contact networks of livestock more broadly [2,3].

All models were applied to generate insights relevant to livestock diseases, with nearly half being used as inputs of infectious disease transmission models. However, the reviewed models varied greatly in their formulation, complexity and realism, use of data, and in the methods by which their performance was assessed. Consequently, we now turn to a comparison of model frameworks and discuss how their particular features can present opportunities and challenges in different use cases. Finally, we discuss issues and possible solutions around model assessment and validation.

A major application of reviewed mathematical models was to explore the relationship between network structure and disease transmission dynamics. Indeed, the relative simplicity of some of these models and, in particular, their ability to yield analytical solutions, lends them towards such applications. These types of models have consequently been applied extensively to explore the diffusion of phenomena on networks in the network literature [38,105,106]. This simplicity—in particular the ability of these models to be calibrated using few parameters—has also resulted in their application towards generating networks when empirical data are limited [47,48,51], or else totally absent, through the adoption of hypothesized parameter values (e.g. [99,100]). Mechanistic approaches, such as ABMs and radiation models, can also be used in cases where network data are unavailable but the processes underlying the formation of the network are understood and can be parametrized, i.e. based on first principles.

Notably, mechanistic models based on first principles may be more suitable for extrapolating beyond the data to which they were calibrated [127]. Hence, by altering their generative rules, such models can be applied to explore, for example, how counterfactual network configuration scenarios influence disease transmission dynamics [53]. Explicit modelling of the assumed generative mechanisms of the network further allows for an examination of its emergent properties. This makes it possible to explore realistic farm (or node) level disease control interventions that act to modify network structure [44]. Importantly, such approaches also allow complex adaptive properties of the system to be explored [113]. This includes agents' behavioural adaptations as a response to disease [49,54], or as an unintended consequence following regulatory changes or top-down interventions (e.g. [64]), as has been observed empirically [128–131].

Despite these important functions, purely mechanistic approaches commonly rely on calibration to select structural features (e.g. degree distribution and clustering coefficients) with no attempt to assess whether these features are necessary, or adequate, for representing an empirical network [36,39]. A comparative strength of statistical network models lies in their utility for assessing which features are relevant for network generation, as well as allowing for a measure of the uncertainty of these estimates given the data [36,38–40,132]. This also allows networks to be simulated while accounting for and incorporating this uncertainty which, in the context of infectious disease modelling, can help avoid overfitting epidemic outcomes to observed networks [39,133,134]. Despite this utility, less than a third of models being applied to simulate networks for infectious disease modelling were statistical models, with the remaining being mechanistic. This may broadly reflect the contrasting applications of these different model groupings in our included studies; namely, the emphasis on hypothesis testing for the statistical models, particularly ERGMs which were the most well-represented model framework in this grouping.

As noted, the major application and strength of statistical models reviewed here was the inference of factors associated with network formation. An important limitation that was not addressed in the reviewed literature is that traditional statistical methods, such as GMs using OLS specifications, assume statistical independence between observations. Due to dependencies inherent to network data, such assumptions may not hold, potentially resulting in biased estimates and hence predictions [40,116,135,136]. While standard OLS specifications of GMs cannot explicitly model these dependencies, corrections have been proposed to account for the effects of assumptions about non-independence (summarized by Broekel *et al.* [116]). However, to our knowledge, these have not been used in GMs applied to livestock contact networks.

A major strength of ERGMs lies in their ability to explicitly model and account for such dependencies; networks can be modelled and simulated as a function of parameters describing structural characteristics (e.g. transitivity or mutuality effects) in addition to node and edge factors [120,136,137]. ERGMs are therefore a powerful means of assessing the statistical significance of a range of factors on edge formation, as well as for simulating networks from these parameterizations. In practice, however, it is not always possible to generate a well-fitting model. This can be due to issues with 'model degeneracy' which can occur when high correlations between network effects result in unrealistically dense or sparse networks [29,120,136].

We identified a single model applying RFs to predict and simulate livestock contact networks. More broadly across the network simulation modelling literature, a variety of supervised machine learning approaches have demonstrated high predictive utility when applied to the movements of humans [138,139] and wild animals [140]. Given increasingly widespread application of machine learning approaches across the network prediction literature and the growing volume and complexity of livestock data, including movement data [141], there is likely to be considerable scope in applying machine learning methods to predict and simulate livestock contact networks.

This review has highlighted significant variation in how models were calibrated and assessed. This is of course strongly reflective of the availability of empirical network data and the purpose or intended application of models. In the context of simulating networks relevant for epidemiological study, however, given the fundamental relationship between network structure and disease transmission dynamics, it is clear that meaningful and realistic outputs rely on simulated networks accurately reproducing epidemiologically relevant features of the empirical networks. A remaining challenge then is understanding which structural features are epidemiologically relevant, and which we should therefore seek to reproduce. Indeed, the importance of these features may be highly disease and context specific [121,122,134,142]. Calibration and validation based on a few select network statistics is unlikely to be sufficient to reproduce networks exhibiting similar structure and diffusion patterns as their empirical counterparts [143–145]. Comparisons based on multiple structural characteristics are likely to be more robust, especially when the selection of these metrics is based on their relevance for diffusion processes, as is routine practice for ERGMs [121,122]. A highly valuable and interpretable form of validation, where data are available, is the comparison of epidemic outcomes on simulated and empirical networks. Comparison of simulated and observed disease incidence or prevalence is also particularly valuable, given that a transmission network is necessarily a subset of the potentially infectious contact network [146].

This review has some limitations. Despite our efforts to keep search terms broadly relevant to network simulation modelling, the lack of standardization in terminology means additional papers may have been missed using our search criteria. We have adopted the term 'network simulation model' from Bellerose *et al.* [35] and suggest its use in future publications on this topic. This would help to make this area of research more visible and avoid overlap with the related, yet distinct, context in which the term 'network modelling' is commonly applied, i.e. simulating disease spread on (empirical or simulated) networks. To keep the scope adequately focused and the synthesis feasible, we have focused on models which were used to simulate empirical-like and empirically informed contact networks of livestock populations. Hence, we highlight that this review does not present a complete compendium of all possible modelling frameworks, nor was it intended to. Alternative frameworks could be identified from the broader literature, such as from related reviews on network simulation models in other contexts [35–39].

This review serves to synthesize and categorize the heterogeneous group of models that have been applied to simulate the contact networks among livestock populations in the context of livestock disease epidemiology. Despite the important remaining challenges with model validation, this review highlights a number of unique functions afforded by network simulation models which enable us to advance beyond simple descriptive analyses of livestock networks, or infectious disease modelling on empirical networks. With increasing recognition of the need for evidence-based approaches to livestock production and health, particularly in the context of multitudinous high-profile, and often economically devastating, livestock and zoonotic disease outbreaks in recent decades, it seems reasonable to assume that efforts towards livestock network data collection will continue to gain ground. The types of modelling approaches reviewed here are well positioned to derive key insights from this data. Furthermore, such models can be used to inform the design of future empirical studies and livestock tracking systems, in order to optimize their efficiency and utility in generating data needed for effective disease surveillance and control [26,28].

Data accessibility. The data extracted for this review and the R code used to generate the figures in this review are available from https://github.com/wtm-leung/Network-modelling-review and are archived on Zenodo (https://doi.org/10.5281/zenodo.7883259).

Database search terms and a full list of full-text articles assessed for eligibility are provided in the electronic supplementary material [147].

Authors' contributions. W.T.M.L.: conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing—original draft and writing—review and editing; J.W.R.: conceptualization, funding acquisition, methodology, supervision and writing—review and editing; G.F.: conceptualization, methodology, supervision and writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

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9.2 Questionnaires: Form A 1 Pig producer survey v4 (ODK questionnaire)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
A_1_province	**Province ISO code**		[12] 12 Phnom Penh [08] 08 Kandal [05] 05 Kampong Speu [21] 21 Takeo
A_3_village_specify	**Village ID**	selected(${A_3_village}, '-88')	[Text]
A_4_household_id	**Farm/Household ID**		[Text]
temporary_note1	**Unique ID: ${unique_ID}**		[Enumerator Note]
A_6_interviewer	**Interviewer initials**		[Text]
A_7_consent	**Agrees to participate & signed consent form**		[yes] Yes [no] No
A_8_GPS	**Obtain GPS coordinates**		[Lat, Long, Alt]
A_9a_interviewee_role	**What is your role on this farm?**		[owner] Farm owner [manager] Farm manager [employee] Employee [trades] In charge of live pig trades [family] Family member [veterinarian] Veterinarian [other] Other
A_9a1_interviewee_role_specify	**Please specify the other type of role:**	selected(${A_9a_interviewee_role}, 'other')	[Text]
A_9b_interviewee_age	**What is your age?**		[Integer]
A_9b1_gender	**Gender**		[male] Male [female] Female [refused] Refuse

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
A_9c_interviewee_ethnicity	**What is your ethnicity?**		[khmer] Khmer [cham] Cham [vietnamese] Vietnamese [chinese] Chinese [other] Other [unsure] Don't know [refused] Refuse
A_9c1_ethnicity_specify	**Please specify your ethnicity**	selected(${A_9c_interviewee_ethnicity}, 'other')	[Text]
A_9d_education	**What is the highest level of education you have completed?**		[none] None [primary] Primary (grades 1 to 6) [lower_secondary] Lower Secondary (grades 7 to 9) [upper_secondary] Upper secondary (grades 10 to 12) [higher] Higher (college/university) [unsure] Don't know [refused] Refused
A_10_primary_income	**Which occupation provides your main source of household income?**		[farmer] Pig farmer [trader] Pig trader [sh_worker] Pig slaughterhouse worker [sh_owner] Slaughterhouse owner [sh_manager] Slaughterhouse manager [meat] Meat retailer [ahw] Animal health worker [professional] Professional/technical/managerial [clercial] Clerical/ office work [skilled_man] Skilled manual (but not agriculture) [unskilled_man] Unskilled manual (but not agriculture) [crop] Agriculture crop [livestock] Livestock and fishing (other) [sales] Sales and services/ trader [refused] Refused [other] Other
A_10a_primary_income_specify	**Please specify your main source of household income**	${A_10_primary_income} = 'other'	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
A_11_secondary_income	**Are there any other occupations which provide further sources of household income?**		[farmer] Pig farmer [trader] Pig trader [sh_worker] Pig slaughterhouse worker [sh_owner] Slaughterhouse owner [sh_manager] Slaughterhouse manager [meat] Meat retailer [ahw] Animal health worker [professional] Professional/technical/managerial [clercial] Clerical/ office work [skilled_man] Skilled manual (but not agriculture) [unskilled_man] Unskilled manual (but not agriculture) [crop] Agriculture crop [livestock] Livestock and fishing (other) [sales] Sales and services/ trader [refused] Refused [other] Other [none] None
A_11a_secondary_income_specify	**Please specify your other sources of household income**	selected(${A_11_secondary_income}, 'other')	[Text]
A_12_years_operating	**How long has this household/farm kept pigs (years)?**		[Decimal]
B_2_purchased	**In the past 6 months, have any LIVE pigs been introduced onto this farm (e.g. any pig purchases, boar hiring), OR have any AI doses been used to inseminate sows/gilts?**		[yes] Yes [no] No [unsure] Unsure
B_2a_purchased_suppliers	**Which supplier types did these pigs (or AI doses) come from?**	${B_2_purchased}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			<5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
broken_header1	**How many suppliers of each type did you receive pigs (or use AI doses) from?**	${B_2_purchased}='yes'	[Enumerator Note]
B_3a_small_hh	**Small households (<10 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'sml_hh')	[Integer]
B_3b_med_hh	**Medium household (10 to 50 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'med_hh')	[Integer]
B_3c_large_hh	**Large household (50 to <100 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'lrg_hh')	[Integer]
B_3c_hh	**Household of unknown size**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'hh')	[Integer]
B_3d_small_farm	**Small farm (100 to <1000 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'sml_farm')	[Integer]
B_3e_med_farm	**Medium farm (1000 to <5000 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'med_farm')	[Integer]
B_3f_lrg_farm	**Large farm (≥5000 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'lrg_farm')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_3f_farm	Farm of unknown size	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'farm')	[Integer]
B_3g_trader	Trader	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'trader')	[Integer]
B_3h_butcher	Butcher	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'butcher')	[Integer]
B_3i_middleman	Middleman	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'middleman')	[Integer]
B_3j_sh	Slaughterhouse	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'SH')	[Integer]
B_3k_kp	Killing point	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'KP')	[Integer]
B_3l_cp	CP	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'CP')	[Integer]
B_3m_cp_central	Central point (any company)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'central_point')	[Integer]
B_3n_cp_acmc	ACMC-M-Pig (Moung Rithy)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'ACMC ')	[Integer]
B_3o_cp_betagro	Betagro	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'betagro')	[Integer]
B_3p_company	Another company	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'company')	[Integer]
B_3q_boar_service	Boar service (Does not keep other pigs)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'boar_service')	[Integer]
B_3r_poahp	POAHP	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'poahp')	[Integer]
B_3s_other	Other	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'other')	[Integer]
B_4a_categories_purchased	In the past 6 months, which types of LIVE pig have been introduced onto this	${B_2_purchased}='yes'	[sow] Sow [boar] Boar (purchase/sale) [boar_hire] Boar (hire)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
	farm? (Please also select AI doses if used)		[piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type) [ai] Artificial Insemination (AI) doses
broken_header2	**How many pigs of each type did you receive in the past 6 months? (Please also select AI doses if used)**	${B_2_purchased}='yes'	[Enumerator Note]
B_4b_sows_purchased	**Sow**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'sow')	[Integer]
B_4d_boars_purchased	**Boar (purchase/sale)**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'boar')	[Integer]
B_4d_boars_hired	**Boar (hire)**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'boar_hire')	[Integer]
B_4e_piglets_purchased	**Piglets**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'piglets')	[Integer]
B_4f_weaners_purchased	**Weaners**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'weaners')	[Integer]
B_4g_growers_purchased	**Growers**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'growers')	[Integer]
B_4h_finishers_purchased	**Finishers**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'finishers')	[Integer]
B_4h_pigs_purchased	**Pigs (unknown type)**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'pigs')	[Integer]
B_4h_ai_purchased	**Artificial Insemination (AI) doses**	${B_2_purchased}='yes' and selected(${B_4a_categories_purchased}, 'ai')	[Integer]
broken_header1.5	**Please provide details of each individual supplier of a) pigs purchased, b) boars hired, and c) AI doses purchased, from the past 6 months:**		[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_1c_1	**Supplier S-${supplier_number}**		[Enumerator Note]
B_2c_supplier_type	**What type of supplier is this?**		[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_2c1_supplier_specify	**Please specify the type of supplier**	${B_2c_supplier_type}='other'	[Text]
B_2c1_company_specify	**Name of company**	selected(${B_2c_supplier_type}, 'company') or selected(${B_2c_supplier_type}, 'central_point')	[Text]
B_2e_relationship	**What is your relationship with this supplier?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[other] Other [unsure] Don't know
B_2e_relation_specify	**Please specify the type of relationship**	${B_2e_relationship}='other'	[Text]
B_2d_breeding_growing	**Breeding / growing unit?**	selected(${B_2c_supplier_type}, 'sml_hh') or selected(${B_2c_supplier_type}, 'med_hh') or selected(${B_2c_supplier_type}, 'lrg_hh') or selected(${B_2c_supplier_type}, 'hh') or selected(${B_2c_supplier_type}, 'sml_farm') or selected(${B_2c_supplier_type}, 'med_farm') or selected(${B_2c_supplier_type}, 'lrg_farm') or selected(${B_2c_supplier_type}, 'farm') or selected(${B_2c_supplier_type}, 'CP')	[breeding] Breeding unit [growing] Growing unit [f_to_f] Farrow to finish [other] Other [none] No special type [unsure] Don't know [refused] Refused
B_2d1_specify_type	**Please specify the type of unit**	selected(${B_2d_breeding_growing}, 'other')	[Text]
broken_header_2f	**_Contact location or site where this contact is based_**		[Enumerator Note]
B_2c1_pig_origin_known	**Do you know where the trader/butcher/middleman acquired the pigs?**	selected(${B_2c_supplier_type}, 'trader') or selected(${B_2c_supplier_type}, 'butcher') or selected(${B_2c_supplier_type}, 'middleman')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
broken_header_B_2c1	**_Questions in blue below, refer to the person/place that the trader/butcher/middleman aquired the pigs_**	${B_2c1_pig_origin_known}='yes'	[Enumerator Note]
B_2c1a_pig_origin_supplier	**Where did the trader/butcher/middleman aquire the pigs?**	${B_2c1_pig_origin_known}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_2c1a_pig_origin_supplier_specify	**Please specify the type of supplier**	selected(${B_2c1a_pig_origin_supplier}, 'other')	[Text]
B_2c1e_village	**_B2c1e. In the paper log book, please now also record the site name, and site village (if known), for supplier ID:_ S-${supplier_number}**	${B_2c1_pig_origin_known}='yes'	[Enumerator Note]
broken_header_B_2c1f	**_Questions are now returning to asking about the trader/butcher/middleman_**	${B_2c1_pig_origin_known}='yes'	[Enumerator Note]
B_2k_transac_freq	**Frequency of transactions with this supplier**		[first_time] First time [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly [6monthly] At least once every 6 months [1yearly] At least once every year [2yearly] At least once every 2 years
broken_header_3	**Number of pigs received (or AI doses used) from this supplier in the past 6 months:**		[Enumerator Note]
B_2l_sows_purchased	**Sow**	selected(${B_4a_categories_purchased}, 'sow')	[Integer]
B_2m_boars_purchased	**Boar (purchase/sale)**	selected(${B_4a_categories_purchased}, 'boar')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_2n_boars_hired	**Boar (hire)**	selected(${B_4a_categories_purchased}, 'boar_hire')	[Integer]
B_2o_piglets_purchased	**Piglets**	selected(${B_4a_categories_purchased}, 'piglets')	[Integer]
B_2p_weaners_purchased	**Weaners**	selected(${B_4a_categories_purchased}, 'weaners')	[Integer]
B_2q_growers_purchased	**Growers**	selected(${B_4a_categories_purchased}, 'growers')	[Integer]
B_2r_finishers_purchased	**Finishers**	selected(${B_4a_categories_purchased}, 'finishers')	[Integer]
B_2s_pigs_purchased	**Pigs (unknown type)**	selected(${B_4a_categories_purchased}, 'pigs')	[Integer]
B_2t_ai_purchased	**Artificial Insemination (AI) doses**	selected(${B_4a_categories_purchased}, 'ai')	[Integer]
B_2t_contact_provided	**Can you provide contact details for this supplier?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
B_2j_village	**In the paper log book, please now also record the site name, and site village (if known), for supplier ID:_ S-${supplier_number}**		[Enumerator Note]
B_2t1_contact_details	**Please record the contact's name, and phone number in the paper log book, for supplier ID:_ S-${supplier_number}**	${B_2t_contact_provided}='yes'	[Enumerator Note]
B_3_clinical_exam	**Is a clinical exam performed before pigs enter the farm? E.g. direct observation of body condition, direct observation of skin, nose, and ear condition, or any other inspection by an animal health worker?**	${B_2_purchased}='yes'	[always] Always [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
B_4_sick_protocol	**What do you do if an incoming pig looks sick?**	${B_2_purchased}='yes'	[n/a] Don't know, never purchased, or identified sick pigs before [reject] Don't accept them on to the farm, or send them back to the supplier [quarantine_batch] Quarantine - all pigs which belonged to the same batch as the sick pig(s)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[quarantine_sick] Quarantine - sick pig(s) only [nothing] Nothing, pig still enters the farm [other] Other [refused] Refused
B_4a_specify_other	**Specify other**	selected(${B_4_sick_protocol}, 'other')	[Text]
B_5_quarantine	**Are all introduced pigs routinely put in quarantine, i.e. regardless of health status?**	${B_2_purchased}='yes'	[always] Always [sometimes] Sometimes [never] Never [na] Not applicable (e.g. when no other pigs are present in the farm at the time of introduction) [unsure] Don't know [refused] Refused
B_5a_quarantine_days	**For how many days are pigs routinely kept in quarantine?**	${B_5_quarantine}='always' or ${B_5_quarantine}='sometimes'	[Integer]
B_9b_trader_load_location	**Where do traders load/unload pigs?**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'trader')	[off] Outside the farm perimeter [on_no_pigs] Inside the farm perimeter; but they never brought other pigs in with them [on_sometimes_pigs] Inside the farm perimeter; and they sometimes brought other pigs in with them (e.g. that they were trading) [on_usually_pigs] Inside the farm perimeter; and they often/always brought other pigs in with them (e.g. that they were trading) [other] Other [unsure] Don't know [refused] Refused
B_6_sales	**In the past 6 months, have any LIVE pigs left this farm (e.g. any sales, pigs sent for slaughter), OR have you sold any AI doses from your boars?**		[yes] Yes [no] No [unsure] Unsure

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6a_sales_suppliers	**Who were pigs (or AI doses) sent to in the past 6 months?**	${B_6_sales}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
broken_header3.1	**How many recipients of each type did you send pigs (or AI doses) to in the past 6 months?**	${B_6_sales}='yes'	[Enumerator Note]
B_6.1a_small_hh	**Small households (<10 pigs)**	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'sml_hh')	[Integer]
B_6.1b_med_hh	**Medium household (10 to 50 pigs)**	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'med_hh')	[Integer]
B_6.1c_large_hh	**Large household (50 to <100 pigs)**	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'lrg_hh')	[Integer]
B_6.1c_hh	**Household of unknown size**	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'hh')	[Integer]
B_6.1d_small_farm	**Small farm (100 to <1000 pigs)**	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'sml_farm')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6.1e_med_farm	Medium farm (1000 to <5000 pigs)	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'med_farm')	[Integer]
B_6.1f_lrg_farm	Large farm (≥5000 pigs)	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'lrg_farm')	[Integer]
B_6.1f_farm	Farm of unknown size	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'farm')	[Integer]
B_6.1g_trader	Trader	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'trader')	[Integer]
B_6.1h_butcher	Butcher	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'butcher')	[Integer]
B_6.1i_middleman	Middleman	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'middleman')	[Integer]
B_6.1j_sh	Slaughterhouse	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'SH')	[Integer]
B_6.1k_kp	Killing point	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'KP')	[Integer]
B_6.1l_cp	CP	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'CP')	[Integer]
B_6.1m_cp_central	Central point (any company)	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'central_point')	[Integer]
B_6.1n_cp_acmc	ACMC-M-Pig (Moung Rithy)	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'ACMC ')	[Integer]
B_6.1o_cp_betagro	Betagro	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'betagro')	[Integer]
B_6.1p_company	Another company	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'company')	[Integer]
B_6.1q_boar_service	Boar service (Does not keep other pigs)	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'boar_service')	[Integer]
B_6.1r_poahp	POAHP	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'poahp')	[Integer]
B_6.1s_other	Other	${B_6_sales}='yes' and selected(${B_6a_sales_suppliers}, 'other')	[Integer]
B_6.2a_categories_sold	In the past 6 months, which types of LIVE pig have left this farm? (Please also select AI doses if used)	${B_6_sales}='yes'	[sow] Sow [boar] Boar (purchase/sale) [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type) [ai] Artificial Insemination (AI) doses

