



CEBRA Report Cover Page

Project Title, ID & Output #	1304A The value of 'early detection' and cost-effective surveillance measures against foot-and-mouth disease in Australia, #7			
Project Type	Final Report (1)			
DAFF Project Sponsor	Karen Schneider	DAFF Project Leader/s	Graeme Gardner	
CEBRA Project Leader	Tom Kompas	NZ MPI Collaborator	Brendon Gould	
Project Objectives	The project aims to provide: (a) practical measures of the cost-effectiveness of various surveillance measures against FMD in Australia, (b) overall guidance on the economic costs of potential FMD establishment and spread, under various risk-based scenarios, and (c) an assessment of the level of optimal expenditures for local surveillance against FMD in Australia.			
Outputs	<p>(1) Guidance to DAFF on the cost effectiveness of active and passive surveillance measures against FMD in Australia, including: (a) information on the effectiveness of different surveillance protocols; (b) the optimal amount of surveillance expenditures; (c) the potential costs and benefits of different levels and times of detection of a potential FMD incursion and spread in Australia and (d) suggested ways to enhance the current passive surveillance program in Australia.</p> <p>(2) End-user, AHA and DAFF workshops on the methods developed and the results obtained from the project. These methods--- both the simulation and optimizing frameworks--- can be adapted to other diseases and pests and will provide useful approaches and tools to DAFF.</p> <p>(3) Project reports and academic and scientific publications.</p>			
CEBRA Workplan Budget	Year 2013-14	Year 2014-15	Year 2015-16	Year 2016-17
	TBA \$0,000	TBA \$0,000	TBA \$0,000	TBA \$0,000
Project Changes	N/A			
Research Outcomes	Previous foot-and-mouth disease (FMD) outbreaks and simulation-based analyses suggest substantial payoffs from detecting an incursion early. However, no specific economic measures for early detection have been analysed in an optimising framework. We investigate the use of bulk milk testing (BMT) for active surveillance against an FMD incursion in Australia. We find that BMT can be justified, but only in cases where the FMD entry probability is high or the cost per bulk milk test is low. However, BMT is well suited for post-outbreak surveillance, to shorten the length of time and size of an epidemic and to facilitate proof of a disease-free state.			
Recommendations	<p>The report examines whether active surveillance using BMT against FMD is economically justified. We investigate two scenarios. In the BMT-prior, an on-going active surveillance regime using BMT for detecting FMD is implemented while in the BMT-post, the testing only starts after an FMD incursion. In both scenarios, BMT active surveillance operates on top of the existing passive surveillance system. We find that the BMT-prior is generally justified when FMD is expected to occur much more frequently than 2 outbreaks/100 year and the unit cost per BMT is much cheaper than \$36, or roughly \$2 per test. Indeed, if the unit cost per BMT remains unchanged, BMT-prior is not economical unless the FMD incursion probability is seen to be 4 outbreaks/100 years or higher. Our result also suggests the need for a more affordable BMT. For example, for an unit cost of \$10, the BMT-prior is well justified when FMD is expected to occur every 12 years or more frequently. Since bulk milk testing is not yet commercially available, perhaps a partnership between the public and private sectors is worth exploring to reduce the cost of this testing method.</p> <p>We also show that BMT is highly suited to active surveillance after an FMD incursion. The result is relatively insensitive to model parameter values, except for parameters especially crucial to the size and the cost of an FMD outbreak. As a result, BMT- post is recommended for active surveillance against FMD to shorten the length and size of an outbreak, even at the current estimated cost of the test in Australia, as well as testing for post-outbreak proof of FMD-free status. In short, it offers an important biosecurity measure to at least partially offset the otherwise devastating effects of an FMD incursion.</p>			
Related Documents	<p>Final Report (2): Assessment of approaches to enhance passive surveillance to detect emergency animal diseases in Australia.</p> <p>Final Report (3): Budgeting and portfolio allocation for biosecurity measures.</p> <p>Final Report (4): Optimal surveillance against FMD: A sample average approximation approach.</p>			
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Optimal Surveillance against Foot-and-Mouth Disease: The Case of Bulk Milk Testing in Australia

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Abstract

Previous foot-and-mouth disease (FMD) outbreaks and simulation-based analyses suggest substantial payoffs from detecting an incursion early. However, no economic measures for early detection have been analysed in an optimising framework. We investigate the use of bulk milk testing (BMT) for active surveillance against an FMD incursion in Australia. We find that BMT can be justified, but only in cases where the FMD entry probability is high or the cost of BMT is low. However, BMT is well suited for post-outbreak surveillance, to shorten the length of time and size of an epidemic and to facilitate proof of a disease-free state.