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header3.2	How many pigs of each type left this farm (e.g. sales, boar lending, or sent for slaughter)	${B_6_sales}='yes'	[Enumerator Note]
B_6.2b_sows_sold	Sow	selected(${B_6.2a_categories_sold}, 'sow')	[Integer]
B_6.2d_boars_sold	Boar (purchase/sale)	selected(${B_6.2a_categories_sold}, 'boar')	[Integer]
B_6.2e_piglets_sold	Piglets	selected(${B_6.2a_categories_sold}, 'piglets')	[Integer]
B_6.2f_weaners_sold	Weaners	selected(${B_6.2a_categories_sold}, 'weaners')	[Integer]
B_6.2g_growers_sold	Growers	selected(${B_6.2a_categories_sold}, 'growers')	[Integer]
B_6.2h_finishers_sold	Finishers	selected(${B_6.2a_categories_sold}, 'finishers')	[Integer]
B_6.2h_pigs_sold	Pigs (unknown type)	selected(${B_6.2a_categories_sold}, 'pigs')	[Integer]
B_6.2h_ai_sold	Artificial Insemination (AI) doses	selected(${B_6.2a_categories_sold}, 'ai')	[Integer]
broken_header_4	Please provide details of each individual recipient of a) pigs sold, b) pigs sent for slaughter, and c) AI doses sold, from the past 6 months:		[Enumerator Note]
broken_header_5	Recipient R-${recipient_number}		[Enumerator Note]
B_6c_recipient_type	Recipient type		[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_6c1_recipient_specify	**Please specify the type of recipient**	${B_6c_recipient_type}='other'	[Text]
B_6c1_company_specify	**Name of company**	selected(${B_6c_recipient_type}, 'company') or selected(${B_6c_recipient_type}, 'central_point')	[Text]
B_6e_relationship	**What is your relationship with this recipient?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
B_6e_relation_specify	**Please specify the type of relationship**	${B_6e_relationship}='other'	[Text]
B_6d_breeding_growing	**Breeding / growing unit?**	selected(${B_6c_recipient_type}, 'sml_hh') or selected(${B_6c_recipient_type}, 'med_hh') or selected(${B_6c_recipient_type}, 'lrg_hh') or selected(${B_6c_recipient_type}, 'hh') or selected(${B_6c_recipient_type}, 'sml_farm') or selected(${B_6c_recipient_type}, 'med_farm') or selected(${B_6c_recipient_type}, 'lrg_farm') or selected(${B_6c_recipient_type}, 'farm') or selected(${B_6c_recipient_type}, 'CP')	[breeding] Breeding unit [growing] Growing unit [f_to_f] Farrow to finish [other] Other [none] No special type [unsure] Don't know [refused] Refused
B_6d1_specify_type	**Please specify the type of unit**	selected(${B_6d_breeding_growing}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_6f	_Contact location or site where this contact is based_		[Enumerator Note]
B_6c1_pig_destination_known	**Do you know where the trader/butcher/middleman sent on the pigs?**	selected(${B_6c_recipient_type}, 'trader') or selected(${B_6c_recipient_type}, 'butcher') or selected(${B_6c_recipient_type}, 'middleman')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
broken_header_B_6c1a	_Questions in blue below, refer to the person/place that the trader/butcher/middleman sent the pigs_	${B_6c1_pig_destination_known}='yes'	[Enumerator Note]
B_6c1a_pig_destination_recipient	**Where did the trader/butcher/middleman send on the pigs?**	${B_6c1_pig_destination_known}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_6c1a_pig_destination_recipient_specify	**Please specify the type of supplier**	selected(${B_6c1a_pig_destination_recipient}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6c1e_village	**In the paper log book, please now also record the site name, and site village (if known), for Recipient _ R-${recipient_number}**	${B_6c1_pig_destination_known}='yes'	[Enumerator Note]
broken_header_B_6c1e	**_Questions are now returning to asking about the trader/butcher/middleman_**	${B_6c1_pig_destination_known}='yes'	[Enumerator Note]
B_6k_transac_freq	**Frequency of transactions with this recipient**		[first_time] First time [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly [6monthly] At least once every 6 months [1yearly] At least once every year [2yearly] At least once every 2 years
broken_header_4.11	**Number of pigs (or AI doses) sent to this recipient in past 6 months:**		[Enumerator Note]
B_6m_sows_qty	**Sow**	selected(${B_6.2a_categories_sold}, 'sow')	[Integer]
B_6o_boars_sold	**Boar (purchase/sale)**	selected(${B_6.2a_categories_sold}, 'boar')	[Integer]
B_6p_piglet	**Piglets**	selected(${B_6.2a_categories_sold}, 'piglets')	[Integer]
B_6q_weaner	**Weaners**	selected(${B_6.2a_categories_sold}, 'weaners')	[Integer]
B_6r_grower	**Growers**	selected(${B_6.2a_categories_sold}, 'growers')	[Integer]
B_6s_finisher	**Finishers**	selected(${B_6.2a_categories_sold}, 'finishers')	[Integer]
B_6s_unknown	**Pigs (unknown type)**	selected(${B_6.2a_categories_sold}, 'pigs')	[Integer]
B_6s_ai	**Artificial Insemination (AI) doses**	selected(${B_6.2a_categories_sold}, 'ai')	[Integer]
B_6t_contact_provided	**Can you provide contact details for this recipient?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6j_village	**In the paper log book, please now also record the site name, and site village (if known), for Recipient _ R-${recipient_number}**		[Enumerator Note]
B_6t1_contact_details	**Please record the contact's name, and phone number in the paper log book, for Recipient _ R-${recipient_number}**	${B_6t_contact_provided}='yes'	[Enumerator Note]
B_7_own_boars	**Do you keep boars (for breeding)?**		[yes] Yes [no] No [unsure] Unsure
B_8_sales	**In the past 14 days, have any of your boar(s) been used for breeding with sows/gilts from other households/farms?**		[yes] Yes [no] No [unsure] Unsure
date_widget_last_sold	**When was the last time your boars were used for breeding with sows/gilts from other households/farms?**	${B_8_sales}='no' or ${B_8_sales}='unsure'	[Date]
B_8a_sales_recipients	**In the past 14 days, which type(s) of recipient have used your boars for breeding?**	${B_8_sales}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_8a1_recipient_specify	**Please specify the other type of recipient**	${B_8a_sales_recipients} = 'other'	[Text]
broken_header_1	**In the past 14 days, how many recipients of each type used your boars for breeding?**	${B_8_sales}='yes'	[Enumerator Note]
B_9a_small_hh	**Small households (<10 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'sml_hh')	[Integer]
B_9b_med_hh	**Medium household (10 to 50 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'med_hh')	[Integer]
B_9c_large_hh	**Large household (50 to <100 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'lrg_hh')	[Integer]
B_9c_hh	**Household of unknown size**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'hh')	[Integer]
B_9d_small_farm	**Small farm (100 to <1000 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'sml_farm')	[Integer]
B_9e_med_farm	**Medium farm (1000 to <5000 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'med_farm')	[Integer]
B_9f_lrg_farm	**Large farm (≥5000 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'lrg_farm')	[Integer]
B_9f_farm	**Farm of unknown size**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'farm')	[Integer]
B_9g_trader	**Another trader**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'trader')	[Integer]
B_9h_butcher	**Butcher**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'butcher')	[Integer]
B_9i_middleman	**Middleman**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'middleman')	[Integer]
B_9i_sh	**Slaughterhouse**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'SH')	[Integer]
B_9k_kp	**Killing point**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'KP')	[Integer]
B_6.1l_cp		${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'CP')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_9m_cp_central	Central point (any company)	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'central_point')	[Integer]
B_6.1n_cp_acmc		${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'ACMC ')	[Integer]
B_6.1o_cp_betagro		${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'betagro')	[Integer]
B_6.1p_company		${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'company')	[Integer]
B_6.1q_boar_service		${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'boar_service')	[Integer]
B_6.1r_poahp		${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'poahp')	[Integer]
B_9j_other	Other	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'other')	[Integer]
broken_header_purchase_locs	In the past 14 days, in which locations have your boars been used for breeding?		[Enumerator Note]
B_6_country	B6) Countries		[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other [unsure] Don't know
B_6.1_country_spec	B6.1) Please specify the other country	selected(${B_6_country}, 'other')	[Text]
broken_header_suppliers	In district: ${current_district_purchases}:		[Enumerator Note]
number_boar_hirers	how many customers hired your boar(s)? (In the past 14 days)		[Integer]
broken_header_y	How many days do people hire your boars for breeding?		[Enumerator Note]
C_7g_kept_ave_other	on average:		[Integer]
C_7g_kept_min_other	min:		[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_7g_kept_max_other	**max:**		[Integer]
same_trip	**Do you provide your boar services to multiple households in a single visit (e.g. multiple households within a village?)**		[always] Always [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
B_6_longitudinal	**Does demand for your boar services vary throughout the year?**		[yes] Yes [no] No [unsure] Unsure
B_6a_busy_months	**When are your boar services in greater demand?**	selected(${B_6_longitudinal}, 'yes')	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
B_6a1_ave_throughput	**During these busy periods, how many customers use your boar service on average? (per week)**	selected(${B_6_longitudinal}, 'yes')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6b_quiet_months	**When are your boar services in least demand?**	selected(${B_6_longitudinal}, 'yes')	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
B_6b1_ave_throughput	**During these quiet periods, how many customers use your boar service on average? (per week)**	selected(${B_6_longitudinal}, 'yes')	[Integer]
C_1_unit_type	**What sort of farm/holding is this?**		[breeding] Breeding unit [growing] Growing unit [f_to_f] Farrow to finish [other] Other [none] No special type [unsure] Don't know [refused] Refused
C_1a_specify_type	**Please specify the type of unit**	selected(${C_1_unit_type}, 'other')	[Text]
C_2_ownership	**What sort of ownership does this farm/site have?**		[single] Single owner/family owned - not a contract farm [single_contract] Single owner/family

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			owned - contract farm [several] Several owners - not a contract farm [several_contract] Several owners - contract farm [company] Owned by a company [other] Other [unsure] Don't know [refused] Refused
C_2_i_ownership_specify	**Please specify**	${C_2_ownership} = 'other'	[Text]
C_2a_contractor	**Name of contractor**	${C_2_ownership}='single_contract' or ${C_2_ownership}='several_contract'	[cp] CP [other] Other [unsure] Don't know [refused] Refused
C_2a1_contractor_specify	**Please specify**	${C_2a_contractor}='other'	[Text]
C_2b_company_name	**Name of company**	${C_2_ownership}='company'	[Text]
C_4a_pigs_present	**Which of the following pig categories have been raised on the farm/site in the _past 6 months_?**		[sow] Sow/gilt for breeding [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers
C_4a_pig_breeds_present	**Which of the following pig _breeds_ have been raised on the farm/site in the _past 6 months_?**	selected(${C_4a_pigs_present}, 'sow') or selected(${C_4a_pigs_present}, 'cull_sow') or selected(${C_4a_pigs_present}, 'boar') or selected(${C_4a_pigs_present}, 'piglets') or selected(${C_4a_pigs_present}, 'weaners') or selected(${C_4a_pigs_present}, 'growers') or selected(${C_4a_pigs_present}, 'finishers')	[local] Local [exotic_local] Exotic breed - locally raised [exotic_imported] Exotic breed - imported from abroad [cross] Cross-breed [unknown] Breed is not known for some/all pigs [other] Other
C_4a_pig_breeds_present_specify	**Please specify**	selected(${C_4a_pig_breeds_present}, 'other')	[Text]
broken_header_sows	**Breeding sows/gilts_**	selected(${C_4a_pigs_present}, 'sow')	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4_1	Are breeding sows _currently_ present on this farm/site?	selected(${C_4a_pigs_present}, 'sow')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b1	Number of breeding sows/gilts, of each breed, present on site at the time of visit:_	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently')	[Enumerator Note]
C_4b1a_local_sows_qty	Breeding sows/gilts - local breed	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b1b_exoticlocal_sows_qty	Breeding sows/gilts - exotic breed, locally raised	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b1c_exoticimported_sows_qty	Breeding sows/gilts - exotic breed, imported from abroad	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b1d_cross_sows_qty	Breeding sows/gilts - cross-breed	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b1e_unknown_sows_qty	Breeding sows/gilts - unknown breed	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
C_4e_total_breed_sows_year	Total number of breeding sows/gilts that have been kept/raised on this farm in the past year	selected(${C_4a_pigs_present}, 'sow')	[Integer]
broken_header_boars	Breeding boars_	selected(${C_4a_pigs_present}, 'boar')	[Enumerator Note]
C_4_3	Are breeding boars _currently_ present on this farm/site?	selected(${C_4a_pigs_present}, 'boar')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b3	Number of breeding boars, of each breed, present on site at the time of visit:_	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently')	[Enumerator Note]
C_4b3a_local_boars_qty	Breeding boars - local breed	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4b3b_exoticlocal_boars_qty	**Breeding boars - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b3c_exoticimported_boars_qty	**Breeding boars - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b3d_cross_boars_qty	**Breeding boars - cross-breed**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b3e_unknown_boars_qty	**Breeding boars - unknown breed**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
C_4e_total_breed_boars_year	**Total number of breeding Breeding boars that have been kept/raised on this farm in the past year**	selected(${C_4a_pigs_present}, 'boar')	[Integer]
broken_header_piglets	**Piglets_**	selected(${C_4a_pigs_present}, 'piglets')	[Enumerator Note]
C_4_4	**Are piglets _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'piglets')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b4	**Number of piglets, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently')	[Enumerator Note]
C_4b4a_local_piglets_qty	**Piglets - local breed**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b4b_exoticlocal_piglets_qty	**Piglets - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b4c_exoticimported_piglets_qty	**Piglets - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b4d_cross_piglets_qty	**Piglets - cross-breed**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4b4e_unknown_piglets_qty	**Piglets - unknown breed**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
C_4c_ave_piglets_litter	**Average number of piglets per litter**	selected(${C_4a_pigs_present}, 'piglets')	[Integer]
C_4d_total_litters_year	**Number of litters in the past year**	selected(${C_4a_pigs_present}, 'piglets')	[Integer]
C_4f_all_in_all_out	**Except from breeding and keeping piglets with their dam, are different batches of pigs kept in separate barns/rooms/pens (i.e. where different batches do not mix)?**		[barn_always] Always in different barns [barn_most] Mostly in different barns [barn_some] Sometimes in different barns [room_always] Always in different rooms [room_most] Mostly in different rooms [room_some] Sometimes in different rooms [pens_always] Always in different pens [pens_most] Mostly in different pens [pens_some] Sometimes in different pens [never] Never
broken_header_weaners	**Weaners_**	selected(${C_4a_pigs_present}, 'weaners')	[Enumerator Note]
C_4_5	**Are weaners _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'weaners')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b5	**Number of weaners, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently')	[Enumerator Note]
C_4b5a_local_weaners_qty	**Weaners - local breed**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b5b_exoticlocal_weaners_qty	**Weaners - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b5c_exoticimported_weaners_qty	**Weaners - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4b5d_cross_weaners_qty	Weaners - cross-breed	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b5e_unknown_weaners_qty	Weaners - unknown breed	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
broken_header_growers	Fattening/growers_	selected(${C_4a_pigs_present}, 'growers')	[Enumerator Note]
C_4_6	Are fatteners/growers _currently_ present on this farm/site?	selected(${C_4a_pigs_present}, 'growers')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b6	Number of fatteners/growers, of each breed, present on site at the time of visit:_	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently')	[Enumerator Note]
C_4b6a_local_growers_qty	Fatteners/growers - local breed	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b6b_exoticlocal_growers_qty	Fatteners/growers - exotic breed, locally raised	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b6c_exoticimported_growers_qty	Fatteners/growers - exotic breed, imported from abroad	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b6d_cross_growers_qty	Fatteners/growers - cross-breed	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b6e_unknown_growers_qty	Fatteners/growers - unknown breed	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
broken_header_finishers	Finishers_	selected(${C_4a_pigs_present}, 'finishers')	[Enumerator Note]
C_4_7	Are finishers _currently_ present on this farm/site?	selected(${C_4a_pigs_present}, 'finishers')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b7	Number of finishers, of each breed, present on site at the time of visit:_	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently')	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4b7a_local_finishers_qty	**Finishers - local breed**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b7b_exoticlocal_finishers_qty	**Finishers - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b7c_exoticimported_finishers_qty	**Finishers - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b7d_cross_finishers_qty	**Finishers - cross-breed**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b7e_unknown_finishers_qty	**Finishers - unknown breed**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
C_4c_ave_per_cycle	**Average number of pigs fattened per cycle**	selected(${C_4a_pigs_present}, 'weaners') or selected(${C_4a_pigs_present}, 'growers') or selected(${C_4a_pigs_present}, 'finishers')	[Integer]
C_4d_cycles_past_year	**Number of fattening cycles in the past year**	selected(${C_4a_pigs_present}, 'weaners') or selected(${C_4a_pigs_present}, 'growers') or selected(${C_4a_pigs_present}, 'finishers')	[Integer]
C_4a1_finishers_housing	**How are pigs housed on this farm/site?**		[individual] Total (individual) confinement [group_same] Group housed - with pigs of the same category [group_mixed] Group housed - mixed with other pig categories [tethered] Tethered [freerange] Free-range [unsure] Don't know [refused] Refused [other] Other
C_4a1_finishers_housing_specify	**Please specify**	selected(${C_4a1_finishers_housing}, 'other')	[Text]
C_4a1a_pen_qty	**How many pigs are kept together in a pen?**	selected(${C_4a1_finishers_housing}, 'group_same') or selected(${C_4a1_finishers_housing}, 'group_mixed')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4a2_indoor_outdoor	**Where are these pigs housed?**		[outdoor] Outdoors [indoor] Sheltered [sheltered] Indoors [unsure] Don't know [refused] Refused [other] Other
C_4a2_indoor_outdoor_specify	**Please specify**	selected(${C_4a2_indoor_outdoor}, 'other')	[Text]
C_5_land_area	**Total land area of the site**		[Integer]
C_5_land_area_unit	**Select the appropriate unit**		[m2] Square metres [hectares] Hectares
C_6_clean_freq	**How often do you clean pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_6a_clean_method	**What is used to clean pens?**	selected(${C_6_clean_freq}, 'between_batch') or selected(${C_6_clean_freq}, 'daily') or selected(${C_6_clean_freq}, 'weekly') or selected(${C_6_clean_freq}, 'monthly') or selected(${C_6_clean_freq}, 'less_monthly') or selected(${C_6_clean_freq}, 'disease')	[water] Water [soap] Soap [disinfectant] Disinfectant [unsure] Don't know [refused] Refused
C_6_disinfect_freq	**How often do you disinfect pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_6_disinfect_specify	**Please specify the type of disinfectant used (type or brand name)**	selected(${C_6a_clean_method}, 'disinfectant') or selected(${C_6_disinfect_freq}, 'between_batch') or selected(${C_6_disinfect_freq}, 'daily') or selected(${C_6_disinfect_freq}, 'weekly') or selected(${C_6_disinfect_freq}, 'monthly') or selected(${C_6_disinfect_freq}, 'less_monthly') or selected(${C_6_disinfect_freq}, 'disease')	[Text]
C_7_empty_between_batches	**Do you usually leave pens empty between two groups of pigs?**		[always] Always [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
broken_header_C7a	**How many days do you usually leave pens empty between two groups of pigs?**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Enumerator Note]
C7a_days_empty_ave	**Average:**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Integer]
C7b_days_empty_min	**Minimum:**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Integer]
C7c_days_empty_max	**Maximum:**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Integer]
C_8_other_animals_yn	**Are any other animals currently present on the farm/site? (Including cats, dogs, poultry etc)**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_8_other_animals	**Which of the following animals are currently present on the farm/site?**	selected(${C_8_other_animals_yn}, 'yes')	[layers] Chicken layers (for eggs) [broilers] Chicken broilers (for meat) [backyard] Backyard chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [dogs] Dogs [cats] Cats [other] Other

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_8_other_animals_specify	**Please specify the other animals that are on this farm/site**	selected(${C_8_other_animals}, 'other')	[Text]
broken_header_C_8	**How many are currently present on the farm/site?**	selected(${C_8_other_animals_yn}, 'yes')	[Enumerator Note]
C_8b1_layers_qty	**Chicken layers (for eggs)**	selected(${C_8_other_animals}, 'layers')	[Integer]
C_8b2_broilers_qty	**Chicken broilers (for meat)**	selected(${C_8_other_animals}, 'broilers')	[Integer]
C_8b3_backyard_qty	**Backyard chickens**	selected(${C_8_other_animals}, 'backyard')	[Integer]
C_8b4_ducks_qty	**Ducks**	selected(${C_8_other_animals}, 'ducks')	[Integer]
C_8b5_geese_qty	**Geese**	selected(${C_8_other_animals}, 'geese')	[Integer]
C_8b6_cattle_qty	**Cattle**	selected(${C_8_other_animals}, 'cattle')	[Integer]
C_8b7_goats_qty	**Goats**	selected(${C_8_other_animals}, 'goats')	[Integer]
C_8b8_dogs_qty	**Dogs**	selected(${C_8_other_animals}, 'dogs')	[Integer]
C_8b9_cats_qty	**Cats**	selected(${C_8_other_animals}, 'cats')	[Integer]
C_8b10_other_qty	**Other**	selected(${C_8_other_animals}, 'other')	[Text]
C_8_animals_contact_pigs_yes_no	**Can any of these animals come into direct contact with pigs?**	selected(${C_8_other_animals_yn}, 'yes')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_8_animals_contact_pigs	**Which of these animals are able to come into direct contact with pigs?**	selected(${C_8_other_animals_yn}, 'yes') and selected(${C_8_animals_contact_pigs_yes_no}, 'yes')	[layers] Chicken layers (for eggs) [broilers] Chicken broilers (for meat) [backyard] Backyard chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [dogs] Dogs [cats] Cats [other] Other [none] None

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_8_animals_contact_other_hh_yes_no	**Can any of these animals come into direct contact with livestock from other households?**	selected(${C_8_other_animals_yn}, 'yes')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_8_animals_contact_other_hh	**Which of these animals are able to come into direct contact with livestock from other households?**	selected(${C_8_other_animals_yn}, 'yes') and selected(${C_8_animals_contact_other_hh_yes_no}, 'yes')	[layers] Chicken layers (for eggs) [broilers] Chicken broilers (for meat) [backyard] Backyard chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [dogs] Dogs [cats] Cats [other] Other [none] None
C_8d_1_neighbour_hh_animals	**Do the neighbouring households (that these animals are able to physically contact) raise pigs or poultry?**	selected(${C_8_other_animals_yn}, 'yes') and selected(${C_8_animals_contact_other_hh_yes_no}, 'yes')	[pigs] Pigs [poultry] Poultry [no] No [unsure] Don't know [refused] Refused
D_1_feed	**What are your pigs fed on?**		[commercial] Commercial pig feed [graze_confined] Forage/graze in confined area [graze_open] Forage/graze openly [swill_hh] Pig swill - own household waste [swill_external] Pig swill - external sources of food waste [homemade_concentrate] Homemade concentrate [agri] Rice grain/agricultrural by-product [other] Other [unsure] Don't know [refused] Refused
D_1a_feed_specify	**Please specify the other type of feed used**	selected(${D_1_feed}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
D_1b_feed_source	**Where do you source pig feed from?**	selected(${D_1_feed}, 'commercial') or selected(${D_1_feed}, 'swill_external') or selected(${D_1_feed}, 'agri') or selected(${D_1_feed}, 'other')	[company] A company [contract] A parent contracted farm [cooperative] A cooperative [neighbour] A neighbour [shop] A shop [restaurant] A restaurant [other] Other [unsure] Don't know
D_1b3_feed_source_specify	**Where do you source pig feed from? (specify)**	selected(${D_1b_feed_source}, 'other')	[Text]
D_1b1_feed_company	**Please specify the name of the company**	selected(${D_1b_feed_source}, 'company')	[Text]
D_1b2_feed_contractor	**Please specify the name of the contracted farm**	selected(${D_1b_feed_source}, 'contract')	[Text]
D_1b2a_feed_contractor_loc	**Enter the highest common administrative area that this contracted farm is located within**	selected(${D_1b_feed_source}, 'contract')	[village] Same village [commune] Same commune [district] Same district [province] Same province [province_different] Different provinces
D_1b3_feed_cooperative	**Please specify the name of the cooperative**	selected(${D_1b_feed_source}, 'cooperative')	[Text]
D_2_feed_stored	**How is pig feed stored on the farm?**		[sealed] Sealed containers (e.g. silos) [open] Open containers [near_pigs] Next to pig pens [away_pigs] Away from pig pens [indoor] Indoors [sheltered] Sheltered [outdoor] Outdoors [unsure] Don't know [refused] Refused
D_3_feed_accessible_birds	**Is pig feed accessible to wild and/or farmed birds?**		[yes_wild] Yes - wild birds [yes_farmed] Yes - farmed poultry [no] No [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
D_4_water_source	**Where is water sourced for your pigs?**		[surface] River/pond/lake [piped] Tap [well_protected] Protected well/pumping well [well_unprotected] Open well [rain] Rainwater [tanker] Water tanker vehicle [other] Other [unsure] Don't know [refused] Refused
D_4a_water_source_specify	**Please specify the type of water source:**	selected(${D_4_water_source}, 'other')	[Text]
D_5_waste_disposal	**What do you do with pig waste (dung, excreta)?**		[drained_public] Drained to a public drainage [drained_current] Drained to a current water [drained_empty] Drained to empty space [drained_blocked] Drained to a blocked water body/low ground [fertiliser] Stored for fertiliser [sent] Send it to another farm/site [taken_away] Taken away by a someone else/a waste disposal company [other] Other [unsure] Don't know [refused] Refused
D_5a_waste_disposal_specify	**Please specify what you do with pig waste:**	selected(${D_5_waste_disposal}, 'other')	[Text]
D_6_latrine_facilities	**What type of latrine facilities are present within the compound?**		[flush] Modern flush toilet [septic] Toilet with septic tank [pit] Pit latrine [none] None [other] Other [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
D_6_latrine_facilities_specify	**Please specify the type of latrine facilities**	selected(${D_6_latrine_facilities}, 'other')	[Text]
D_7_pig_access_latrine	**Do pigs have any access to the area around latrine facilities?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_1_vaccinate	**Are any of your pigs vaccinated?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_1a_vaccines	**Which vaccine(s) have your pigs received?**	${E_1_vaccinate} = 'yes'	[salmonella] Salmonella [pasteurollosis] Pasteurollosis [csf] Classical swine fever [aujeszky] Aujeszky [fmd] Foot and mouth disease [prrs] PRRS [other] Other [unsure] Don't know
E_1a1_vaccine_specify	**Please specify the other vaccine(s)**	selected(${E_1a_vaccines}, 'other')	[Text]
E_2_morbidity	**Have you had any sick pigs in the past 6 months?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_2a1_i_disease_known	**Disease(s) known?**	${E_2_morbidity} = 'yes'	[yes] Yes [no] No
E_2a1a_i_disease_specify	**Please specify the disease(s)**	${E_2a1_i_disease_known} = 'yes'	[salmonella] Salmonella [pasteurollosis] Pasteurollosis [csf] Classical swine fever [aujeszky] Aujeszky [fmd] Foot and mouth disease [prrs] PRRS [other] Other [unsure] Don't know
E_2a1a1_i_disease_other	**Please specify the other disease**	selected(${E_2a1a_i_disease_specify}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
E_2a1b_i_symptoms	**Have your pigs had any of the following symptoms in the past 6 months?**		[lame] Lameness [inappetence] Inappetence [constipation] Constipation [diarrhoea] Diarrhoea [abscesses] Abscesses [sneeze] Sneezing [cough] Coughing [breath] Heavy breathing [skin_colour] Skin discolouration [skin_greasy] Greasy skin [mange] Mange [eyes] Discharge (eyes) [nose] Discharge (nose) [preg_fail] Pregnancy failures [abortion] Abortion [mastitis] Mastitis [other] Other
E_2a1b1_i_symptoms_other	**Please specify the other symptom(s)**	selected(${E_2a1b_i_symptoms}, 'other')	[Text]
E_2a2_i_sick_qty	**Number of pigs affected:**	${E_2_morbidity} = 'yes'	[Integer]
E_2a2_i_pigs_affected	**Which pig types were affected?**	${E_2_morbidity} = 'yes'	[sow] Sow [boar] Boar (purchase/sale) [boar_hire] Boar (hire) [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type) [ai] Artificial Insemination (AI) doses
E_2c_sick_action	**What did you do with the sick pig(s)?**	${E_2_morbidity} = 'yes'	[quarantine] Placed in quarantine [report_chief] Reported to the village/commune chief [report_ahw] Reported to an animal health worker [sold] Sold the pigs while sick [treat] Treated/medicated [cull] Culled [nothing] Nothing [unsure] Don't know

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[refused] Refused [other] Other
E_2c1_sick_action_other	**Please specify what you did with the sick pigs:**	selected(${E_2c_sick_action}, 'other')	[Text]
E_2b_i_deaths	**Have you had any pig mortalities in the past 6 months?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_2b1_i_deaths_qty	**Number of mortalities**	${E_2b_i_deaths} = 'yes'	[Integer]
E_2b1_i_deaths_pig_type	**Which pig types were pig affected?**	${E_2b_i_deaths} = 'yes'	[sow] Sow [boar] Boar (purchase/sale) [boar_hire] Boar (hire) [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type) [ai] Artificial Insemination (AI) doses
E_2d_carcass_dispose	**What did you do with the carcasses of pigs that died/were culled?**	${E_2b_i_deaths} = 'yes'	[incinerated] Incinerated on site [buried] Buried on site [taken_away] Taken away by person/company [pm] Sent for post mortem [sold] Sold the carcass/meat [consumed] Consumed the meat at home [unsure] Don't know [refused] Refused [other] Other
E_2d1_carcass_dispose_specify	**Please specify what you did with the carcasses**	selected(${E_2d_carcass_dispose}, 'other')	[Text]
F_1_biosecurity	**Are any of the following biosecurity measures in place on the farm/site?**		[wheel_entrance] Vehicle wheel washes at site entrance [boot_entrance] Boot dip stations at site entrance [boot_pens] Boot dip stations at pig

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			house entrances [shoe_covers] Disposable shoe covers used when entering pig pens/houses [ppe_staff] Staff PPE (clothing and footwear) is used, and kept on site [ppe_visitor] Visitor PPE (clothing and footwear) is used, and kept on site [fence] Site is contained within a livestock-proof (not including poultry) perimeter fence [nets] Use mosquito nets [access_pens] Restrict visitors' access to pig pens [access_site] Restrict access to people who have contacted other pigs [unsure] Don't know [other] Other [none] None
F_1_biosecurity_other	**Specify other**	selected(${F_1_biosecurity}, 'other')	[Text]
F_2_pigs_near_farmer	**Are the pigs kept near the house of the interviewee (e.g. <50m)?**		[yes] Yes [no] No
F_2a_pigs_farmer_distance	**How far from from the interviewee's house?**	${F_2_pigs_near_farmer} = 'no'	[Integer]
F_2a_pigs_farmer_unit	**Metres / Kilometers**	${F_2_pigs_near_farmer} = 'no'	[m] Metres [km] Kilometers
F_3_pigs_accessible_birds	**Is the area that the pigs are kept accessible to wild and/or farmed birds?**		[yes_wild] Yes - wild birds [yes_farmed] Yes - farmed poultry [no] No [unsure] Don't know [refused] Refused
F_4_nearby	**Is the farm/site situated near any of the following?**		[buildings] Residential buildings [crop] Rice/crop fields [sh] Slaughterhouse [poultry_farm] Poultry farm [water_body] Body of water (river/lake/reservoir)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[road] A road [unsure] Don't know

9.3 Questionnaires: Form A 2 Pig trader survey v3 (ODK questionnaire)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
province_1	**Province ISO code**		[12] 12 Phnom Penh [08] 08 Kandal [05] 05 Kampong Speu [21] 21 Takeo
A_3_village_specify	**Village ID**	selected(${A_3_village}, '-88')	[Text]
A_4_trader_id	**Unique trader code**		[Text]
temporary_note1	**Unique ID: ${unique_ID}**		[Enumerator Note]
consent	**Interviewee has read the information sheet and signed consent form**		[yes] Yes [no] No
A_2_interviewer	**Interviewer initials**		[Text]
A_4_interviewee_age	**Interviewee age**		[Integer]
A_5_gender	**Gender**		[male] Male [female] Female [refused] Refused
A_6_interviewee_ethnicity	**What is your ethnicity?**		[khmer] Khmer [cham] Cham [vietnamese] Vietnamese [chinese] Chinese [other] Other [unsure] Don't know [refused] Refused
A_6a_interviewee_ethnicity_specify	**Please specify your ethnicity**	selected(${A_6_interviewee_ethnicity}, 'other')	[Text]
A_7_education	**What is the highest level of education you have completed?**		[none] None [primary] Primary (grades 1 to 6) [lower_secondary] Lower Secondary (grades 7 to 9)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[upper_secondary] Upper secondary (grades 10 to 12) [higher] Higher (college/university) [unsure] Don't know [refused] Refused
A_7a_trader_type	**Which of the following options best describes you?**		[trader] Licensed pig trader [butcher] Licensed butcher [middleman] Middleman [unlicensed] Unlicensed pig trader/exchanger [other] Other
A_7a_trader_type_specify	**Please specify**	selected(${A_7a_trader_type}, 'other')	[Text]
A_8_work_with	**Do you work with other people?**		[ind_alone] I am an independent trader and work alone [ind_work_others] I am an independent trader but often work with other traders [employ] I employ other people as part of this operation [contractor] I work for a contractor [company] I work for a company [sh] I work for/closely with a slaughterhouse [other] Other [refused] Refused
A_8a_work_with_specify	**Please specify**	selected(${A_8_work_with}, 'other')	[Text]
A_8a_employ_qty	**How many other people do you employ/work with?**	selected(${A_8_work_with}, 'ind_work_others') or selected(${A_8_work_with}, 'employ')	[Integer]
A_8b_company_name	**Name of company/contractor:**	selected(${A_8_work_with}, 'contractor') or selected(${A_8_work_with}, 'company')	[Text]
broken_header_most_trade	**In which _district(s)_ do you conduct most of your trading activity?**		[Enumerator Note]
A_10_primary_income	**Which occupation provides your main source of household income?**		[farmer] Pig farmer [trader] Pig trader [sh_worker] Pig slaughterhouse worker [sh_owner] Slaughterhouse owner [sh_manager] Slaughterhouse manager [meat] Meat retailer [ahw] Animal health worker [professional] Professional/technical/managerial

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[clercial] Clerical/ office work [skilled_man] Skilled manual (but not agriculture) [unskilled_man] Unskilled manual (but not agriculture) [crop] Agriculture crop [livestock] Livestock and fishing (other) [sales] Sales and services/ trader [boar_serv] Boar breeding service [refused] Refused [other] Other
A_10a_primary_income_specify	**Please specify your main source of household income**	${A_10_primary_income} = 'other'	[Text]
A_11_secondary_income	**Are there any other occupations which provide further sources of household income?**		[farmer] Pig farmer [trader] Pig trader [sh_worker] Pig slaughterhouse worker [sh_owner] Slaughterhouse owner [sh_manager] Slaughterhouse manager [meat] Meat retailer [ahw] Animal health worker [professional] Professional/technical/managerial [clercial] Clerical/ office work [skilled_man] Skilled manual (but not agriculture) [unskilled_man] Unskilled manual (but not agriculture) [crop] Agriculture crop [livestock] Livestock and fishing (other) [sales] Sales and services/ trader [boar_serv] Boar breeding service [refused] Refused [other] Other [none] None
A_11a_secondary_income_specify	**Please specify your other sources of household income**	selected(${A_11_secondary_income}, 'other')	[Text]
A_12_years_operating	**How long have you been working as a pig trader (years)?**		[Decimal]
A_13_days_active	**How many days have you been actively trading in the past 14 days?**		[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_2_purchased	**In the past 14 days, have you purchased (or otherwise acquired) any LIVE pigs?**		[yes] Yes [no] No [unsure] Unsure
date_widget_last_purchased	**When was the last time you purchased live pigs?**	${B_2_purchased}='no' or ${B_2_purchased}='unsure'	[Date]
B_2a_purchased_suppliers	**Which supplier types have you purchased (or otherwise acquired) LIVE pigs from in the past 14 days?**	${B_2_purchased}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_2a1_recipient_specify	**Please specify the other type of supplier(s)**	${B_2a_purchased_suppliers} = 'other'	[Text]
broken_header1	**How many suppliers/sellers of each type did you acquire pigs from in the past 14 days?**	${B_2_purchased}='yes'	[Enumerator Note]
B_3a_small_hh	**Small households (<10 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'sml_hh')	[Integer]
B_3b_med_hh	**Medium household (10 to 50 pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'med_hh')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_3c_large_hh	Large household (50 to <100 pigs)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'lrg_hh')	[Integer]
B_3c_hh	Household of unknown size	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'hh')	[Integer]
B_3d_small_farm	Small farm (100 to <1000 pigs)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'sml_farm')	[Integer]
B_3e_med_farm	Medium farm (1000 to <5000 pigs)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'med_farm')	[Integer]
B_3f_lrg_farm	Large farm (≥5000 pigs)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'lrg_farm')	[Integer]
B_3f_farm	Farm of unknown size	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'farm')	[Integer]
B_3g_trader	Trader	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'trader')	[Integer]
B_3h_butcher	Butcher	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'butcher')	[Integer]
B_3i_middleman	Middleman	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'middleman')	[Integer]
B_3i_sh	Slaughterhouse	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'SH')	[Integer]
B_3k_kp	Killing point	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'KP')	[Integer]
B_3l_cp	CP	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'CP')	[Integer]
B_3m_cp_central	Central point (any company)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'central_point')	[Integer]
B_3n_cp_acmc	ACMC-M-Pig (Moung Rithy)	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'ACMC ')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_3o_cp_betagro	**Betagro**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'betagro')	[Integer]
B_3p_company	**Another company**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'company')	[Integer]
B_3q_boar_service	**Boar service (Does not keep other pigs)**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'boar_service')	[Integer]
B_3r_poahp	**POAHP**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'poahp')	[Integer]
B_3j_other	**Other**	${B_2_purchased}='yes' and selected(${B_2a_purchased_suppliers}, 'other')	[Integer]
B_3k_total_suppliers	**Total number of suppliers**	${B_2_purchased}='yes'	[Calculation]
B_4_categories_purchased	**Which of the following types of LIVE pig have you purchased in the past 14 days?**	${B_2_purchased}='yes'	[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type)
broken_header2	**Number of pigs acquired of this category (approx.) in past 14 days**	${B_2_purchased}='yes'	[Enumerator Note]
B_4a_sows_purchased	**Sows**	${B_2_purchased}='yes' and selected(${B_4_categories_purchased}, 'sow')	[Integer]
B_4c_boars_purchased	**Boars**	${B_2_purchased}='yes' and selected(${B_4_categories_purchased}, 'boar')	[Integer]
B_4d_piglets_purchased	**Piglets**	${B_2_purchased}='yes' and selected(${B_4_categories_purchased}, 'piglets')	[Integer]
B_4e_weaners_purchased	**Weaners**	${B_2_purchased}='yes' and selected(${B_4_categories_purchased}, 'weaners')	[Integer]
B_4f_growers_purchased	**Growers**	${B_2_purchased}='yes' and selected(${B_4_categories_purchased}, 'growers')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_4g_finishers_purchased	**Finishers**	${B_2_purchased}='yes' and selected(${B_4_categories_purchased}, 'finishers')	[Integer]
B_4b_pigs_purchased	**Pigs (unknown type)**	${B_2_purchased}='yes' and selected(${B_4_categories_purchased}, 'pigs')	[Integer]
broken_header1.5	**Please provide details of each individual supplier of a) pigs purchased, from thepast 14 days:**		[Enumerator Note]
broken_header_1c_1	**Supplier S-${supplier_number}**		[Enumerator Note]
B_2c_supplier_type	**What type of supplier is this?**		[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_2c1_supplier_specify	**Please specify the type of supplier**	${B_2c_supplier_type}='other'	[Text]
B_2c1_company	**Name of company**	selected(${B_2c_supplier_type}, 'company') or selected(${B_2c_supplier_type}, 'central_point')	[CP] CP [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_2c1_company_specify	**Please specify**	selected(${B_2c1_company}, 'company')	[Text]
B_2j_exchange_location	**Where did you exchange these pigs?**	${B_2c_supplier_type}='trader' or ${B_2c_supplier_type}='butcher' or ${B_2c_supplier_type}='middleman'	[SH] Slaughterhouse [KP] Killing point [central_point] Central point (any company) [farm] Farm [home] Where I live [other] Other [unsure] Don't know [refused] Refused
B_2k_country	**Where did you exchange these pigs?: Country**	${B_2c_supplier_type}='trader' or ${B_2c_supplier_type}='butcher' or ${B_2c_supplier_type}='middleman'	[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other [unsure] Don't know
B_2k1_country_spec	**Please specify the other country**	selected(${B_2k_country}, 'other')	[Text]
B_2e_relationship	**What is your relationship with this supplier?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
B_2e_relation_specify	**Please specify the type of relationship**	${B_2e_relationship}='other'	[Text]
broken_header_2f	**_Contact location or site where this contact is based_**		[Enumerator Note]
B_2f_country	**Country**		[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other [unsure] Don't know
B_2f1_country_spec	**Please specify the other country**	selected(${B_2f_country}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_2k_transac_freq	**Frequency of transactions with this supplier**		[first_time] First time [daily] Daily [2daily] At least every other day [3daily] At least twice per week [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly [6monthly] At least 6 monthly [yearly] At least yearly [unsure] Unknown
broken_header_3	**Number of pigs received from this supplier in the past 14 days:**		[Enumerator Note]
B_2l_sows_purchased	**Sows**	selected(${B_4_categories_purchased}, 'sow')	[Integer]
B_2m_boars_purchased	**Boars**	selected(${B_4_categories_purchased}, 'boar')	[Integer]
B_2o_piglets_purchased	**Piglets**	selected(${B_4_categories_purchased}, 'piglets')	[Integer]
B_2p_weaners_purchased	**Weaners**	selected(${B_4_categories_purchased}, 'weaners')	[Integer]
B_2q_growers_purchased	**Growers**	selected(${B_4_categories_purchased}, 'growers')	[Integer]
B_2r_finishers_purchased	**Finishers**	selected(${B_4_categories_purchased}, 'finishers')	[Integer]
B_2s_pigs_purchased	**Pigs (unknown type)**	selected(${B_4_categories_purchased}, 'pigs')	[Integer]
B_2t_contact_provided	**Can you provide contact details for this supplier?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
B_2j_village	**In the paper log book, please now also record the site name, and site village (if known), for supplier ID:_ S-${supplier_number}**		[Enumerator Note]
B_2t1_contact_details	**Please record the contact's name, and phone number in the paper log**	${B_2t_contact_provided}='yes'	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
	book, for supplier ID:_ S-${supplier_number}		
B_7_pigs_kept_bi	**In the past 14 days, were purchased pigs either kept at an intermediary location for any length of time before sale/slaughter, OR kept at the place of slaughter for over 24 hours before they were killed?**		[yes] Yes [no] No [unsure] Unsure
B_7a_pigs_kept_location	**In which of these places do you keep pigs before selling them, or before they are slaughtered?**	selected(${B_7_pigs_kept_bi}, 'yes')	[slaughtered] Where they are slaughtered [home] Where I live [other] Other [unsure] Don't know [refused] Refused
B_7a1_kept_location_specify	**Specify**	selected(${B_7a_pigs_kept_location}, 'other')	[Text]
C_7b_pig_housing	**How are purchased pigs housed?**	selected(${B_7_pigs_kept_bi}, 'yes')	[individual] Total (individual) confinement [group_same] Group housed - with pigs of the same category [group_mixed] Group housed - mixed with other pig categories [tethered] Tethered [freerange] Free-range [other] Other [unsure] Don't know [refused] Refused
C_7b_pig_housing_specify	**Specify**	selected(${C_7b_pig_housing}, 'other')	[Text]
C_7b1_pen_qty_pigs	**How many pigs are kept together in a pen?**	selected(${C_7b_pig_housing}, 'group_same') or selected(${C_7b_pig_housing}, 'group_mixed')	[Integer]
C_7c_indoor_outdoor	**Where are pigs housed?**	selected(${B_7_pigs_kept_bi}, 'yes')	[outdoor] Outdoors [indoor] Sheltered [sheltered] Indoors [unsure] Don't know [refused] Refused [other] Other

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_7d_pigs_contact_diff_origins	**Are pigs from different origins able to come into direct contact with each other?**	selected(${B_7_pigs_kept_bi}, 'yes')	[yes] Yes [no] No [unsure] Don't know [refused] Refused [na] Not applicable
C_7e_pigs_contact_pigs_raised	**Are traded pigs able to come into direct contact with other pigs being raised on site (e.g. if a farm/household**	selected(${B_7_pigs_kept_bi}, 'yes')	[yes] Yes [no] No [unsure] Don't know [refused] Refused [na] Not applicable
C_3d_clean_freq	**How often do you clean pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_3d1_clean_method	**What is used to clean pens?**	selected(${C_3d_clean_freq}, 'between_batch') or selected(${C_3d_clean_freq}, 'daily') or selected(${C_3d_clean_freq}, 'weekly') or selected(${C_3d_clean_freq}, 'monthly') or selected(${C_3d_clean_freq}, 'less_monthly') or selected(${C_3d_clean_freq}, 'disease')	[water] Water [soap] Soap [disinfectant] Disinfectant [unsure] Don't know [refused] Refused
C_3d_disinfect_freq	**How often do you disinfect pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_3d1a_specify_disinfectant	**Please specify the type of disinfectant used (type or brand name**	selected(${C_3d1_clean_method}, 'disinfectant') or selected(${C_3d_disinfect_freq}, 'between_batch') or selected(${C_3d_disinfect_freq}, 'daily') or	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
		selected(${C_3d_disinfect_freq}, 'weekly') or selected(${C_3d_disinfect_freq}, 'monthly') or selected(${C_3d_disinfect_freq}, 'less_monthly') or selected(${C_3d_disinfect_freq}, 'disease')	
broken_header_C_7	**How long are purchased pigs usually kept before selling /slaughtering them?:**		[Enumerator Note]
C_7g_kept_ave_other	**on average:**		[Integer]
C_7g_hours_days_ave_other	**hours/days**		[hours] Hours [days] Days
C_7g_kept_min_other	**min:**		[Integer]
C_7g_hours_days_min_other	**hours/days**		[hours] Hours [days] Days
C_7g_kept_max_other	**max:**		[Integer]
C_7g_hours_days_max_other	**hours/days**		[hours] Hours [days] Days
B_8_sales	**In the past 14 days have you sold (or otherwise given away) or delivered any LIVE pigs, including pigs sent to slaughter?**		[yes] Yes [no] No [unsure] Unsure
date_widget_last_sold	**When was the last time you sold live pigs? (Including pigs slaughtered at slaughterhouses)?**	${B_8_sales}='no' or ${B_8_sales}='unsure'	[Date]
B_8a_sales_recipients	**Which recipient types have you sold/delivered LIVE pigs to in the past 14 days?**	${B_8_sales}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_8a1_recipient_specify	**Please specify the other type of recipient**	${B_8a_sales_recipients} = 'other'	[Text]
broken_header_1	**In the past 14 days, how many recipients of each type did you sell/deliver pigs to?**	${B_8_sales}='yes'	[Enumerator Note]
B_9a_small_hh	**Small households (<10 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'sml_hh')	[Integer]
B_9b_med_hh	**Medium household (10 to 50 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'med_hh')	[Integer]
B_9c_large_hh	**Large household (50 to <100 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'lrg_hh')	[Integer]
B_9c_hh	**Household of unknown size**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'hh')	[Integer]
B_9d_small_farm	**Small farm (100 to <1000 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'sml_farm')	[Integer]
B_9e_med_farm	**Medium farm (1000 to <5000 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'med_farm')	[Integer]
B_9f_lrg_farm	**Large farm (≥5000 pigs)**	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'lrg_farm')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_9f_farm	Farm of unknown size	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'farm')	[Integer]
B_9g_trader	Another trader	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'trader')	[Integer]
B_9h_butcher	Butcher	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'butcher')	[Integer]
B_9i_middleman	Middleman	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'middleman')	[Integer]
B_9i_sh	Slaughterhouse	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'SH')	[Integer]
B_9k_kp	Killing point	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'KP')	[Integer]
B_6.1l_cp	CP	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'CP')	[Integer]
B_9m_cp_central	Central point (any company)	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'central_point')	[Integer]
B_6.1n_cp_acmc	ACMC-M-Pig (Moung Rithy)	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'ACMC ')	[Integer]
B_6.1o_cp_betagro	Betagro	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'betagro')	[Integer]
B_6.1p_company	Another company	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'company')	[Integer]
B_6.1q_boar_service	Boar service (Does not keep other pigs)	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'boar_service')	[Integer]
B_6.1r_poahp	POAHP	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'poahp')	[Integer]
B_9j_other	Other	${B_8_sales}='yes' and selected(${B_8a_sales_recipients}, 'other')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_9l_total_recipients	**Total number of recipients**	${B_8_sales}='yes'	[Calculation]
B_10_categories_sold	**Which of the following types of LIVE pig have you sold/delivered in the past 14 days?**	${B_8_sales}='yes'	[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type)
broken_header_2	**Number of pigs sold/delivered of this category (approx.) in past 14 days**	${B_8_sales}='yes'	[Enumerator Note]
B_10a_sows_sold	**Sows**	${B_8_sales}='yes' and selected(${B_10_categories_sold}, 'sow')	[Integer]
B_10c_boars_sold	**Boars**	${B_8_sales}='yes' and selected(${B_10_categories_sold}, 'boar')	[Integer]
B_10d_piglets_sold	**Piglets**	${B_8_sales}='yes' and selected(${B_10_categories_sold}, 'piglets')	[Integer]
B_10e_weaners_sold	**Weaners**	${B_8_sales}='yes' and selected(${B_10_categories_sold}, 'weaners')	[Integer]
B_10f_growers_sold	**Growers**	${B_8_sales}='yes' and selected(${B_10_categories_sold}, 'growers')	[Integer]
B_10g_finishers_sold	**Finishers**	${B_8_sales}='yes' and selected(${B_10_categories_sold}, 'finishers')	[Integer]
B_10b_pigs_sold	**Pigs (unknown type)**	${B_8_sales}='yes' and selected(${B_10_categories_sold}, 'pigs')	[Integer]
broken_header_4	**Please provide details of each individual recipient of a) pigs sold, b) pigs sent for slaughter from the past 14 days:**		[Enumerator Note]
broken_header_5	**Recipient R-${recipient_number}**		[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6c_recipient_type	**Recipient type**		[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_6c1_recipient_specify	**Please specify the type of recipient**	${B_6c_recipient_type}='other'	[Text]
B_6c1_company_specify	**Name of company**	selected(${B_6c_recipient_type}, 'company') or selected(${B_6c_recipient_type}, 'central_point')	[Text]
B_6j_exchange_location	**Where did you exchange these pigs?**	${B_6c_recipient_type}='trader' or ${B_6c_recipient_type}='butcher' or ${B_6c_recipient_type}='middleman'	[SH] Slaughterhouse [KP] Killing point [central_point] Central point (any company) [farm] Farm [home] Where I live [other] Other [unsure] Don't know [refused] Refused
B_6k_country	**Where did you exchange these pigs?: Country**	${B_6c_recipient_type}='trader' or ${B_6c_recipient_type}='butcher' or ${B_6c_recipient_type}='middleman'	[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other [unsure] Don't know

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6k1_country_spec	**Please specify the other country**	selected(${B_6k_country}, 'other')	[Text]
B_6e_relationship	**What is your relationship with this recipient?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
B_6e_relation_specify	**Please specify the type of relationship**	${B_6e_relationship}='other'	[Text]
B_1o_who_kills_pigs_trader	**Who killed the pigs?**	selected(${B_6c_recipient_type}, 'SH')	[trader] Killed pigs myself [employee] An external person was hired to kill the pigs [sh_kp_worker] People who work at a killing point/slaughterhouse [other] Other [unsure] Don't know [refused] Refused
B_1o1_who_kills_specify	**Please specify who killed the pigs**	selected(${B_1o_who_kills_pigs_trader},'other')	[Text]
broken_header_6f	**_Contact location or site where this contact is based_**		[Enumerator Note]
B_6f_country	**Country**		[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other [unsure] Don't know
B_6f1_country_spec	**Please specify the other country**	selected(${B_6f_country}, 'other')	[Text]
B_6k_transac_freq	**Frequency of transactions with this recipient**		[first_time] First time [daily] Daily [2daily] At least every other day [3daily] At least twice per week [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[3monthly] At least 3 monthly [6monthly] At least 6 monthly [yearly] At least yearly [unsure] Unknown
broken_header_4.11	**Number of pigs sent to this recipient in past 14 days:**		[Enumerator Note]
B_6m_sows_qty	**Sows**	selected(${B_10_categories_sold}, 'sow')	[Integer]
B_6o_boars_sold	**Boars**	selected(${B_10_categories_sold}, 'boar')	[Integer]
B_6p_piglet	**Piglets**	selected(${B_10_categories_sold}, 'piglets')	[Integer]
B_6q_weaner	**Weaners**	selected(${B_10_categories_sold}, 'weaners')	[Integer]
B_6r_grower	**Growers**	selected(${B_10_categories_sold}, 'growers')	[Integer]
B_6s_finisher	**Finishers**	selected(${B_10_categories_sold}, 'finishers')	[Integer]
B_6s_unknown	**Pigs (unknown type)**	selected(${B_10_categories_sold}, 'pigs')	[Integer]
B_6t_contact_provided	**Can you provide contact details for this recipient?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
B_6j_village	**In the paper log book, please now also record the site name, and site village (if known), for Recipient _ R-${recipient_number}**		[Enumerator Note]
B_6t1_contact_details	**Please record the contact's name, and phone number in the paper log book, for Recipient _ R-${recipient_number}**	${B_6t_contact_provided}='yes'	[Enumerator Note]
B_18_longitudinal_bi	**Does the quantity, and/or the types of pigs you trade, vary across the year?**		[yes] Yes [no] No [unsure] Unsure

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_19_categories_traded_year	**Which pig types have you traded in the past year?**	${B_18_longitudinal_bi}='yes'	[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type)
broken_header_longitudinal	**For each selected pig type, does the number of pigs you trade of this type vary across the year?**	${B_18_longitudinal_bi}='yes'	[Enumerator Note]
B_19a_sows_purchased	**Sows**	${B_18_longitudinal_bi}='yes' and selected(${B_19_categories_traded_year},'sow')	[yes] Yes [no] No [unsure] Unsure
broken_header_a	**a) Sows**	${B_19a_sows_purchased}='yes'	[Enumerator Note]
B_19a1_busy_months	**When do you trade the most pigs of this category?**	${B_19a_sows_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_B_19a2	**During these busy periods, how many pigs do you trade of each category _per day_?:**	${B_19a_sows_purchased}='yes'	[Enumerator Note]
B_19a2_ave_throughput	**Average:**	${B_19a_sows_purchased}='yes'	[Decimal]
B_19a5_quiet_months	**When do you trade the least pigs of this category?**	${B_19a_sows_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19a6	**During these quiet periods, how many pigs do you trade of each category _per day_?:**	${B_19a_sows_purchased}='yes'	[Enumerator Note]
B_19a6_ave_throughput	**Average:**	${B_19a_sows_purchased}='yes'	[Decimal]
B_19c_boars_purchased	**Boars**	${B_18_longitudinal_bi}='yes' and selected(${B_19_categories_traded_year},'boar')	[yes] Yes [no] No [unsure] Unsure
broken_header_c	**c) Boars**	${B_19c_boars_purchased}='yes'	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_19c1_busy_months	**When do you trade the most pigs of this category?**	${B_19c_boars_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19c2	**During these busy periods, how many pigs do you trade of each category _per day_?:**	${B_19c_boars_purchased}='yes'	[Enumerator Note]
B_19c2_ave_throughput	**Average:**	${B_19c_boars_purchased}='yes'	[Decimal]
B_19c5_quiet_months	**When do you trade the least pigs of this category?**	${B_19c_boars_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19c6	**During these quiet periods, how many pigs do you trade of each category _per day_?:**	${B_19c_boars_purchased}='yes'	[Enumerator Note]
B_19c6_ave_throughput	**Average:**	${B_19c_boars_purchased}='yes'	[Decimal]
B_19d_piglets_purchased	**Piglets**	${B_18_longitudinal_bi}='yes' and selected(${B_19_categories_traded_year},'piglets')	[yes] Yes [no] No [unsure] Unsure
broken_header_d	**d) Piglets**	${B_19d_piglets_purchased}='yes'	[Enumerator Note]
B_19d1_busy_months	**When do you trade the most pigs of this category?**	${B_19d_piglets_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19d2	**During these busy periods, how many pigs do you trade of each category _per day_?:**	${B_19d_piglets_purchased}='yes'	[Enumerator Note]
B_19d2_ave_throughput	**Average:**	${B_19d_piglets_purchased}='yes'	[Decimal]
B_19d5_quiet_months	**When do you trade the least pigs of this category?**	${B_19d_piglets_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19d6	**During these quiet periods, how many pigs do you trade of each category _per day_?:**	${B_19d_piglets_purchased}='yes'	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_19d6_ave_throughput	**Average:**	${B_19d_piglets_purchased}='yes'	[Decimal]
B_19e_weaners_purchased	**Weaners**	${B_18_longitudinal_bi}='yes' and selected(${B_19_categories_traded_year},'weaners')	[yes] Yes [no] No [unsure] Unsure
broken_header_e	**e) Weaners**	${B_19e_weaners_purchased}='yes'	[Enumerator Note]
B_19e1_busy_months	**When do you trade the most pigs of this category?**	${B_19e_weaners_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19e2	**During these busy periods, how many pigs do you trade of each category _per day_?:**	${B_19e_weaners_purchased}='yes'	[Enumerator Note]
B_19e2_ave_throughput	**Average:**	${B_19e_weaners_purchased}='yes'	[Decimal]
B_19e5_quiet_months	**When do you trade the least pigs of this category?**	${B_19e_weaners_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19e6	**During these quiet periods, how many pigs do you trade of each category _per day_?:**	${B_19e_weaners_purchased}='yes'	[Enumerator Note]
B_19e6_ave_throughput	**Average:**	${B_19e_weaners_purchased}='yes'	[Decimal]
B_19f_growers_purchased	**Growers**	${B_18_longitudinal_bi}='yes' and selected(${B_19_categories_traded_year},'growers')	[yes] Yes [no] No [unsure] Unsure
broken_header_f	**f) Growers**	${B_19f_growers_purchased}='yes'	[Enumerator Note]
B_19f1_busy_months	**When do you trade the most pigs of this category?**	${B_19f_growers_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19f2	**During these busy periods, how many pigs do you trade of each category _per day_?:**	${B_19f_growers_purchased}='yes'	[Enumerator Note]
B_19f2_ave_throughput	**Average:**	${B_19f_growers_purchased}='yes'	[Decimal]
B_19f5_quiet_months	**When do you trade the least pigs of this category?**	${B_19f_growers_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19f6	**During these quiet periods, how many pigs do you trade of each category _per day_?:**	${B_19f_growers_purchased}='yes'	[Enumerator Note]
B_19f6_ave_throughput	**Average:**	${B_19f_growers_purchased}='yes'	[Decimal]
B_19g_finishers_purchased	**Finishers**	${B_18_longitudinal_bi}='yes' and selected(${B_19_categories_traded_year},'finishers')	[yes] Yes [no] No [unsure] Unsure
broken_header_g	**g) Finishers**	${B_19g_finishers_purchased}='yes'	[Enumerator Note]
B_19g1_busy_months	**When do you trade the most pigs of this category?**	${B_19g_finishers_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_B_19g2	**During these busy periods, how many pigs do you trade of each category _per day_?:**	${B_19g_finishers_purchased}='yes'	[Enumerator Note]
B_19g2_ave_throughput	**Average:**	${B_19g_finishers_purchased}='yes'	[Decimal]
B_19g5_quiet_months	**When do you trade the least pigs of this category?**	${B_19g_finishers_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19g6	**During these quiet periods, how many pigs do you trade of each category _per day_?:**	${B_19g_finishers_purchased}='yes'	[Enumerator Note]
B_19g6_ave_throughput	**Average:**	${B_19g_finishers_purchased}='yes'	[Decimal]
B_19b_pigs_purchased	**Pigs (unknown type)**	${B_18_longitudinal_bi}='yes' and selected(${B_19_categories_traded_year},'pigs')	[yes] Yes [no] No [unsure] Unsure
broken_header_b	**b) Pigs (unknown type)**	${B_19b_pigs_purchased}='yes'	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_19b1_busy_months	**When do you trade the most pigs of this category?**	${B_19b_pigs_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19b2	**During these busy periods, how many pigs do you trade of each category _per day_?:**	${B_19b_pigs_purchased}='yes'	[Enumerator Note]
B_19b2_ave_throughput	**Average:**	${B_19b_pigs_purchased}='yes'	[Decimal]
B_19b5_quiet_months	**When do you trade the least pigs of this category?**	${B_19b_pigs_purchased}='yes'	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_19b6	**During these quiet periods, how many pigs do you trade of each category _per day_?:**	${B_19b_pigs_purchased}='yes'	[Enumerator Note]
B_19b6_ave_throughput	**Average:**	${B_19b_pigs_purchased}='yes'	[Decimal]
C_1_transport_bi	**Do you transport pigs for your trading activity?**		[yes] Yes [no] No [unsure] Unsure
C_2_vehicle_types	**What vehicle(s) do you use to transport pigs?**	${C_1_transport_bi}='yes'	[car] Car/four wheeled vehicle [lorry] Lorry [tuktuk] TukTuk [moto] Motorbike / moto [cart] Cart [other] Other
C_2a_vehicle_specify	**Please specify the other vehicle type(s) used:**	selected(${C_2_vehicle_types}, 'other')	[Text]
broken_header_C2a	**For each vehicle type, please complete the following:**	${C_1_transport_bi}='yes'	[Enumerator Note]
broken_header_C2a1	**Car/four wheeled vehicle**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'car')	[Enumerator Note]
C_2a1_vehicle_qty	**How many vehicles of this type are used by the trading operation?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'car')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_2a2_vehicle_pigs_qty	**How many pigs are usually transported in a single trip with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'car')	[Integer]
C_2a3_vehicle_other_animals_bi	**Is this vehicle type used to transport other animal types?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'car')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_2a4_vehicle_other_animals	**What other animal types are transported with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'car') and ${C_2a3_vehicle_other_animals_bi}='yes'	[chickens] Chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [other] Other
C_2a4_vehicle_other_animals_specify	**Please specify**	selected(${C_2a4_vehicle_other_animals}, 'other')	[Text]
broken_header_C2b1	**Lorry**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'lorry')	[Enumerator Note]
C_2b1_vehicle_qty	**How many vehicles of this type are used by the trading operation?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'lorry')	[Integer]
C_2b2_vehicle_pigs_qty	**How many pigs are usually transported in a single trip with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'lorry')	[Integer]
C_2b3_vehicle_other_animals_bi	**Is this vehicle type used to transport other animal types?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'lorry')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_2b4_vehicle_other_animals	**What other animal types are transported with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'lorry') and ${C_2b3_vehicle_other_animals_bi}='yes'	[chickens] Chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [other] Other
C_2b4_vehicle_other_animals_specify	**Please specify**	selected(${C_2b4_vehicle_other_animals}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_C2c1	**Tuk Tuk**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'tuktuk')	[Enumerator Note]
C_2c1_vehicle_qty	**How many vehicles of this type are used by the trading operation?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'tuktuk')	[Integer]
C_2c2_vehicle_pigs_qty	**How many pigs are usually transported in a single trip with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'tuktuk')	[Integer]
C_2c3_vehicle_other_animals_bi	**Is this vehicle type used to transport other animal types?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'tuktuk')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_2c4_vehicle_other_animals	**What other animal types are transported with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'tuktuk') and ${C_2c3_vehicle_other_animals_bi}='yes'	[chickens] Chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [other] Other
C_2c4_vehicle_other_animals_specify	**Please specify**	selected(${C_2c4_vehicle_other_animals}, 'other')	[Text]
broken_header_C2d1	**Motorbike / moto**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'moto')	[Enumerator Note]
C_2d1_vehicle_qty	**How many vehicles of this type are used by the trading operation?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'moto')	[Integer]
C_2d2_vehicle_pigs_qty	**How many pigs are usually transported in a single trip with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'moto')	[Integer]
C_2d3_vehicle_other_animals_bi	**Is this vehicle type used to transport other animal types?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'moto')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_2d4_vehicle_other_animals	**What other animal types are transported with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'moto') and ${C_2d3_vehicle_other_animals_bi}='yes'	[chickens] Chickens [ducks] Ducks [geese] Geese

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[cattle] Cattle [goats] Goats [other] Other
C_2d4_vehicle_other_animals_specify	**Please specify**	selected(${C_2d4_vehicle_other_animals}, 'other')	[Text]
broken_header_C2e1	**Cart**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'cart')	[Enumerator Note]
C_2e1_vehicle_qty	**How many vehicles of this type are used by the trading operation?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'cart')	[Integer]
C_2e2_vehicle_pigs_qty	**How many pigs are usually transported in a single trip with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'cart')	[Integer]
C_2e3_vehicle_other_animals_bi	**Is this vehicle type used to transport other animal types?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'cart')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_2e4_vehicle_other_animals	**What other animal types are transported with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'cart') and ${C_2e3_vehicle_other_animals_bi}='yes'	[chickens] Chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [other] Other
C_2e4_vehicle_other_animals_specify	**Please specify**	selected(${C_2e4_vehicle_other_animals}, 'other')	[Text]
broken_header_C2f1	**Other**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'other')	[Enumerator Note]
C_2f1_vehicle_qty	**How many vehicles of this type are used by the trading operation?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'other')	[Integer]
C_2f2_vehicle_pigs_qty	**How many pigs are usually transported in a single trip with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'other')	[Integer]
C_2f3_vehicle_other_animals_bi	**Is this vehicle type used to transport other animal types?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'other')	[yes] Yes [no] No

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[unsure] Unsure [refused] Refused
C_2f4_vehicle_other_animals	**What other animal types are transported with this vehicle type?**	${C_1_transport_bi}='yes' and selected(${C_2_vehicle_types}, 'other') and ${C_2f3_vehicle_other_animals_bi}='yes'	[chickens] Chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [other] Other
C_2f4_vehicle_other_animals_specify	**Please specify**	selected(${C_2f4_vehicle_other_animals}, 'other')	[Text]
C_3_clean_freq	**How often, on average, is the vehicle used for transporting pigs cleaned/disinfected?**	${C_1_transport_bi}='yes'	[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_3a_clean_method	**What is used to clean/disinfect your vehicle?**	selected(${C_3_clean_freq}, 'between_batch') or selected(${C_3_clean_freq}, 'daily') or selected(${C_3_clean_freq}, 'weekly') or selected(${C_3_clean_freq}, 'monthly') or selected(${C_3_clean_freq}, 'less_monthly') or selected(${C_3_clean_freq}, 'disease')	[water] Water [soap] Soap [disinfectant] Disinfectant [unsure] Don't know [refused] Refused
C_3a1_specify_disinfectant	**Please specify the type of disinfectant used (type or brand name)**	selected(${C_3a_clean_method}, 'disinfectant')	[Text]
C_4_load_location	**Where do you load/unload pigs at a farm you are trading with?**	${C_1_transport_bi}='yes'	[off] I load/unload pigs outside the farm perimeter [on_no_pigs] I bring my vehicle onto the farm premises but never with other pigs in the vehicle [on_sometimes_pigs] I bring my vehicle onto the farm premises and sometimes have other pigs in the vehicle [on_usually_pigs] I bring my vehicle onto the farm premises and usually/always have other pigs in the vehicle [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_5_purchase_multiple_sites	**For purchases, do you collect pigs from several farms/sites in the same trip?**		[always] Always [mostly] Mostly [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
C_6_deliver_multiple_sites	**For sales, do you deliver live pigs to several farms/sites in the same trip?**		[always] Always [mostly] Mostly [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
C_7_enter_pens	**Do you ever enter the pig pens/housing on sites that you are trading with?**		[always] Always [mostly] Mostly [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
C_8_health_inspection	**Is a health inspection conducted for traded pigs?**		[always] Always [mostly] Mostly [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
C_8a_sick_protocol_trader	**What do you do if you detect sick/unhealthy pigs?**	${C_8_health_inspection}='yes'	[n/a] Don't know, never purchased, or identified sick pigs before [reject] Do not purchase/trade them [quarantine_batch] Purchase and quarantine all pigs which belonged to the same batch as the sick pig(s) [quarantine_sick] Purchase and quarantine sick pig(s) only [nothing] Nothing – purchase and sell as usual [other] Other [unsure] Don't know [refused] Refused
C_keep_pigs_yn	**Do you own/raise any pigs (including boars for breeding)?**		[yes] Yes [no] No [unsure] Unsure

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_1_unit_type	**What sort of farm/holding is this?**		[breeding] Breeding unit [growing] Growing unit [f_to_f] Farrow to finish [other] Other [none] No special type [unsure] Don't know [refused] Refused
C_1a_specify_type	**Please specify the type of unit**	selected(${C_1_unit_type}, 'other')	[Text]
C_2_ownership	**What sort of ownership does this farm/site have?**		[single] Single owner/family owned - not a contract farm [single_contract] Single owner/family owned - contract farm [several] Several owners - not a contract farm [several_contract] Several owners - contract farm [company] Owned by a company [other] Other [unsure] Don't know [refused] Refused
C_2_i_ownership_specify	**Please specify**	${C_2_ownership} = 'other'	[Text]
C_2a_contractor	**Name of contractor**	${C_2_ownership}='single_contract' or ${C_2_ownership}='several_contract'	[cp] CP [other] Other [unsure] Don't know [refused] Refused
C_2a1_contractor_specify	**Please specify**	${C_2a_contractor}='other'	[Text]
C_2b_company_name	**Name of company**	${C_2_ownership}='company'	[Text]
C_4a_pigs_present	**Which of the following pig categories have been raised on the farm/site in the _past 6 months_?**		[sow] Sow/gilt for breeding [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers
C_4a_pig_breeds_present	**Which of the following pig _breeds_ have been raised on the farm/site in the _past 6 months_?**	selected(${C_4a_pigs_present}, 'sow') or selected(${C_4a_pigs_present}, 'cull_sow') or selected(${C_4a_pigs_present}, 'boar') or selected(${C_4a_pigs_present}, 'piglets') or selected(${C_4a_pigs_present}, 'weaners') or	[local] Local [exotic_local] Exotic breed - locally raised [exotic_imported] Exotic breed - imported from abroad [cross] Cross-breed

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
		selected(${C_4a_pigs_present}, 'growers') or selected(${C_4a_pigs_present}, 'finishers')	[unknown] Breed is not known for some/all pigs [other] Other
C_4a_pig_breeds_present_specify	**Please specify**	selected(${C_4a_pig_breeds_present}, 'other')	[Text]
broken_header_sows	**Breeding sows/gilts_**	selected(${C_4a_pigs_present}, 'sow')	[Enumerator Note]
C_4_1	**Are breeding sows _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'sow')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b1	**Number of breeding sows/gilts, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently')	[Enumerator Note]
C_4b1a_local_sows_qty	**Breeding sows/gilts - local breed**	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b1b_exoticlocal_sows_qty	**Breeding sows/gilts - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b1c_exoticimported_sows_qty	**Breeding sows/gilts - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b1d_cross_sows_qty	**Breeding sows/gilts - cross-breed**	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b1e_unknown_sows_qty	**Breeding sows/gilts - unknown breed**	selected(${C_4a_pigs_present}, 'sow') and selected(${C_4_1}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
C_4e_total_breed_sows_year	**Total number of breeding sows/gilts that have been kept/raised on this farm in the past year**	selected(${C_4a_pigs_present}, 'sow')	[Integer]
broken_header_boars	**Breeding boars_**	selected(${C_4a_pigs_present}, 'boar')	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4_3	**Are breeding boars _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'boar')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b3	**Number of breeding boars, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently')	[Enumerator Note]
C_4b3a_local_boars_qty	**Breeding boars - local breed**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b3b_exoticlocal_boars_qty	**Breeding boars - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b3c_exoticimported_boars_qty	**Breeding boars - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b3d_cross_boars_qty	**Breeding boars - cross-breed**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b3e_unknown_boars_qty	**Breeding boars - unknown breed**	selected(${C_4a_pigs_present}, 'boar') and selected(${C_4_3}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
C_4e_total_breed_boars_year	**Total number of breeding Breeding boars that have been kept/raised on this farm in the past year**	selected(${C_4a_pigs_present}, 'boar')	[Integer]
broken_header_piglets	**Piglets_**	selected(${C_4a_pigs_present}, 'piglets')	[Enumerator Note]
C_4_4	**Are piglets _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'piglets')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b4	**Number of piglets, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently')	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4b4a_local_piglets_qty	**Piglets - local breed**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b4b_exoticlocal_piglets_qty	**Piglets - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b4c_exoticimported_piglets_qty	**Piglets - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b4d_cross_piglets_qty	**Piglets - cross-breed**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b4e_unknown_piglets_qty	**Piglets - unknown breed**	selected(${C_4a_pigs_present}, 'piglets') and selected(${C_4_4}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
C_4c_ave_piglets_litter	**Average number of piglets per litter**	selected(${C_4a_pigs_present}, 'piglets')	[Integer]
C_4d_total_litters_year	**Number of litters in the past year**	selected(${C_4a_pigs_present}, 'piglets')	[Integer]
C_4f_all_in_all_out	**Except from breeding and keeping piglets with their dam, are different batches of pigs kept in separate barns/rooms/pens (i.e. where different batches do not mix)?**		[barn_always] Always in different barns [barn_most] Mostly in different barns [barn_some] Sometimes in different barns [room_always] Always in different rooms [room_most] Mostly in different rooms [room_some] Sometimes in different rooms [pens_always] Always in different pens [pens_most] Mostly in different pens [pens_some] Sometimes in different pens [never] Never
broken_header_weaners	**Weaners_**	selected(${C_4a_pigs_present}, 'weaners')	[Enumerator Note]
C_4_5	**Are weaners _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'weaners')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_C4b5	**Number of weaners, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently')	[Enumerator Note]
C_4b5a_local_weaners_qty	**Weaners - local breed**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b5b_exoticlocal_weaners_qty	**Weaners - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b5c_exoticimported_weaners_qty	**Weaners - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b5d_cross_weaners_qty	**Weaners - cross-breed**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b5e_unknown_weaners_qty	**Weaners - unknown breed**	selected(${C_4a_pigs_present}, 'weaners') and selected(${C_4_5}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
broken_header_growers	**Fattening/growers_**	selected(${C_4a_pigs_present}, 'growers')	[Enumerator Note]
C_4_6	**Are fatteners/growers _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'growers')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b6	**Number of fatteners/growers, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently')	[Enumerator Note]
C_4b6a_local_growers_qty	**Fatteners/growers - local breed**	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b6b_exoticlocal_growers_qty	**Fatteners/growers - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4b6c_exoticimported_growers_qty	**Fatteners/growers - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b6d_cross_growers_qty	**Fatteners/growers - cross-breed**	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b6e_unknown_growers_qty	**Fatteners/growers - unknown breed**	selected(${C_4a_pigs_present}, 'growers') and selected(${C_4_6}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]
broken_header_finishers	**Finishers_**	selected(${C_4a_pigs_present}, 'finishers')	[Enumerator Note]
C_4_7	**Are finishers _currently_ present on this farm/site?**	selected(${C_4a_pigs_present}, 'finishers')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
broken_header_C4b7	**Number of finishers, of each breed, present on site at the time of visit:_**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently')	[Enumerator Note]
C_4b7a_local_finishers_qty	**Finishers - local breed**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'local')	[Integer]
C_4b7b_exoticlocal_finishers_qty	**Finishers - exotic breed, locally raised**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_local')	[Integer]
C_4b7c_exoticimported_finishers_qty	**Finishers - exotic breed, imported from abroad**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'exotic_imported')	[Integer]
C_4b7d_cross_finishers_qty	**Finishers - cross-breed**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'cross')	[Integer]
C_4b7e_unknown_finishers_qty	**Finishers - unknown breed**	selected(${C_4a_pigs_present}, 'finishers') and selected(${C_4_7}, 'present_currently') and selected(${C_4a_pig_breeds_present}, 'unknown')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4c_ave_per_cycle	**Average number of pigs fattened per cycle**	selected(${C_4a_pigs_present}, 'weaners') or selected(${C_4a_pigs_present}, 'growers') or selected(${C_4a_pigs_present}, 'finishers')	[Integer]
C_4d_cycles_past_year	**Number of fattening cycles in the past year**	selected(${C_4a_pigs_present}, 'weaners') or selected(${C_4a_pigs_present}, 'growers') or selected(${C_4a_pigs_present}, 'finishers')	[Integer]
B_8_boars_used_for_breeding	**In the past 14 days, have any of your boar(s) been used for breeding with sows/gilts from other households/farms?**		[yes] Yes [no] No [unsure] Unsure
date_widget_last_sold1	**When was the last time your boars were used for breeding with sows/gilts from other households/farms?**	${B_8_boars_used_for_breeding}='no' or ${B_8_boars_used_for_breeding}='unsure'	[Date]
B_8a_sales_recipients1	**In the past 14 days, which type(s) of recipient have used your boars for breeding?**	${B_8_boars_used_for_breeding}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [butcher] Butcher [middleman] Middleman [SH] Slaughterhouse [KP] Killing point [CP] CP [central_point] Central point (any company) [ACMC] ACMC-M-Pig (Moung Rithy) [betagro] Betagro [company] Another company [boar_service] Boar service (Does not keep other pigs) [poahp] POAHP [other] Other
B_8a1_recipient_specify1	**Please specify the other type of recipient**	${B_8a_sales_recipients1} = 'other'	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_11	In the past 14 days, how many recipients of each type used your boars for breeding?	${B_8_boars_used_for_breeding}='yes'	[Enumerator Note]
B_9a_small_hh1	Small households (<10 pigs)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'sml_hh')	[Integer]
B_9b_med_hh1	Medium household (10 to 50 pigs)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'med_hh')	[Integer]
B_9c_large_hh1	Large household (50 to <100 pigs)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'lrg_hh')	[Integer]
B_9c_hh1	Household of unknown size	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'hh')	[Integer]
B_9d_small_farm1	Small farm (100 to <1000 pigs)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'sml_farm')	[Integer]
B_9e_med_farm1	Medium farm (1000 to <5000 pigs)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'med_farm')	[Integer]
B_9f_lrg_farm1	Large farm (≥5000 pigs)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'lrg_farm')	[Integer]
B_9f_farm1	Farm of unknown size	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'farm')	[Integer]
B_9g_trader1	Another trader	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'trader')	[Integer]
B_9h_butcher1	Butcher	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'butcher')	[Integer]
B_9i_middleman1	Middleman	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'middleman')	[Integer]
B_9i_sh1	Slaughterhouse	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'SH')	[Integer]
B_9k_kp1	Killing point	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'KP')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6.1l_cp1	CP	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'CP')	[Integer]
B_9m_cp_central1	Central point (any company)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'central_point')	[Integer]
B_6.1n_cp_acmc1	ACMC-M-Pig (Moung Rithy)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'ACMC ')	[Integer]
B_6.1o_cp_betagro1	Betagro	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'betagro')	[Integer]
B_6.1p_company1	Another company	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'company')	[Integer]
B_6.1q_boar_service1	Boar service (Does not keep other pigs)	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'boar_service')	[Integer]
B_6.1r_poahp1	POAHP	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'poahp')	[Integer]
B_9j_other1	Other	${B_8_boars_used_for_breeding}='yes' and selected(${B_8a_sales_recipients1}, 'other')	[Integer]
broken_header_purchase_locs	In the past 14 days, in which locations have your boars been used for breeding?		[Enumerator Note]
B_6_country	B6) Countries		[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other [unsure] Don't know
B_6.1_country_spec	B6.1) Please specify the other country	selected(${B_6_country}, 'other')	[Text]
broken_header_suppliers	In district: ${current_district_purchases}:		[Enumerator Note]
number_boar_hirers	how many customers hired your boar(s)? (In the past 14 days)		[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_y	**How many days do people hire your boars for breeding?**		[Enumerator Note]
C_7g_kept_ave_other1	**on average:**		[Integer]
C_7g_kept_min_other1	**min:**		[Integer]
C_7g_kept_max_other1	**max:**		[Integer]
same_trip	**Do you provide your boar services to multiple households in a single visit (e.g. multiple households within a village?)**		[always] Always [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
B_6_longitudinal	**Does demand for your boar services vary throughout the year?**		[yes] Yes [no] No [unsure] Unsure
B_6a_busy_months	**When are your boar services in greater demand?**	selected(${B_6_longitudinal}, 'yes')	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[dec_a] December - 1st half [dec_b] December - 2nd half
B_6a1_ave_throughput	**During these busy periods, how many customers use your boar service on average? (per week)**	selected(${B_6_longitudinal}, 'yes')	[Integer]
B_6b_quiet_months	**When are your boar services in least demand?**	selected(${B_6_longitudinal}, 'yes')	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
B_6b1_ave_throughput	**During these quiet periods, how many customers use your boar service on average? (per week)**	selected(${B_6_longitudinal}, 'yes')	[Integer]
C_4a1_finishers_housing	**How are pigs housed on this farm/site?**		[individual] Total (individual) confinement [group_same] Group housed - with pigs of the same category [group_mixed] Group housed - mixed with other pig categories [tethered] Tethered [freerange] Free-range [other] Other

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[unsure] Don't know [refused] Refused
C_4a1_finishers_housing_specify	**Please specify**	selected(${C_4a1_finishers_housing}, 'other')	[Text]
C_4a1a_pen_qty	**How many pigs are kept together in a pen?**	selected(${C_4a1_finishers_housing}, 'group_same') or selected(${C_4a1_finishers_housing}, 'group_mixed')	[Integer]
C_4a2_indoor_outdoor	**Where are these pigs housed?**		[outdoor] Outdoors [indoor] Sheltered [sheltered] Indoors [unsure] Don't know [refused] Refused [other] Other
C_4a2_indoor_outdoor_specify	**Please specify**	selected(${C_4a2_indoor_outdoor}, 'other')	[Text]
C_5_land_area	**Total land area of the site**		[Integer]
C_5_land_area_unit	**Select the appropriate unit**		[m2] Square metres [f2] Square feet [hectares] Hectares
C_6_clean_freq	**How often do you clean pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_6a_clean_method	**What is used to clean pens?**	selected(${C_6_clean_freq}, 'between_batch') or selected(${C_6_clean_freq}, 'daily') or selected(${C_6_clean_freq}, 'weekly') or selected(${C_6_clean_freq}, 'monthly') or selected(${C_6_clean_freq}, 'less_monthly') or selected(${C_6_clean_freq}, 'disease')	[water] Water [soap] Soap [disinfectant] Disinfectant [unsure] Don't know [refused] Refused
C_6_disinfect_freq	**How often do you disinfect pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_6_disinfect_specify	**Please specify the type of disinfectant used (type or brand name)**	selected(${C_6a_clean_method}, 'disinfectant') or selected(${C_6_disinfect_freq}, 'between_batch') or selected(${C_6_disinfect_freq}, 'daily') or selected(${C_6_disinfect_freq}, 'weekly') or selected(${C_6_disinfect_freq}, 'monthly') or selected(${C_6_disinfect_freq}, 'less_monthly') or selected(${C_6_disinfect_freq}, 'disease')	[Text]
C_7_empty_between_batches	**Do you usually leave pens empty between two groups of pigs?**		[always] Always [sometimes] Sometimes [never] Never [unsure] Don't know [refused] Refused
broken_header_C7a	**How many days do you usually leave pens empty between two groups of pigs?**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Enumerator Note]
C7a_days_empty_ave	**Average:**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Integer]
C7b_days_empty_min	**Minimum:**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Integer]
C7c_days_empty_max	**Maximum:**	selected(${C_7_empty_between_batches}, 'always') or selected(${C_7_empty_between_batches}, 'sometimes')	[Integer]
C_8_other_animals_yn	**Are any other animals currently present on the farm/site? (Including cats, dogs, poultry etc)**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_8_other_animals	**Which of the following animals are currently present on the farm/site?**	selected(${C_8_other_animals_yn}, 'yes')	[layers] Chicken layers (for eggs) [broilers] Chicken broilers (for meat) [backyard] Backyard chickens

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [dogs] Dogs [cats] Cats [other] Other
C_8_other_animals_specify	**Please specify the other animals that are on this farm/site**	selected(${C_8_other_animals}, 'other')	[Text]
broken_header_C_8	**How many are currently present on the farm/site?**	selected(${C_8_other_animals_yn}, 'yes')	[Enumerator Note]
C_8b1_layers_qty	**Chicken layers (for eggs)**	selected(${C_8_other_animals}, 'layers')	[Integer]
C_8b2_broilers_qty	**Chicken broilers (for meat)**	selected(${C_8_other_animals}, 'broilers')	[Integer]
C_8b3_backyard_qty	**Backyard chickens**	selected(${C_8_other_animals}, 'backyard')	[Integer]
C_8b4_ducks_qty	**Ducks**	selected(${C_8_other_animals}, 'ducks')	[Integer]
C_8b5_geese_qty	**Geese**	selected(${C_8_other_animals}, 'geese')	[Integer]
C_8b6_cattle_qty	**Cattle**	selected(${C_8_other_animals}, 'cattle')	[Integer]
C_8b7_goats_qty	**Goats**	selected(${C_8_other_animals}, 'goats')	[Integer]
C_8b8_dogs_qty	**Dogs**	selected(${C_8_other_animals}, 'dogs')	[Integer]
C_8b9_cats_qty	**Cats**	selected(${C_8_other_animals}, 'cats')	[Integer]
C_8b10_other_qty	**Other**	selected(${C_8_other_animals}, 'other')	[Text]
C_8_animals_contact_pigs_yes_no	**Can any of these animals come into direct contact with pigs?**	selected(${C_8_other_animals_yn}, 'yes')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_8_animals_contact_pigs	**Which of these animals are able to come into direct contact with pigs?**	selected(${C_8_other_animals_yn}, 'yes') and selected(${C_8_animals_contact_pigs_yes_no}, 'yes')	[layers] Chicken layers (for eggs) [broilers] Chicken broilers (for meat) [backyard] Backyard chickens [ducks] Ducks

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[geese] Geese [cattle] Cattle [goats] Goats [dogs] Dogs [cats] Cats [other] Other [none] None
C_8_animals_contact_other_hh_yes_no	**Can any of these animals come into direct contact with livestock from other households?**	selected(${C_8_other_animals_yn}, 'yes')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_8_animals_contact_other_hh	**Which of these animals are able to come into direct contact with livestock from other households?**	selected(${C_8_other_animals_yn}, 'yes') and selected(${C_8_animals_contact_other_hh_yes_no}, 'yes')	[layers] Chicken layers (for eggs) [broilers] Chicken broilers (for meat) [backyard] Backyard chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [dogs] Dogs [cats] Cats [other] Other [none] None
C_8d_1_neighbour_hh_animals	**Do the neighbouring households (that these animals are able to physically contact) raise pigs or poultry?**	selected(${C_8_other_animals_yn}, 'yes') and selected(${C_8_animals_contact_other_hh_yes_no}, 'yes')	[pigs] Pigs [poultry] Poultry [no] No [unsure] Don't know [refused] Refused
D_1_feed	**What are your pigs fed on?**		[commercial] Commercial pig feed [graze_confined] Forage/graze in confined area [graze_open] Forage/graze openly [swill_hh] Pig swill - own household waste [swill_external] Pig swill - external sources of food waste [homemade_concentrate] Homemade concentrate [agri] Rice grain/agricultrural by-product [other] Other [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
D_1a_feed_specify	**Please specify the other type of feed used**	selected(${D_1_feed}, 'other')	[Text]
D_1b_feed_source	**Where do you source pig feed from?**	selected(${D_1_feed}, 'commercial') or selected(${D_1_feed}, 'swill_external') or selected(${D_1_feed}, 'agri') or selected(${D_1_feed}, 'other')	[company] A company [contract] A parent contracted farm [cooperative] A cooperative [neighbour] A neighbour [shop] A shop [restaurant] A restaurant [other] Other [unsure] Don't know
D_1b3_feed_source_specify	**Where do you source pig feed from? (specify)**	selected(${D_1b_feed_source}, 'other')	[Text]
D_1b1_feed_company	**Please specify the name of the company**	selected(${D_1b_feed_source}, 'company')	[Text]
D_1b2_feed_contractor	**Please specify the name of the contracted farm**	selected(${D_1b_feed_source}, 'contract')	[Text]
D_1b2a_feed_contractor_loc	**Enter the highest common administrative area that this contracted farm is located within**	selected(${D_1b_feed_source}, 'contract')	[village] Same village [commune] Same commune [district] Same district [province] Same province [province_different] Different provinces
D_1b3_feed_cooperative	**Please specify the name of the cooperative**	selected(${D_1b_feed_source}, 'cooperative')	[Text]
D_2_feed_stored	**How is pig feed stored on the farm?**		[sealed] Sealed containers (e.g. silos) [open] Open containers [near_pigs] Next to pig pens [away_pigs] Away from pig pens [indoor] Indoors [sheltered] Sheltered [outdoor] Outdoors [unsure] Don't know [refused] Refused
D_3_feed_accessible_birds	**Is pig feed accessible to wild and/or farmed birds?**		[yes_wild] Yes - wild birds [yes_farmed] Yes - farmed poultry

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[no] No [unsure] Don't know [refused] Refused
D_4_water_source	**Where is water sourced for your pigs?**		[surface] River/pond/lake [piped] Tap [well_protected] Protected well/pumping well [well_unprotected] Open well [rain] Rainwater [tanker] Water tanker vehicle [other] Other [unsure] Don't know [refused] Refused
D_4a_water_source_specify	**Please specify the type of water source:**	selected(${D_4_water_source}, 'other')	[Text]
D_5_waste_disposal	**What do you do with pig waste (dung, excreta)?**		[drained_public] Drained to a public drainage [drained_current] Drained to a current water [drained_empty] Drained to empty space [drained_blocked] Drained to a blocked water body/low ground [fertiliser] Stored for fertiliser [sent] Send it to another farm/site [taken_away] Taken away by a someone else/a waste disposal company [other] Other [unsure] Don't know [refused] Refused
D_5a_waste_disposal_specify	**Please specify what you do with pig waste:**	selected(${D_5_waste_disposal}, 'other')	[Text]
D_6_latrine_facilities	**What type of latrine facilities are present within the compound?**		[flush] Modern flush toilet [septic] Toilet with septic tank [pit] Pit latrine [none] None [other] Other [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
D_6_latrine_facilities_specify	**Please specify the type of latrine facilities**	selected(${D_6_latrine_facilities}, 'other')	[Text]
D_7_pig_access_latrine	**Do pigs have any access to the area around latrine facilities?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_1_vaccinate	**Are any of your pigs vaccinated?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_1a_vaccines	**Which vaccine(s) have your pigs received?**	${E_1_vaccinate} = 'yes'	[salmonella] Salmonella [pasteurollosis] Pasteurollosis [csf] Classical swine fever [aujeszky] Aujeszky [fmd] Foot and mouth disease [prrs] PRRS [other] Other [unsure] Don't know
E_1a1_vaccine_specify	**Please specify the other vaccine(s)**	selected(${E_1a_vaccines}, 'other')	[Text]
E_2_morbidity	**Have you had any sick pigs in the past 6 months?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_2a1_i_disease_known	**Disease(s) known?**	${E_2_morbidity} = 'yes'	[yes] Yes [no] No
E_2a1a_i_disease_specify	**Please specify the disease(s)**	${E_2a1_i_disease_known} = 'yes'	[salmonella] Salmonella [pasteurollosis] Pasteurollosis [csf] Classical swine fever [aujeszky] Aujeszky [fmd] Foot and mouth disease [prrs] PRRS [other] Other [unsure] Don't know
E_2a1a1_i_disease_other	**Please specify the other disease**	selected(${E_2a1a_i_disease_specify}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
E_2a1b_i_symptoms	**Have your pigs had any of the following symptoms in the past 6 months?**		[lame] Lameness [inappetence] Inappetence [constipation] Constipation [diarrhoea] Diarrhoea [abscesses] Abscesses [sneeze] Sneezing [cough] Coughing [breath] Heavy breathing [skin_colour] Skin discolouration [skin_greasy] Greasy skin [mange] Mange [eyes] Discharge (eyes) [nose] Discharge (nose) [preg_fail] Pregnancy failures [abortion] Abortion [mastitis] Mastitis [other] Other [none] None [refused] Refused
E_2a1b1_i_symptoms_other	**Please specify the other symptom(s)**	selected(${E_2a1b_i_symptoms}, 'other')	[Text]
E_2a2_i_sick_qty	**Number of pigs affected:**	${E_2_morbidity} = 'yes'	[Integer]
E_2a2_i_pigs_affected	**Which pig types were affected?**	${E_2_morbidity} = 'yes'	[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type)
E_2c_sick_action	**What did you do with the sick pig(s)?**	${E_2_morbidity} = 'yes'	[quarantine] Placed in quarantine [report_chief] Reported to the village/commune chief [report_ahw] Reported to an animal health worker [sold] Sold the pigs while sick [treat] Treated/medicated [cull] Culled [nothing] Nothing [unsure] Don't know [refused] Refused [other] Other

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
E_2c1_sick_action_other	**Please specify what you did with the sick pigs:**	selected(${E_2c_sick_action}, 'other')	[Text]
E_2b_i_deaths	**Have you had any pig mortalities in the past 6 months?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_2b1_i_deaths_qty	**Number of mortalities**	${E_2b_i_deaths} = 'yes'	[Integer]
E_2b1_i_deaths_pig_type	**Which pig types were pig affected?**	${E_2b_i_deaths} = 'yes'	[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type)
E_2d_carcass_dispose	**What did you do with the carcasses of pigs that died/were culled?**	${E_2b_i_deaths} = 'yes'	[incinerated] Incinerated on site [buried] Buried on site [taken_away] Taken away by person/company [pm] Sent for post mortem [sold] Sold the carcass/meat [consumed] Consumed the meat at home [unsure] Don't know [refused] Refused [other] Other
E_2d1_carcass_dispose_specify	**Please specify what you did with the carcasses**	selected(${E_2d_carcass_dispose}, 'other')	[Text]

9.4 Questionnaires: Form A 3 Pig slaughterhouse survey v1 (ODK questionnaire)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
province	**Province code**		[12] 12 Phnom Penh [8] 08 Kandal [5] 05 Kampong Speu [21] 21 Takeo
village	**Village code**		[Text]
sh_code	**Slaughterhouse ID**		[Text]
consent	**Agrees to participate & signed consent form**		[yes] Yes [no] No
A_2_GPS	**Obtain GPS coordinates**		[Lat, Long, Alt]
A_3_interviewer	**Interviewer initials**		[Text]
A_4_interviewee_role	**What is your role on this slaughterhouse?**		[owner] Owner [manager] Manager [employee] Employee [family] Family member [veterinarian] Veterinarian [other] Other
A_4a_interviewee_role_specify	**Please specify the other type of role:**	selected(${A_4_interviewee_role}, 'other')	[Text]
A_5_interviewee_age	**Interviewee age**		[Integer]
A_6_gender	**Gender**		[male] Male [female] Female [refused] Refused
A_7_interviewee_ethnicity	**What is your ethnicity?**		[khmer] Khmer [cham] Cham [vietnamese] Vietnamese [chinese] Chinese [other] Other

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[unsure] Don't know [refused] Refused
A_7a_interviewee_ethnicity_specify	**Please specify your ethnicity**	selected(${A_7_interviewee_ethnicity}, 'other')	[Text]
A_8_education	**What is the highest level of education you have completed?**		[none] None [primary] Primary (grades 1 to 6) [lower_secondary] Lower Secondary (grades 7 to 9) [upper_secondary] Upper secondary (grades 10 to 12) [higher] Higher (college/university) [unsure] Don't know [refused] Refused
A_9_primary_income	**Which occupation provides your main source of household income?**		[sh_owner] Slaughterhouse owner [sh_manager] Slaughterhouse manager [sh_worker] Pig slaughterhouse worker [farmer] Pig farmer [trader] Pig trader [meat] Meat retailer [ahw] Animal health worker [professional] Professional/technical/managerial [clercial] Clerical/ office work [skilled_man] Skilled manual (but not agriculture) [unskilled_man] Unskilled manual (but not agriculture) [crop] Agriculture crop [livestock] Livestock and fishing (other) [sales] Sales and services/ trader [refused] Refused [other] Other
A_9a_primary_income_specify	**Please specify your main source of household income**	${A_9_primary_income} = 'other'	[Text]
A_10_secondary_income	**Are there any other occupations which provide further sources of household income?**		[sh_owner] Slaughterhouse owner [sh_manager] Slaughterhouse manager

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[sh_worker] Pig slaughterhouse worker [farmer] Pig farmer [trader] Pig trader [meat] Meat retailer [ahw] Animal health worker [professional] Professional/technical/managerial [clercial] Clerical/ office work [skilled_man] Skilled manual (but not agriculture) [unskilled_man] Unskilled manual (but not agriculture) [crop] Agriculture crop [livestock] Livestock and fishing (other) [sales] Sales and services/ trader [refused] Refused [other] Other
A_10a_secondary_income_specify	**Please specify your other sources of household income**	selected(${A_10_secondary_income}, 'other')	[Text]
A_11_years_operating	**How long has this slaughterhouse been in operation (years)?**		[Decimal]
B_1_services	**What services does this slaughterhouse offer?**		[for_hire] People hire space in the SH to kill pigs they own [hub] Traders use the SH site to exchange pigs [house] Houses animals before sale elsewhere [purchase] SH purchases pigs [sell] SH sells pigs [other] Other
B_1s_services_specify	**Please specify the other services provided**	selected(${B_1_services}, 'other')	[Text]
broken_header_B_4a	**How many pigs are slaughtered on this site per day?:**		[Enumerator Note]
B_4a_ave_throughput	**Average:**		[Integer]
B_4b_min_throughput	**Minimum:**		[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_4c_max_throughput	**Maximum:**		[Integer]
B_1a_records	**Do you keep a written record of the slaughterhouse users OR the slaughterhouse throughput (number of pigs slaughtered at this site)?**		[users] Users (people hiring space) [throughput] Throughput (number of pigs killed) [no] No [unsure] Don't know
broken_header_Ba1	**_If yes, ask permission to see the register. If the interviewee agrees then fill out the questions below using this register_**	selected(${B_1a_records},'users') or selected(${B_1a_records},'throughput')	[Enumerator Note]
B_1a1_recorded	**What information is recorded on the slaughterhouse users register?**	selected(${B_1a_records},'users')	[name] Contact names [phone] Contact phone numbers [address] Contact addresses [date] Dates that the contacts used SH [time] Times that contacts used SH [qty] Number of pigs slaughtered by contact [type] Type of pigs slaughtered by contact [other] Other
B_1a1a_recorded_specify	**Please specify the other info**	selected(${B_1a1_recorded}, 'other')	[Text]
B_3a_whats_recorded	**What information is recorded in the slaughterhouse throughput records?**	selected(${B_1a_records},'throughput')	[qty_day] Total pig slaughtered per day [type] Types of pigs that are slaughtered (finishers, piglets etc) [origin] Origin of slaughtered pigs [breed] Breed of slaughtered pigs [age] Age of slaughtered pigs [other] Other [unsure] Don't know [refused] Refused
B_3a1_recorded_define	**Please specify the other info**	selected(${B_3a_whats_recorded}, 'other')	[Text]
B_0_users	**In the past 7 days, who has hired space in this SH?**		[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader (including traders who hired someone else to kill the pigs) [other] Other
broken_header_B_0_i	**In the past 7 days, how many SH users of each type have hired space in this SH?**		[Enumerator Note]
B_0.1a_small_hh	**Small households (<10 pigs)**	selected(${B_0_users}, 'sml_hh')	[Integer]
B_0.1b_med_hh	**Medium household (10 to 50 pigs)**	selected(${B_0_users}, 'med_hh')	[Integer]
B_0.1c_large_hh	**Large household (50 to <100 pigs)**	selected(${B_0_users}, 'lrg_hh')	[Integer]
B_0.1f_hh	**B1.2c1 Household of unknown size**	selected(${B_0_users}, 'hh')	[Integer]
B_0.1d_small_farm	**Small farm (100 to <1000 pigs)**	selected(${B_0_users}, 'sml_farm')	[Integer]
B_0.1e_med_farm	**Medium farm (1000 to <5000 pigs)**	selected(${B_0_users}, 'med_farm')	[Integer]
B_0.1f_lrg_farm	**Large farm (≥5000 pigs)**	selected(${B_0_users}, 'lrg_farm')	[Integer]
B_0.1f_farm	**Farm of unknown size**	selected(${B_0_users}, 'farm')	[Integer]
B_0.1g_trader	**Trader**	selected(${B_0_users}, 'trader')	[Integer]
B_0.1i_other	**Other**	selected(${B_0_users}, 'other')	[Integer]
B_0.1j_total_suppliers	**Total number of SH users**		[Calculation]
B_0_throughput_pig_type	**What types of pig have been slaughtered at this site in the past 7 days?**		[sow] Sow [boar] Boar [piglets] Piglets

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type) [refused] Refused [unsure] Don't know
broken_header_B_0	**Number of pigs slaughtered of this category in the past 7 days:**	selected(${B_0_throughput_pig_type}, 'sow') or selected(${B_0_throughput_pig_type}, 'boar') or selected(${B_0_throughput_pig_type}, 'piglets') or selected(${B_0_throughput_pig_type}, 'weaners') or selected(${B_0_throughput_pig_type}, 'growers') or selected(${B_0_throughput_pig_type}, 'finishers')	[Enumerator Note]
B_0_throughput_qty_sow	**Sows**	selected(${B_0_throughput_pig_type}, 'sow')	[Integer]
B_0_throughput_qty_boar	**Boars**	selected(${B_0_throughput_pig_type}, 'boar')	[Integer]
B_0_throughput_qty_piglets	**Piglets**	selected(${B_0_throughput_pig_type}, 'piglets')	[Integer]
B_0_throughput_qty_weaners	**Weaners**	selected(${B_0_throughput_pig_type}, 'weaners')	[Integer]
B_0_throughput_qty_growers	**Growers**	selected(${B_0_throughput_pig_type}, 'growers')	[Integer]
B_0_throughput_qty_finishers	**Finishers**	selected(${B_0_throughput_pig_type}, 'finishers')	[Integer]
B_0_throughput_qty_unknown	**Pigs (unknown type)**	selected(${B_0_throughput_pig_type}, 'pigs')	[Integer]
broken_header_1b	**For the _past 7 days,_ please provide details of each user that has _hired space_ in this SH**		[Enumerator Note]
broken_header_1b_1	**Slaughterhouse user U-${sh_user_number}**		[Enumerator Note]
B_1b2_user_type	**What type of user is this?**		[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader (including traders who hired someone else to kill the pigs) [other] Other
B_1b2a_user_specify	**Please specify the type of user**	${B_1b2_user_type}='other'	[Text]
B_1b2b_who_kills_pigs	**If answered Trader to B.2.1, who killed the pigs?**	selected(${B_1b2_user_type}, 'trader')	[trader] The trader [employee] An external person employed by the trader [unsure] Don't know [refused] Refused [other] Other
B_1b2b1_kills_pigs_specify	**Please specify who kills the pigs**	selected(${B_1b2b_who_kills_pigs}, 'other')	[Text]
B_1b4_relationship	**What is your relationship with this SH user?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
B_1b4a_relation_specify	**Please specify the type of relationship**	${B_1b4_relationship}='other'	[Text]
broken_header_1b_4	**_Contact location or site where this contact is based_**		[Enumerator Note]
B_1b9_hire_freq	**How often does this person kill pigs here?**		[first_time] First time [daily] Daily [2daily] At least every other day [3daily] At least twice per week [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[6monthly] At least 6 monthly [yearly] At least yearly [unsure] Unknown
broken_header_B1b11	**How many pigs has this person killed here in the past 7 days?**		[Enumerator Note]
B_1b12_sows	**Sows**	selected(${B_0_throughput_pig_type}, 'sow')	[Integer]
B_1b14_boars	**Boars**	selected(${B_0_throughput_pig_type}, 'boar')	[Integer]
B_1b15_piglet	**Piglets**	selected(${B_0_throughput_pig_type}, 'piglets')	[Integer]
B_1b16_weaner	**Weaners**	selected(${B_0_throughput_pig_type}, 'weaners')	[Integer]
B_1b17_grower	**Growers**	selected(${B_0_throughput_pig_type}, 'growers')	[Integer]
B_1b18_finisher	**Finishers**	selected(${B_0_throughput_pig_type}, 'finishers')	[Integer]
B1b19_unknown_pigs	**Pigs (unknown type)**	selected(${B_0_throughput_pig_type}, 'pigs')	[Integer]
B_1b18_contact_provided	**Can you provide contact details for this user?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
B_1b18a_contact_details	**Please record the contact's name, and phone number in the paper log book, for SH user U-${sh_user_number}**	${B_1b18_contact_provided} = 'yes'	[Enumerator Note]
B_1b2c_pig_origin_known	**Do you know the production origin of the pigs that this SH user killed here in the past 7 days?**	selected(${B_1b2_user_type}, 'trader')	[yes] Yes [no] No [unsure] Unsure [refused] Refused
broken_header_B_1b2c	**_Questions in blue below, refer to the production origin of the pigs killed here_**	${B_1b2c_pig_origin_known}='yes'	[Enumerator Note]
B_1b2c1_pig_origin_supplier	**From which type of producer, do these pigs originate from?**	${B_1b2c_pig_origin_known}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader (including traders who hired someone else to kill the pigs) [CP] CP [ACMC] ACMC-M-Pig (Moung Rithy) [company] Another company [other] Other [unsure] Don't know
B_1b2c1a_company_specufy	**What is the name of the company?**	selected(${B_1b2c1_pig_origin_supplier}, 'company')	[Text]
broken_header_B1b	**Where is the geographical production origin of these pigs?**	${B_1b2c_pig_origin_known}='yes'	[Enumerator Note]
B_1b2c1.1_country	**Country**	${B_1b2c_pig_origin_known}='yes'	[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other
B_1b2c1.1a_country_spec	**Please specify the other country**	selected(${B_1b2c1.1_country}, 'other')	[Text]
B_1b2c5_village	**In the paper log book, please now also record the site name, and site village (if known), along with Slaughterhouse User _ UO-${sh_user_number}**	selected(${B_1b2c1.1_country}, 'cambodia') and ${B_1b2c_pig_origin_known}='yes'	[Enumerator Note]
sh_hirer_repeat_count	**0**		[Calculation]
B1b19	**_Individual entry has been completed for ${sh_hirer_repeat_count}/${B_0.1j_total_suppliers} contacts. Please ensure entry is complete.**	${B_0.1j_total_suppliers} > ${sh_hirer_repeat_count}	[Enumerator Note]
B_0_suppliers	**In the past 7 days, who has this SH purchased LIVE pigs from?**		[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [SH] Slaughterhouse [other] Other [unsure] Don't know
broken_header_B_0_i2	**In the past 7 days, how many suppliers of each type has this SH purchased LIVE pigs from?**		[Enumerator Note]
B_0a_small_hh	**Small households (<10 pigs)**	selected(${B_0_suppliers}, 'sml_hh')	[Integer]
B_0b_med_hh	**Medium household (10 to 50 pigs)**	selected(${B_0_suppliers}, 'med_hh')	[Integer]
B_0c_large_hh	**Large household (50 to <100 pigs)**	selected(${B_0_suppliers}, 'lrg_hh')	[Integer]
B_0f_hh	**Household of unknown size**	selected(${B_0_suppliers}, 'hh')	[Integer]
B_0d_small_farm	**Small farm (100 to <1000 pigs)**	selected(${B_0_suppliers}, 'sml_farm')	[Integer]
B_0e_med_farm	**Medium farm (1000 to <5000 pigs)**	selected(${B_0_suppliers}, 'med_farm')	[Integer]
B_0f_lrg_farm	**Large farm (≥5000 pigs)**	selected(${B_0_suppliers}, 'lrg_farm')	[Integer]
B_0f_farm	**Farm of unknown size**	selected(${B_0_suppliers}, 'farm')	[Integer]
B_0g_trader	**Trader**	selected(${B_0_suppliers}, 'trader')	[Integer]
B_0h_sh	**Slaughterhouse**	selected(${B_0_suppliers}, 'SH')	[Integer]
B_0i_other	**Other**	selected(${B_0_suppliers}, 'other')	[Integer]
B_0j_total_suppliers	**Total number of SH suppliers**		[Calculation]
B_P_purchases_pig_type	**What types of pig has this SH purchased LIVE in the past 7 days?**		[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[growers] Growers [finishers] Finishers [pigs] Pigs (unknown type) [refused] Refused [unsure] Don't know
broken_header_B_P	**Number of pigs purchased of this category in the past 7 days:**	selected(${B_P_purchases_pig_type}, 'sow') or selected(${B_P_purchases_pig_type}, 'boar') or selected(${B_P_purchases_pig_type}, 'piglets') or selected(${B_P_purchases_pig_type}, 'weaners') or selected(${B_P_purchases_pig_type}, 'growers') or selected(${B_P_purchases_pig_type}, 'finishers')	[Enumerator Note]
B_P_purchases_qty_sow	**Sows**	selected(${B_P_purchases_pig_type}, 'sow')	[Integer]
B_P_purchases_qty_boar	**Boars**	selected(${B_P_purchases_pig_type}, 'boar')	[Integer]
B_P_purchases_qty_piglets	**Piglets**	selected(${B_P_purchases_pig_type}, 'piglets')	[Integer]
B_P_purchases_qty_weaners	**Weaners**	selected(${B_P_purchases_pig_type}, 'weaners')	[Integer]
B_P_purchases_qty_growers	**Growers**	selected(${B_P_purchases_pig_type}, 'growers')	[Integer]
B_P_purchases_qty_finishers	**Finishers**	selected(${B_P_purchases_pig_type}, 'finishers')	[Integer]
B_P_purchases_qty_unknown	**Pigs (unknown type)**	selected(${B_P_purchases_pig_type}, 'pigs')	[Integer]
broken_header_1c	**For the past 7 days, please provide the details of each person that this SH has purchased LIVE pigs from:**		[Enumerator Note]
broken_header_1c_1	**Slaughterhouse supplier S-${sh_supplier_number}**		[Enumerator Note]
B_1c2_supplier_type	**What type of supplier is this?**		[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			<5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [SH] Slaughterhouse [other] Other [unsure] Don't know
B_1c2_i_supplier_specify	Please specify the type of supplier	${B_1c2_supplier_type}='other'	[Text]
B_1c4_relationship	What is your relationship with this supplier?		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
B_1c4a_relation_specify	Please specify the type of relationship	${B_1c4_relationship}='other'	[Text]
broken_header_1c_2	_Contact location or site where this contact is based._		[Enumerator Note]
B_1c10_transac_freq_sh	Frequency of transactions with this supplier		[first_time] First time [daily] Daily [2daily] At least every other day [3daily] At least twice per week [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly [6monthly] At least 6 monthly [yearly] At least yearly [unsure] Unknown
broken_header_B1c11	Number of pigs received from this supplier in the past 7 days:		[Enumerator Note]
B_1c12_sows	Sows	selected(${B_P_purchases_pig_type}, 'sow')	[Integer]
B_1c14_boars	Boars	selected(${B_P_purchases_pig_type}, 'boar')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_1c15_piglet	**Piglets**	selected(${B_P_purchases_pig_type}, 'piglets')	[Integer]
B_1c16_weaner	**Weaners**	selected(${B_P_purchases_pig_type}, 'weaners')	[Integer]
B_1c17_grower	**Growers**	selected(${B_P_purchases_pig_type}, 'growers')	[Integer]
B_1c18_finisher	**Finishers**	selected(${B_P_purchases_pig_type}, 'finishers')	[Integer]
B_1b18a_unknown_pigs	**Pigs (unknown type)**	selected(${B_0_throughput_pig_type}, 'pigs')	[Integer]
B_1c19_contact_provided	**Can you provide contact details for this supplier?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
B_1c9_village	**In the paper log book, please now also record the site name, and site village (if known), for supplier _ S-${sh_supplier_number}**		[Enumerator Note]
B_1c19a_contact_details	**Please record the contact's name, and phone number in the paper log book, for supplier _ S-${sh_supplier_number}**	${B_1c19_contact_provided}='yes'	[Enumerator Note]
B_1c2a_pig_origin_known	**Do you know the production origin of the pigs this trader sold LIVE to this SH?**	${B_1c2_supplier_type}='trader'	[yes] Yes [no] No [unsure] Unsure [refused] Refused
broken_header_B_1c1a	**_Questions in blue below, refer to the production origin site/location_**	${B_1c2a_pig_origin_known}='yes'	[Enumerator Note]
B_1c1a_pig_origin_supplier	**From which type of producer(s), did these pigs originate from?**	${B_1c2a_pig_origin_known}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[trader] Trader (including traders who hired someone else to kill the pigs) [CP] CP [ACMC] ACMC-M-Pig (Moung Rithy) [company] Another company [other] Other [unsure] Don't know
B_1c1a1_company_specify	**What is the name of the company?**	selected(${B_1c1a_pig_origin_supplier}, 'company')	[Text]
broken_header_B1c	**Where was the geographical production origin of these pigs?**	${B_1c2a_pig_origin_known}='yes'	[Enumerator Note]
B_1c2a1_country	**Country**	${B_1c2a_pig_origin_known}='yes'	[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other
B_1c2a1a_country_specify	**Please specify the other country**	selected(${B_1c2a1_country}, 'other')	[Text]
B_1c2a5_village	**In the paper log book, please now also record the site name, and site village (if known), along with the contact ID:_SO-${sh_supplier_number}**	selected(${B_1c2a1_country}, 'cambodia') and ${B_1c2a_pig_origin_known}='yes'	[Enumerator Note]
sh_purhcases_repeat_count	**0**		[Calculation]
B_1c20	**_Individual entry has been completed for ${sh_purhcases_repeat_count}/${B_0j_total_suppliers} contacts. Please ensure entry is complete.**	${B_0j_total_suppliers} > ${sh_purhcases_repeat_count}	[Enumerator Note]
broken_header_BDS	**In the past 7 days, how many traders have used this SH to sell/distribute pigs?**		[Enumerator Note]
BDS_1	**Traders**		[Integer]
BDS_0_throughput_pig_type	**In the past 7 days, which pig types have these traders sold/distributed at this SH?**		[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type)

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[refused] Refused [unsure] Don't know
broken_header_BDS_0	**Number of pigs sold/distributed of this category in the past 7 days:**	selected(${BDS_0_throughput_pig_type}, 'sow') or selected(${BDS_0_throughput_pig_type}, 'boar') or selected(${BDS_0_throughput_pig_type}, 'piglets') or selected(${BDS_0_throughput_pig_type}, 'weaners') or selected(${BDS_0_throughput_pig_type}, 'growers') or selected(${BDS_0_throughput_pig_type}, 'finishers')	[Enumerator Note]
BDS_0_throughput_qty_sow	**Sows**	selected(${BDS_0_throughput_pig_type}, 'sow')	[Integer]
BDS_0_throughput_qty_boar	**Boars**	selected(${BDS_0_throughput_pig_type}, 'boar')	[Integer]
BDS_0_throughput_qty_piglets	**Piglets**	selected(${BDS_0_throughput_pig_type}, 'piglets')	[Integer]
BDS_0_throughput_qty_weaners	**Weaners**	selected(${BDS_0_throughput_pig_type}, 'weaners')	[Integer]
BDS_0_throughput_qty_growers	**Growers**	selected(${BDS_0_throughput_pig_type}, 'growers')	[Integer]
BDS_0_throughput_qty_finishers	**Finishers**	selected(${BDS_0_throughput_pig_type}, 'finishers')	[Integer]
BDS_0_throughput_qty_unknown	**Pigs (unknown type)**	selected(${BDS_0_throughput_pig_type}, 'pigs')	[Integer]
broken_header_B2_1	**_For the past 7 days_, please provide details of each trader that has brought pigs into the SH premises to sell LIVE to other traders/buyers**		[Enumerator Note]
broken_header_BD_2	**Distributing trader D-${distributing_trader_number}**		[Enumerator Note]
BD_5_relationship	**What is your relationship with this trader?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
BD_5A_relation_specify	**Please specify the type of relationship**	${BD_5_relationship}='other'	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_BD_5	**_Location where this trader is based_**		[Enumerator Note]
BD_6z_country	**Country**		[cambodia] Cambodia [thailand] Thailand [veitnam] Vietnam [other] Other
BD_6z1_country_spec	**Please specify the other country**	selected(${BD_6z_country}, 'other')	[Text]
BD_7_hire_freq	**How often does this trader use this SH to distribute pigs to other buyers**		[first_time] First time [daily] Daily [2daily] At least every other day [3daily] At least twice per week [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly [6monthly] At least 6 monthly [yearly] At least yearly [unsure] Unknown
broken_header_BD_7	**How many pigs has this trader distributed from this SH site in the past 7 days?**		[Enumerator Note]
BD_7a_sows	**Sows**	selected(${BDS_0_throughput_pig_type}, 'sow')	[Integer]
BD_7b_boars	**Boars**	selected(${BDS_0_throughput_pig_type}, 'boar')	[Integer]
BD_7c_piglet	**Piglets**	selected(${BDS_0_throughput_pig_type}, 'piglets')	[Integer]
BD_7d_weaner	**Weaners**	selected(${BDS_0_throughput_pig_type}, 'weaners')	[Integer]
BD_7e_grower	**Growers**	selected(${BDS_0_throughput_pig_type}, 'growers')	[Integer]
BD_7f_finisher	**Finishers**	selected(${BDS_0_throughput_pig_type}, 'finishers')	[Integer]
BD_7g_unknown_pigs	**Pigs (unknown type)**	selected(${BDS_0_throughput_pig_type}, 'pigs')	[Integer]
BD_8_exchange_location	**Do exchanged pigs enter the pig holding areas in the SH?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
BD_9_contact_provided	**Can you provide contact details for this trader?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
BD_9a_contact_details	**Please record the contact's name, and phone number in the paper log book, for distributing-trader D-${distributing_trader_number}**	${BD_9_contact_provided} = 'yes'	[Enumerator Note]
BD_3_pig_origin_known	**Do you know the production origin of the pigs this trader sold from this SH site in the past 7 days?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
BD_3a_pig_origin_supplier	**From which type of producer(s), did these pigs originate from?**	${BD_3_pig_origin_known}='yes'	[sml_hh] Small household (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader (including traders who hired someone else to kill the pigs) [CP] CP [ACMC] ACMC-M-Pig (Moung Rithy) [company] Another company [other] Other [unsure] Don't know
BD_3a1_company_specify	**What is the name of the company?**	selected(${BD_3a_pig_origin_supplier}, 'company')	[Text]
broken_header_BD_4	**Where was the geographical production origin of these pigs?**	${BD_3_pig_origin_known}='yes'	[Enumerator Note]
BD_4a_country	**Country**	${BD_3_pig_origin_known}='yes'	[cambodia] Cambodia [thailand] Thailand

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[veitnam] Vietnam [other] Other
BD_4b_country_spec	**Please specify the other country**	selected(${BD_4a_country}, 'other')	[Text]
BD_4f_village	**In the paper log book, please now also record the site name, and site village (if known), along with the contact ID:_ DO-${distributing_trader_number}**	selected(${BD_4a_country}, 'cambodia') and ${BD_3_pig_origin_known}='yes'	[Enumerator Note]
distributing_traders_count	**0**		[Calculation]
BD_4fg_count	**_Individual entry has been completed for ${distributing_traders_count}/${BDS_1} contacts. Please ensure entry is complete.**	${BDS_1} > ${distributing_traders_count}	[Enumerator Note]
broken_header_BPS	**In the past 7 days, how many traders have purchased LIVE pigs on this SH premises (e.g. traders buying pigs from another trader to take elsewhere):**		[Enumerator Note]
BPS_1	**Traders**		[Integer]
broken_header_1d	**_For the past 7 days,_ please record the details of each trader who has purchased LIVE pigs on this SH premises (e.g. traders buying pigs from another trader to take elsewhere):**		[Enumerator Note]
broken_header_BP_2	**Purchasing trader C-${collecting_trader_number}**		[Enumerator Note]
BP_5_relationship	**What is your relationship with this purchasing trader?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
BP_5A_relation_specify	**Please specify the type of relationship**	${BP_5_relationship}='other'	[Text]
broken_header_BP_5	**_Location where this purchasing trader is based_**		[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
BP_7_hire_freq	**How often does this trader purchase pigs from other traders on this SH premises**		[first_time] First time [daily] Daily [2daily] At least every other day [3daily] At least twice per week [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly [6monthly] At least 6 monthly [yearly] At least yearly [unsure] Unknown
broken_header_BP_7	**How many LIVE pigs has this trader collected from this SH in the past 7 days?**		[Enumerator Note]
BP_7a_sows	**Sows**	selected(${BDS_0_throughput_pig_type}, 'sow')	[Integer]
BP_7b_boars	**Boars**	selected(${BDS_0_throughput_pig_type}, 'boar')	[Integer]
BP_7c_piglet	**Piglets**	selected(${BDS_0_throughput_pig_type}, 'piglets')	[Integer]
BP_7d_weaner	**Weaners**	selected(${BDS_0_throughput_pig_type}, 'weaners')	[Integer]
BP_7e_grower	**Growers**	selected(${BDS_0_throughput_pig_type}, 'growers')	[Integer]
BP_7f_finisher	**Finishers**	selected(${BDS_0_throughput_pig_type}, 'finishers')	[Integer]
BP_7g_unknown_pigs	**Pigs (unknown type)**	selected(${BDS_0_throughput_pig_type}, 'pigs')	[Integer]
BP_9_contact_provided	**Can you provide contact details for this purchasing trader?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
BP_9a_contact_details	**Please record the contact's name, and phone number in the paper log book, for purchasing-trader _ C-${collecting_trader_number}**	${BP_9_contact_provided} = 'yes'	[Enumerator Note]
BP_3_pig_origin_known	**Do you know where this trader took the pigs to, after purchasing them?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
BP_3a_pig_origin_supplier	**Where did the purchasing trader take the pigs?**	${BP_3_pig_origin_known}='yes'	[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [hh] Household of unknown size [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [farm] Farm of unknown size [trader] Trader [SH] Slaughterhouse [other] Other [unsure] Don't know
broken_header_BP_4	**In which geographical location were the pigs taken to?**	${BP_3_pig_origin_known}='yes'	[Enumerator Note]
BP_4f_village	**In the paper log book, please now also record the site name, and site village (if known), along with the contact ID:_ CD-${collecting_trader_number}**	${BP_3_pig_origin_known}='yes'	[Enumerator Note]
collecting_traders_count	**0**		[Calculation]
BP_4f_count	**_Individual entry has been completed for ${collecting_traders_count}/${BPS_1} contacts. Please ensure entry is complete.**	${BPS_1} > ${collecting_traders_count}	[Enumerator Note]
BR_0_recipients	**In the past 7 days, who has this SH sold LIVE pigs to?**		[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [trader] Trader

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[CP] CP [SH] Slaughterhouse [other] Other
broken_header_BR_0_i2	**In the past 7 days, how many recipients of each type has this SH sold LIVE pigs to?**		[Enumerator Note]
BR_0a_small_hh	**Small households (<10 pigs)**	selected(${BR_0_recipients}, 'sml_hh')	[Integer]
BR_0BR_med_hh	**Medium household (10 to 50 pigs)**	selected(${BR_0_recipients}, 'med_hh')	[Integer]
BR_0c_large_hh	**Large household (50 to <100 pigs)**	selected(${BR_0_recipients}, 'lrg_hh')	[Integer]
BR_0f_hh	**Household of unknown size**	selected(${BR_0_recipients}, 'hh')	[Integer]
BR_0d_small_farm	**Small farm (100 to <1000 pigs)**	selected(${BR_0_recipients}, 'sml_farm')	[Integer]
BR_0e_med_farm	**Medium farm (1000 to <5000 pigs)**	selected(${BR_0_recipients}, 'med_farm')	[Integer]
BR_0f_lrg_farm	**Large farm (≥5000 pigs)**	selected(${BR_0_recipients}, 'lrg_farm')	[Integer]
BR_0f_farm	**Farm of unknown size**	selected(${BR_0_recipients}, 'farm')	[Integer]
BR_0g_trader	**Trader**	selected(${BR_0_recipients}, 'trader')	[Integer]
BR_0h_sh	**Slaughterhouse**	selected(${BR_0_recipients}, 'SH')	[Integer]
BR_0i_other	**Other**	selected(${BR_0_recipients}, 'other')	[Integer]
BR_0j_total_recipients	**Total number of SH recipients**		[Calculation]
BR_purchases_pig_type	**What types of pig has this SH sold LIVE in the past 7 days?**		[sow] Sow [boar] Boar [piglets] Piglets [weaners] Weaners [growers] Growers [finishers] Finishers [pigs] Pigs (unknown type) [refused] Refused [unsure] Don't know
broken_header_BR	**Number of pigs sold of this category in the past 7 days:**	selected(${BR_purchases_pig_type}, 'sow') or selected(${BR_purchases_pig_type}, 'boar') or	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
		selected(${BR_purchases_pig_type}, 'piglets') or selected(${BR_purchases_pig_type}, 'weaners') or selected(${BR_purchases_pig_type}, 'growers') or selected(${BR_purchases_pig_type}, 'finishers')	
BR_purchases_qty_sow	**Sows**	selected(${BR_purchases_pig_type}, 'sow')	[Integer]
BR_purchases_qty_boar	**Boars**	selected(${BR_purchases_pig_type}, 'boar')	[Integer]
BR_purchases_qty_piglets	**Piglets**	selected(${BR_purchases_pig_type}, 'piglets')	[Integer]
BR_purchases_qty_weaners	**Weaners**	selected(${BR_purchases_pig_type}, 'weaners')	[Integer]
BR_purchases_qty_growers	**Growers**	selected(${BR_purchases_pig_type}, 'growers')	[Integer]
BR_purchases_qty_finishers	**Finishers**	selected(${BR_purchases_pig_type}, 'finishers')	[Integer]
BR_purchases_qty_unknown	**Pigs (unknown type)**	selected(${BR_purchases_pig_type}, 'pigs')	[Integer]
broken_header_B1d2	**_For the past 7 days,_ please record the details of each person this SH has sold LIVE pig to:**		[Enumerator Note]
broken_header_BR_2	**SH recipient R-${sh_recipient_number}**		[Enumerator Note]
B_6c_recipient_type	**Recipient type**		[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [trader] Trader [CP] CP [SH] Slaughterhouse [other] Other
B_6c1_recipient_specify	**Please specify the type of recipient**	${B_6c_recipient_type}='other'	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6e_relationship	**What is your relationship with this recipient?**		[cp_contract] Contract CP [other_contract] Contract other [same_company] Supplier same person/company [family] Family connection [friend] Friend [no_formal_relationship] None [other] Other [unsure] Don't know
B_6e_relation_specify	**Please specify the type of relationship**	${B_6e_relationship}='other'	[Text]
broken_header_6f	**_Contact location or site where this contact is based_**		[Enumerator Note]
B_6k_transac_freq	**Frequency of transactions with this recipient**		[first_time] First time [daily] Daily [2daily] At least every other day [3daily] At least twice per week [weekly] At least weekly [2weekly] At least 2 weekly [monthly] At least monthly [3monthly] At least 3 monthly [6monthly] At least 6 monthly [yearly] At least yearly [unsure] Unknown
broken_header_4.11	**Number of pigs sent to this recipient in past 7 days:**		[Enumerator Note]
B_6m_sows	**Sows**	selected(${BR_purchases_pig_type}, 'sow')	[Integer]
B_6n_boars	**Boars**	selected(${BR_purchases_pig_type}, 'boar')	[Integer]
B_6o_piglet	**Piglets**	selected(${BR_purchases_pig_type}, 'piglets')	[Integer]
B_6p_weaner	**Weaners**	selected(${BR_purchases_pig_type}, 'weaners')	[Integer]
B_6q_grower	**Growers**	selected(${BR_purchases_pig_type}, 'growers')	[Integer]
B_6r_finisher	**Finishers**	selected(${BR_purchases_pig_type}, 'finishers')	[Integer]
B_6s_unknown_pigs	**Pigs (unknown type)**	selected(${BR_purchases_pig_type}, 'pigs')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6t_contact_provided	**Can you provide contact details for this recipient?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
B_6j_village	**In the paper log book, please now also record the site name, and site village (if known), along with the contact ID used above: _ R-${sh_recipient_number}**		[Enumerator Note]
B_6t1_contact_details	**Please record the contact's name, and phone number in the paper log book, along with the contact ID used above: _ R-${sh_recipient_number}**	${B_6t_contact_provided}='yes'	[Enumerator Note]
B_6c1_pig_destination_known	**Do you know where the trader sent on the pigs?**	${B_6c_recipient_type}='trader'	[yes] Yes [no] No [unsure] Unsure [refused] Refused
broken_header_B_6c1a	**_Questions in blue below, refer to the person/place that the trader sent the pigs_**	${B_6c1_pig_destination_known}='yes'	[Enumerator Note]
B_6c1a_pig_destination_recipient	**Where did the trader send on the pigs?**	${B_6c1_pig_destination_known}='yes'	[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [trader] Trader [CP] CP [SH] Slaughterhouse [other] Other
broken_header_2.61	**In which geographical location were the pigs taken to?**	${B_6c1_pig_destination_known}='yes'	[Enumerator Note]
B_6c1e_village	**In the paper log book, please now also record the site name, and site village (if known), along with the contact ID used above:_ RD-${sh_recipient_number}**	${B_6c1_pig_destination_known}='yes'	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
sh_recipient_count	**0**		[Calculation]
B_6c1e_count	**_Individual entry has been completed for ${sh_recipient_count}/${BR_0j_total_recipients} contacts. Please ensure entry is complete.**	${BR_0j_total_recipients} > ${sh_recipient_count}	[Enumerator Note]
B_2_sh_workers	**In the past 7 days, has anyone else worked at this slaughterhouse?**		[employee] Slaughterhouse employees [family] Family members involved with the slaughterhouse business [other] Other [no] No [unsure] Don't know [refused] Refused
B_2_i_sh_worker_define	**Please specify the other types of slaughterhouse workers:**	selected(${B_2_sh_workers}, 'other')	[Text]
broken_header_B_2a_i	**Slaughterhouse employees:**	selected(${B_2_sh_workers}, 'employee')	[Enumerator Note]
B_2a_i_employees_qty	**How many employees have worked at this slaughterhouse in the past 7 days?**	selected(${B_2_sh_workers}, 'employee')	[Integer]
B_2b_i_employees_roles	**Roles in the slaughterhouse?**	selected(${B_2_sh_workers}, 'employee')	[supervise] Supervising the site [care] Take care of pigs [kill] Kill pigs [clean] Clean slaughterhouse [process] Processing pig carcasses [transport] Transporting pigs [other] Other [unsure] Don't know [refused] Refused
B_2b_i_employee_role_define	**Please specify the other roles that employees have in this slaughterhouse**	selected(${B_2b_i_employees_roles}, 'other')	[Text]
broken_header_B_2a_ii	**Family members:**	selected(${B_2_sh_workers}, 'family')	[Enumerator Note]
B_2a_ii_family_qty	**How many family members have worked at this slaughterhouse in the past 7 days?**	selected(${B_2_sh_workers}, 'family')	[Integer]
B_2b_ii_family_roles	**Roles in the slaughterhouse?**	selected(${B_2_sh_workers}, 'family')	[supervise] Supervising the site [care] Take care of pigs

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[kill] Kill pigs [clean] Clean slaughterhouse [process] Processing pig carcasses [transport] Transporting pigs [other] Other [unsure] Don't know [refused] Refused
B_2b_ii_family_role_define	**Please specify the other roles that family members have in this slaughterhouse**	selected(${B_2b_ii_family_roles}, 'other')	[Text]
B_6_longitudinal	**Has the number of pigs slaughtered at this site varied across the past year?**		[yes] Yes [no] No [unsure] Unsure
B_6a_busy_months	**When were _most_ pigs slaughtered?**	selected(${B_6_longitudinal}, 'yes')	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_6a	**During these busy periods, how many pigs did you slaughter _per day_?:**	selected(${B_6_longitudinal}, 'yes')	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
B_6a1_ave_throughput	**Average:**	selected(${B_6_longitudinal}, 'yes')	[Integer]
B_6b_quiet_months	**When were the _least_ pigs slaughtered?**	selected(${B_6_longitudinal}, 'yes')	[jan_a] January - 1st half [jan_b] January - 2nd half [feb_a] February - 1st half [feb_b] February - 2nd half [mar_a] March - 1st half [mar_b] March - 2nd half [apr_a] April - 1st half [apr_b] April - 2nd half [may_a] May - 1st half [may_b] May - 2nd half [jun_a] June - 1st half [jun_b] June - 2nd half [jul_a] July - 1st half [jul_b] July - 2nd half [aug_a] August - 1st half [aug_b] August - 2nd half [sep_a] September - 1st half [sep_b] September - 2nd half [oct_a] October - 1st half [oct_b] October - 2nd half [nov_a] November - 1st half [nov_b] November - 2nd half [dec_a] December - 1st half [dec_b] December - 2nd half
broken_header_B_6b	**During these quieter periods, how many pigs did you slaughter _per day_?:**	selected(${B_6_longitudinal}, 'yes')	[Enumerator Note]
B_6b1_ave_throughput	**Average:**	selected(${B_6_longitudinal}, 'yes')	[Integer]
C_1_ownership	**What sort of ownership does this slaughterhouse have?**		[single] Single owner/family owned [several] Several owners [company] Owned by a company [other] Other [unsure] Don't know [refused] Refused
C_1a_company_define	**Name of company:**	selected(${C_1_ownership}, 'company')	[Text]
C_1b_ownership_define	**Please define the type of ownership:**	selected(${C_1_ownership}, 'other')	[Text]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_2_other_animals_slaughtered	**Have any other types of animal been slaughtered on this site in the past 7 days?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
C_2a_animals_slaughtered	**Which other types of animal have been slaughtered on this site in the past 7 days?**	selected(${C_2_other_animals_slaughtered}, 'yes')	[chickens] Chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [other] Other [unsure] Don't know
C_2ai_animals_define	**Please specify these other animal types:**	selected(${C_2a_animals_slaughtered}, 'other')	[Text]
broken_header_C_2b_chicken	**For each animal type that is slaughtered at this site, please complete the following:**	selected(${C_2a_animals_slaughtered}, 'yes')	[Enumerator Note]
broken_header_C_2b1_chickens	**_CHICKENS_**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Enumerator Note]
broken_header_C_2b2_chickens	**In the past 7 days, how many were slaughtered on this site per day?:**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Enumerator Note]
C_2b_throughput_ave_chickens	**on average:**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Integer]
C_2b_throughput_min_chickens	**min:**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Integer]
C_2b_throughput_max_chickens	**max:**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Integer]
broken_header_C_2c_chickens	**In the past 7 days, how long were they kept on site before slaughtering?:**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Enumerator Note]
C_2c_kept_ave_chickens	**on average:**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Integer]
C_2c_hours_days_ave_chickens	**hours/days**	selected(${C_2a_animals_slaughtered}, 'chickens')	[hours] Hours [days] Days
C_2c_kept_min_chickens	**min:**	selected(${C_2a_animals_slaughtered}, 'chickens')	[Integer]
C_2c_hours_days_min_chickens	**hours/days**	selected(${C_2a_animals_slaughtered}, 'chickens')	[hours] Hours [days] Days

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_2c_kept_max_chickens	max:	selected(${C_2a_animals_slaughtered}, 'chickens')	[Integer]
C_2c_hours_days_max_chickens	hours/days	selected(${C_2a_animals_slaughtered}, 'chickens')	[hours] Hours [days] Days
C_2d_pig_contact_chickens	Were these animals able to directly contact pigs being held before slaughter?	selected(${C_2a_animals_slaughtered}, 'chickens')	[yes] Yes [no] No [unsure] Unsure
C_2d1_pig_distance_chickens	If no, minimum distance from pig houses (metres)	selected(${C_2d_pig_contact_chickens}, 'no')	[Integer]
broken_header_C_2b1_ducks	_DUCKS_	selected(${C_2a_animals_slaughtered}, 'ducks')	[Enumerator Note]
broken_header_C_2b2_ducks	In the past 7 days, how many were slaughtered on this site per day?:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Enumerator Note]
C_2b_throughput_ave_ducks	on average:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Integer]
C_2b_throughput_min_ducks	min:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Integer]
C_2b_throughput_max_ducks	max:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Integer]
broken_header_C_2c_ducks	In the past 7 days, how long were they kept on site before slaughtering?:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Enumerator Note]
C_2c_kept_ave_ducks	on average:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Integer]
C_2c_hours_days_ave_ducks	hours/days	selected(${C_2a_animals_slaughtered}, 'ducks')	[hours] Hours [days] Days
C_2c_kept_min_ducks	min:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Integer]
C_2c_hours_days_min_ducks	hours/days	selected(${C_2a_animals_slaughtered}, 'ducks')	[hours] Hours [days] Days
C_2c_kept_max_ducks	max:	selected(${C_2a_animals_slaughtered}, 'ducks')	[Integer]
C_2c_hours_days_max_ducks	hours/days	selected(${C_2a_animals_slaughtered}, 'ducks')	[hours] Hours [days] Days

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_2d_pig_contact_ducks	**Were these animals able to directly contact pigs being held before slaughter?**	selected(${C_2a_animals_slaughtered}, 'ducks')	[yes] Yes [no] No [unsure] Unsure
C_2d1_pig_distance_ducks	**If no, minimum distance from pig houses (metres)**	selected(${C_2d_pig_contact_ducks}, 'no')	[Integer]
broken_header_C_2b1_geese	**_GEESE_**	selected(${C_2a_animals_slaughtered}, 'geese')	[Enumerator Note]
broken_header_C_2b2_geese	**In the past 7 days, how many were slaughtered on this site per day?:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Enumerator Note]
C_2b_throughput_ave_geese	**on average:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Integer]
C_2b_throughput_min_geese	**min:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Integer]
C_2b_throughput_max_geese	**max:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Integer]
broken_header_C_2c_geese	**In the past 7 days, how long were they kept on site before slaughtering?:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Enumerator Note]
C_2c_kept_ave_geese	**on average:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Integer]
C_2c_hours_days_ave_geese	**hours/days**	selected(${C_2a_animals_slaughtered}, 'geese')	[hours] Hours [days] Days
C_2c_kept_min_geese	**min:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Integer]
C_2c_hours_days_min_geese	**hours/days**	selected(${C_2a_animals_slaughtered}, 'geese')	[hours] Hours [days] Days
C_2c_kept_max_geese	**max:**	selected(${C_2a_animals_slaughtered}, 'geese')	[Integer]
C_2c_hours_days_max_geese	**hours/days**	selected(${C_2a_animals_slaughtered}, 'geese')	[hours] Hours [days] Days
C_2d_pig_contact_geese	**Were these animals able to directly contact pigs being held before slaughter?**	selected(${C_2a_animals_slaughtered}, 'geese')	[yes] Yes [no] No [unsure] Unsure
C_2d1_pig_distance_geese	**If no, minimum distance from pig houses (metres)**	selected(${C_2d_pig_contact_geese}, 'no')	[Integer]
broken_header_C_2b1_cattle	**_CATTLE_**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
broken_header_C_2b2_cattle	**In the past 7 days, how many were slaughtered on this site per day?:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Enumerator Note]
C_2b_throughput_ave_cattle	**on average:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Integer]
C_2b_throughput_min_cattle	**min:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Integer]
C_2b_throughput_max_cattle	**max:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Integer]
broken_header_C_2c_cattle	**In the past 7 days, how long were they kept on site before slaughtering?:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Enumerator Note]
C_2c_kept_ave_cattle	**on average:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Integer]
C_2c_hours_days_ave_cattle	**hours/days**	selected(${C_2a_animals_slaughtered}, 'cattle')	[hours] Hours [days] Days
C_2c_kept_min_cattle	**min:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Integer]
C_2c_hours_days_min_cattle	**hours/days**	selected(${C_2a_animals_slaughtered}, 'cattle')	[hours] Hours [days] Days
C_2c_kept_max_cattle	**max:**	selected(${C_2a_animals_slaughtered}, 'cattle')	[Integer]
C_2c_hours_days_max_cattle	**hours/days**	selected(${C_2a_animals_slaughtered}, 'cattle')	[hours] Hours [days] Days
C_2d_pig_contact_cattle	**Were these animals able to directly contact pigs being held before slaughter?**	selected(${C_2a_animals_slaughtered}, 'cattle')	[yes] Yes [no] No [unsure] Unsure
C_2d1_pig_distance_cattle	**If no, minimum distance from pig houses (metres)**	selected(${C_2d_pig_contact_cattle}, 'no')	[Integer]
broken_header_C_2b1_goats	**_GOATS_**	selected(${C_2a_animals_slaughtered}, 'goats')	[Enumerator Note]
broken_header_C_2b2_goats	**In the past 7 days, how many were slaughtered on this site per day?:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Enumerator Note]
C_2b_throughput_ave_goats	**on average:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Integer]
C_2b_throughput_min_goats	**min:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_2b_throughput_max_goats	**max:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Integer]
broken_header_C_2c_goats	**In the past 7 days, how long were they kept on site before slaughtering?:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Enumerator Note]
C_2c_kept_ave_goats	**on average:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Integer]
C_2c_hours_days_ave_goats	**hours/days**	selected(${C_2a_animals_slaughtered}, 'goats')	[hours] Hours [days] Days
C_2c_kept_min_goats	**min:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Integer]
C_2c_hours_days_min_goats	**hours/days**	selected(${C_2a_animals_slaughtered}, 'goats')	[hours] Hours [days] Days
C_2c_kept_max_goats	**max:**	selected(${C_2a_animals_slaughtered}, 'goats')	[Integer]
C_2c_hours_days_max_goats	**hours/days**	selected(${C_2a_animals_slaughtered}, 'goats')	[hours] Hours [days] Days
C_2d_pig_contact_goats	**Were these animals able to directly contact pigs being held before slaughter?**	selected(${C_2a_animals_slaughtered}, 'goats')	[yes] Yes [no] No [unsure] Unsure
C_2d1_pig_distance_goats	**If no, minimum distance from pig houses (metres)**	selected(${C_2d_pig_contact_goats}, 'no')	[Integer]
broken_header_C_2b1_other	**_OTHER_**	selected(${C_2a_animals_slaughtered}, 'other')	[Enumerator Note]
C_2b_animal_type_define	**Type of other animal:**	selected(${C_2a_animals_slaughtered}, 'other')	[Text]
broken_header_C_2b2_other	**In the past 7 days, how many were slaughtered on this site per day?:**	selected(${C_2a_animals_slaughtered}, 'other')	[Enumerator Note]
C_2b_throughput_ave_other	**on average:**	selected(${C_2a_animals_slaughtered}, 'other')	[Integer]
C_2b_throughput_min_other	**min:**	selected(${C_2a_animals_slaughtered}, 'other')	[Integer]
C_2b_throughput_max_other	**max:**	selected(${C_2a_animals_slaughtered}, 'other')	[Integer]
broken_header_C_2c_other	**In the past 7 days, how long were they kept on site before slaughtering?:**	selected(${C_2a_animals_slaughtered}, 'other')	[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_2c_kept_ave_other	**on average:**	selected(${C_2a_animals_slaughtered}, 'other')	[Integer]
C_2c_hours_days_ave_other	**hours/days**	selected(${C_2a_animals_slaughtered}, 'other')	[hours] Hours [days] Days
C_2c_kept_min_other	**min:**	selected(${C_2a_animals_slaughtered}, 'other')	[Integer]
C_2c_hours_days_min_other	**hours/days**	selected(${C_2a_animals_slaughtered}, 'other')	[hours] Hours [days] Days
C_2c_kept_max_other	**max:**	selected(${C_2a_animals_slaughtered}, 'other')	[Integer]
C_2c_hours_days_max_other	**hours/days**	selected(${C_2a_animals_slaughtered}, 'other')	[hours] Hours [days] Days
C_2d_pig_contact_other	**Were these animals able to directly contact pigs being held before slaughter?**	selected(${C_2a_animals_slaughtered}, 'other')	[yes] Yes [no] No [unsure] Don't know [refused] Refused [na] Not applicable
C_2d1_pig_distance_other	**If no, minimum distance from pig houses (metres)**	selected(${C_2d_pig_contact_other}, 'no')	[Integer]
C_3a_pig_housing	**How are pigs housed before slaughter**		[individual] Individual cage/pen [group_same] Group housed - with pigs of the same category [group_mixed] Group housed - mixed with other pig categories [tethered] Tethered [freerange] Free-range [unsure] Don't know [refused] Refused
C_3a1_pen_qty_pigs	**How many pigs are kept together in a pen?**	selected(${C_3a_pig_housing}, 'group_same') or selected(${C_3a_pig_housing}, 'group_mixed')	[Integer]
C_3c_pigs_contact_diff_origins	**Are pigs from different origins able to come into direct contact with each other?**		[yes] Yes [no] No [unsure] Don't know [refused] Refused [na] Not applicable

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_3d_clean_freq	**How often do you clean pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_3d1_clean_method	**What is used to clean pens?**	selected(${C_3d_clean_freq}, 'between_batch') or selected(${C_3d_clean_freq}, 'daily') or selected(${C_3d_clean_freq}, 'weekly') or selected(${C_3d_clean_freq}, 'monthly') or selected(${C_3d_clean_freq}, 'less_monthly') or selected(${C_3d_clean_freq}, 'disease')	[water] Water [soap] Soap [disinfectant] Disinfectant [unsure] Don't know [refused] Refused
C_3d_disinfect_freq	**How often do you disinfect pig holding areas?**		[between_batch] Between batches of pigs [daily] Daily [weekly] Weekly [monthly] Monthly [less_monthly] Less than monthly [disease] After a pig illness/disease [never] Never [unsure] Don't know [refused] Refused
C_3d1a_specify_disinfectant	**Please specify the type of disinfectant used (type or brand name)**	selected(${C_3d1_clean_method}, 'disinfectant') or selected(${C_3d_disinfect_freq}, 'between_batch') or selected(${C_3d_disinfect_freq}, 'daily') or selected(${C_3d_disinfect_freq}, 'weekly') or selected(${C_3d_disinfect_freq}, 'monthly') or selected(${C_3d_disinfect_freq}, 'less_monthly') or selected(${C_3d_disinfect_freq}, 'disease')	[Text]
broken_header_C_3e	**How long do you keep pigs before slaughtering?:**		[Enumerator Note]
C_3e_kept_ave_other	**on average:**		[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_3e_hours_days_ave_other	**hours/days**		[hours] Hours [days] Days
C_3e_kept_min_other	**min:**		[Integer]
C_3e_hours_days_min_other	**hours/days**		[hours] Hours [days] Days
C_3e_kept_max_other	**max:**		[Integer]
C_3e_hours_days_max_other	**hours/days**		[hours] Hours [days] Days
C_4_other_animals	**Which of the following animals are currently present on the farm/site, OR have been present on the farm/site in the past 6 months**		[pigs] Pigs (RAISED on site) [layers] Chicken layers (for eggs) [broilers] Chicken broilers (for meat) [backyard] Backyard chickens [ducks] Ducks [geese] Geese [cattle] Cattle [goats] Goats [dogs] Dogs [cats] Cats [other] Other [none] None
broken_header_C4a	**_For each animal type, please specify whether they are currently present, or whether they were present in the past 6 months_**	selected(${C_4_other_animals}, 'pigs') or selected(${C_4_other_animals}, 'layers') or selected(${C_4_other_animals}, 'broilers') or selected(${C_4_other_animals}, 'backyard') or selected(${C_4_other_animals}, 'ducks') or selected(${C_4_other_animals}, 'geese') or selected(${C_4_other_animals}, 'cattle') or selected(${C_4_other_animals}, 'goats') or selected(${C_4_other_animals}, 'dogs') or selected(${C_4_other_animals}, 'cats') or selected(${C_4_other_animals}, 'other')	[Enumerator Note]
C_4a0_pigs_present	**Pigs (RAISED on site)**	selected(${C_4_other_animals}, 'pigs')	[present_currently] Currently present [present_previously] Not currently

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			present, but kept in the past 6 months
C_4b0_pigs_qty	**How many pigs are currently being raised on the farm/site?**	${C_4a0_pigs_present} = 'present_currently'	[Integer]
C_4c0_pigs_pigs	**Are the pigs that are being raised on site, able to come into direct contact with pigs for slaughter?**	${C_4a0_pigs_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c0_pigs_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c0_pigs_pigs} = 'no'	[Integer]
C_4d0_pigs_contact_other_hh	**Are the pigs being raised on site, able to physically come into contact with livestock from other households?**	${C_4a0_pigs_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a1_layers_present	**Layer chickens (for eggs)**	selected(${C_4_other_animals}, 'layers')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b1_layers_qty	**How many layers are currently present on the farm/site?**	${C_4a1_layers_present} = 'present_currently'	[Integer]
C_4c1_layers_pigs	**Are the layers able to come into direct contact with pigs for slaughter?**	${C_4a1_layers_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c1a_layer_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c1_layers_pigs} = 'no'	[Integer]
C_4d1_layers_contact_other_hh	**Are the layers able to physically come into contact with livestock from other households?**	${C_4a1_layers_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a2_broilers_present	**Broiler chickens (for meat)**	selected(${C_4_other_animals}, 'broilers')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b2_broilers_qty	**How many broilers are currently present on the farm/site?**	${C_4a2_broilers_present} = 'present_currently'	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4c2_broilers_pigs	**Are the broilers able to come into direct contact with pigs for slaughter?**	${C_4a2_broilers_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c2a_broilers_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c2_broilers_pigs} = 'no'	[Integer]
C_4d2_broilers_contact_other_hh	**Are the broilers able to physically come into contact with livestock from OTHER households?**	${C_4a2_broilers_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a3_backyard_present	**Backyard chickens**	selected(${C_4_other_animals}, 'backyard')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b3_backyard_qty	**How many backyard chickens are currently present on the farm/site?**	${C_4a3_backyard_present} = 'present_currently'	[Integer]
C_4c3_bckchk_pigs	**Are the backyard chickens able to come into direct contact with pigs for slaughter?**	${C_4a3_backyard_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c3a_bckchk_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c3_bckchk_pigs} = 'no'	[Integer]
C_4d3_bckchk_contact_other_hh	**Are the backyard chickens able to physically come into contact with livestock from OTHER households?**	${C_4a3_backyard_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a4_ducks_present	**Ducks**	selected(${C_4_other_animals}, 'ducks')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b4_ducks_qty	**How many ducks are currently present on the farm/site?**	${C_4a4_ducks_present} = 'present_currently'	[Integer]
C_4c4_ducks_pigs	**Are the ducks able to come into direct contact with pigs for slaughter?**	${C_4a4_ducks_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c4a_ducks_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c4_ducks_pigs} = 'no'	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4d4_ducks_contact_other_hh	**Are the ducks able to physically come into contact with livestock from OTHER households?**	${C_4a4_ducks_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a5_geese_present	**Geese**	selected(${C_4_other_animals}, 'geese')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b5_geese_qty	**How many geese are currently present on the farm/site?**	${C_4a5_geese_present} = 'present_currently'	[Integer]
C_4c5_geese_pigs	**Are the geese able to come into direct contact with pigs for slaughter?**	${C_4a5_geese_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c5a_geese_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c5_geese_pigs} = 'no'	[Integer]
C_4d5_geese_contact_other_hh	**Are the geese able to physically come into contact with livestock from OTHER households?**	${C_4a5_geese_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a6_cattle_present	**Cattle**	selected(${C_4_other_animals}, 'cattle')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b6_cattle_qty	**How many cattle are currently present on the farm/site?**	${C_4a6_cattle_present} = 'present_currently'	[Integer]
C_4c6_cattle_pigs	**Are the cattle able to come into direct contact with pigs for slaughter?**	${C_4a6_cattle_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c6a_cattle_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c6_cattle_pigs} = 'no'	[Integer]
C_4d6_cattle_contact_other_hh	**Are the cattle able to physically come into contact with livestock from OTHER households?**	${C_4a6_cattle_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a7_goats_present	**Goats**	selected(${C_4_other_animals}, 'goats')	[present_currently] Currently present

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			[present_previously] Not currently present, but kept in the past 6 months
C_4b7_goats_qty	**How many goats are currently present on the farm/site?**	${C_4a7_goats_present} = 'present_currently'	[Integer]
C_4c7_goats_pigs	**Are the goats able to come into direct contact with pigs for slaughter?**	${C_4a7_goats_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c7a_goats_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c7_goats_pigs} = 'no'	[Integer]
C_4d7_goats_contact_other_hh	**Are the goats able to physically come into contact with livestock from OTHER households?**	${C_4a7_goats_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a8_dogs_present	**Dogs**	selected(${C_4_other_animals}, 'dogs')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b8_dogs_qty	**How many dogs are currently present on the farm/site?**	${C_4a8_dogs_present} = 'present_currently'	[Integer]
C_4c8_dogs_pigs	**Are the dogs able to come into direct contact with pigs for slaughter?**	${C_4a8_dogs_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c8a_dogs_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c8_dogs_pigs} = 'no'	[Integer]
C_4d8_dogs_contact_other_hh	**Are the dogs able to physically come into contact with livestock from OTHER households?**	${C_4a8_dogs_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a9_cats_present	**Cats**	selected(${C_4_other_animals}, 'cats')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4b9_cats_qty	**How many cats are currently present on the farm/site?**	${C_4a9_cats_present} = 'present_currently'	[Integer]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_4c9_cats_pigs	**Are the cats able to come into direct contact with pigs for slaughter?**	${C_4a9_cats_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c9a_cats_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c9_cats_pigs} = 'no'	[Integer]
C_4d9_cats_contact_other_hh	**Are the cats able to physically come into contact with livestock from OTHER households?**	${C_4a9_cats_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4a10_other_present	**Are any other types of animal kept on the farm/site?**	selected(${C_4_other_animals}, 'other')	[present_currently] Currently present [present_previously] Not currently present, but kept in the past 6 months
C_4a10a_animal_specify	**Please specify the other type of animal**	selected(${C_4_other_animals}, 'other')	[Text]
C_4b10_other_qty	**How many of this animal are currently present on the farm/site?**	${C_4a10_other_present} = 'present_currently'	[Integer]
C_4c10_other_pigs	**Are these animals able to come into direct contact with pigs for slaughter?**	${C_4a10_other_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4c10a_other_pigs_distance	**Minimum distance from pig houses (metres)**	${C_4c10_other_pigs} = 'no'	[Integer]
C_4d10_other_contact_other_hh	**Are the other animals able to physically come into contact with livestock from OTHER households?**	${C_4a10_other_present} = 'present_currently'	[yes] Yes [no] No [unsure] Unsure
C_4d_1_neighbour_hh_animals	**Do the neighbouring households (that these animals are able to physically contact) raise pigs or poultry?**	${C_4d0_pigs_contact_other_hh} = 'yes' or ${C_4d1_layers_contact_other_hh} = 'yes' or ${C_4d2_broilers_contact_other_hh} = 'yes' or ${C_4d3_bckchk_contact_other_hh} = 'yes' or ${C_4d4_ducks_contact_other_hh} = 'yes' or ${C_4d5_geese_contact_other_hh} = 'yes' or ${C_4d6_cattle_contact_other_hh} = 'yes' or ${C_4d7_goats_contact_other_hh} = 'yes' or ${C_4d8_dogs_contact_other_hh} = 'yes' or ${C_4d9_cats_contact_other_hh} = 'yes' or ${C_4d10_other_contact_other_hh} = 'yes'	[pigs] Pigs [poultry] Poultry [no] No [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
C_5_land_area	**Total land area of slaughterhouse site**		[Decimal]
C_5_land_area_unit	**Select the appropriate unit**		[m2] Square metres [hectares] Hectares
C_6_other_pig_enterprises	**Do you/the company which own this slaughterhouse, own any other smallholdings, pig farms, pig trading outfits, or slaughterhouses?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
broken_header_C_6	**Enter details of these other sites or enterprises (enter a separate entry for each site/enterprise type):**	${C_6_other_pig_enterprises}='yes'	[Enumerator Note]
C_6a_enterprise	**Which site/enterprise**		[sml_hh] Small households (<10 pigs) [med_hh] Medium household (10 to 50 pigs) [lrg_hh] Large household (50 to <100 pigs) [sml_farm] Small farm (100 to <1000 pigs) [med_farm] Medium farm (1000 to <5000 pigs) [lrg_farm] Large farm (≥5000 pigs) [trade] Trading business [sh] Slaughterhouse [other] Other
C_6a1_enterprise_define	**Define the other type of enterprise**	${C_6a_enterprise}='other'	[Text]
C_6b_enterprise_qty	**of this type of site/enterprises owned?**		[Integer]
C_6c_enterprise_loc	**Enter the highest common administrative area that these are located within**		[village] Same village [commune] Same commune [district] Same district [province] Same province [province_different] Different provinces
broken_header_D1	**How do you manage pig product waste at the slaughterhouse?:**		[Enumerator Note]

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
D_1_disposal_blood	**Blood**		[drained_public] Drained to a public drainage [drained_blocked] Drained to a blocked water body (e.g. pond/lake) [drained_current] Drained to flowing water (e.g. river/stream) [drained_land] Drained on land [fertiliser] Stored for fertiliser [sent] Sell / send to another site [taken_away] Taken away (e.g. by waste disposal) [other] Other [unsure] Don't know [refused] Refused
D_1a_disposal_blood_specify	**Please specify:**	selected(${D_1_disposal_blood}, 'other')	[Text]
D_1_disposal_excreta	**Excreta**		[drained_public] Drained to a public drainage [drained_blocked] Drained to a blocked water body (e.g. pond/lake) [drained_current] Drained to flowing water (e.g. river/stream) [drained_land] Drained on land [fertiliser] Stored for fertiliser [sent] Sell / send to another site [taken_away] Taken away (e.g. by waste disposal) [other] Other [unsure] Don't know [refused] Refused
D_1a_disposal_excreta_specify	**Please specify:**	selected(${D_1_disposal_excreta}, 'other')	[Text]
D_1b_excreta_sent	**Where did you sell/send excreta?**	selected(${D_1_disposal_excreta}, 'sent') or selected(${D_1_disposal_excreta}, 'taken_away')	[Text]
D_1_disposal_bones	**Bones**		[drained_public] Drained to a public drainage [drained_blocked] Drained to a blocked water body (e.g. pond/lake) [drained_current] Drained to

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			flowing water (e.g. river/stream) [drained_land] Drained on land [fertiliser] Stored for fertiliser [sent] Sell / send to another site [taken_away] Taken away (e.g. by waste disposal) [other] Other [unsure] Don't know [refused] Refused
D_1a_disposal_bones_specify	**Please specify:**	selected(${D_1_disposal_bones}, 'other')	[Text]
D_1b_bones_sent	**Where did you sell/send bones?**	selected(${D_1_disposal_bones}, 'sent') or selected(${D_1_disposal_bones}, 'taken_away')	[Text]
D_1_disposal_offal	**Offal remnants**		[drained_public] Drained to a public drainage [drained_blocked] Drained to a blocked water body (e.g. pond/lake) [drained_current] Drained to flowing water (e.g. river/stream) [drained_land] Drained on land [fertiliser] Stored for fertiliser [sent] Sell / send to another site [taken_away] Taken away (e.g. by waste disposal) [other] Other [unsure] Don't know [refused] Refused
D_1a_disposal_offal_specify	**Please specify:**	selected(${D_1_disposal_offal}, 'other')	[Text]
D_1b_offal_sent	**Where did you sell/send offal remnants?**	selected(${D_1_disposal_offal}, 'sent') or selected(${D_1_disposal_offal}, 'taken_away')	[Text]
D_2_sick_action	**What do you do if sick pigs are detected upon inspection?**		[quarantine] Put them in quarantine [reject] Do not buy / reject them from the slaughterhouse site [slaughter] Slaughter as normal [slaughter_separate] Slaughter but keep separate from healthy carcasses [n/a] Don't know, never purchased,

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
			or identified sick pigs before [other] Other [refused] Refused
D_2a_sick_action_other	**Please specify what you did with the sick pigs:**	selected(${D_2_sick_action}, 'other')	[Text]
E_1_biosecurity	**Are any of the following biosecurity measures in place on the farm/site?**		[wheel_entrance] Vehicle wheel washes at site entrance [boot_entrance] Boot dip stations at site entrance [boot_pens] Boot dip stations at pig house entrances [shoe_covers] Disposable shoe covers used when entering pig pens/houses [ppe_staff] Staff PPE (clothing and footwear) is used, and kept on site [ppe_visitor] Visitor PPE (clothing and footwear) is used, and kept on site [fence] Site is contained within a livestock-proof (not including poultry) perimeter fence [unsure] Don't know [none] None
E_2_pigs_near_interviewee	**Are the pigs kept near the house of the interviewee (e.g. <50m)?**		[yes] Yes [no] No [unsure] Unsure [refused] Refused
E_2a_pigs_interviewee_distance	**How far from from the interviewee's house?**	${E_2_pigs_near_interviewee} = 'no'	[Integer]
E_2a1_unit_of_measurement	**Metres / Kilometers**	${E_2_pigs_near_interviewee} = 'no'	[m] Metres [km] Kilometers
E_3_pigs_accessible_birds	**Is the area that the pigs are kept accessible to wild and/or farmed birds?**		[yes_wild] Yes - wild birds [yes_farmed] Yes - farmed poultry [no] No [unsure] Don't know [refused] Refused

Variable	Question	Logic (i.e. relevant only if defined choices are selected)	Choices
E_4_nearby	**Is the slaughterhouse situated near any of the following? (e.g. <50m approx)**		[buildings] Residential buildings [crop] Rice/crop fields [sh] Slaughterhouse [poultry_farm] Poultry farm [pig_farm] Pig farm [water_body] Body of water (river/lake/reservoir) [road] A road [unsure] Don't know