Keywords: foot-and-mouth disease; surveillance; dynamic optimisation; bulk milk testing; Australia

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Introduction

Foot-and-mouth disease (FMD) is considered to be one of the most contagious animal diseases, affecting cloven hoofed animals (OIE and FAO, 2012). The FMD virus (FMDV) can survive for a long period of time in many parts of the environment and in the recovered animal, as well as spread rapidly via various pathways to other animals (Grubman and Baxt, 2004). The disease produces debilitating effects including weight loss, decrease in milk production, loss in productivity and high mortality in young animals (Grubman and Baxt, 2004). FMD also brings significant trade barriers and substantial economic losses to affected countries (Leforban, 1999; Kompas et al., 2015).

To avoid large potential damages, FMD-free countries have focused on attempts to minimise the entry and spread of FMD. Measures include stringent quarantine at ports of entry and across main disease pathways (GAO, 2002). No matter how aggressive these measures are, complete prevention has proved to be impossible, as seen in a loss of roughly \$US25 billion over the last 15 years in countries that were previously free of FMD (Knight-Jones and Rushton, 2013). In fact, with FMDV being prevalent in two thirds of the world, coupled with rapid increases in global trade and mobility, FMD-free countries continuously face the threat of FMD outbreaks (Muroga et al., 2012). As a result, in these countries, there have been calls for more attention to be paid to post-border measures, namely active surveillance in the local animal population for early detection and rapid response to an incursion (GAO, 2002; Matthews, 2011).

Delayed detection of FMD has been found to cause substantial damage. It is a key reason that recent outbreaks have been so widespread and debilitating (Yang et al., 1998; Ferguson et al., 2001; Bouma et al., 2003; Muroga et al., 2012; Park et al., 2013). These delays often stem from the fact that infected (and infectious) animals experience a long incubation period before showing any clinical signs (Orsel et al., 2009). FMD detection traditionally relies on visual inspection (Bates et al., 2003; Matthews, 2011). But even when clinical symptoms are evident, FMD can be easily misdiagnosed and is often clinically indistinguishable from other more common diseases, as seen in several past epidemics (Bates et al., 2003). Existing analyses using simulation-based modelling suggest substantial economic payoffs from detecting an FMD incursion early (Ward et al., 2009; Hayama et al., 2013). However, none of this work has proposed any specific measures to achieve early detection, or how early that detection should optimally be, comparing costs to potential benefits.

Since early detection requires considerable upfront investment, while delays in detection result in potentially large economic losses, there is a clear trade-off between the two costs (Mehta et al., 2007). Early detection results in avoided losses, but the cost of detection is larger the earlier FMD is detected. The challenge in defining the optimal detection level, which basically minimises the sum of these two costs, is rooted in complications surrounding the growth and spread of the disease. As FMD spreads across time and space, its proliferation is formally described by a spatial-dynamic process. This process is complicated by the fact that not only does FMD spread locally, FMDV also transmits rapidly over a long distance, with a spread rate that varies across different animal types as well as landscapes (Donaldson et al., 1982; Kao, 2001; Keeling et al., 2001; Grubman and Baxt, 2004). These features

make the spatial dynamics of FMD too complicated to simply apply recent (albeit useful) developments in the literature on spatial dynamic optimisation (Sharov, 2004; Epanchin-Niell et al., 2012; Epanchin-Niell and Wilen, 2012).¹ In particular, the nature of this multi-host dynamic process, so characteristic of FMD, spreading not only within but across regions during an outbreak, has not been considered in any existing optimisation models. A principal reason is the ‘curse of dimensionality’ (Bellman, 2003), which makes the resulting large scale problems difficult if not practically impossible to solve.

In terms of policy responses to an incursion, existing literature largely focuses on the relative effectiveness of various FMD control strategies based on disease and spread simulations. These simulations are performed on epidemiological models developed using farm data, transmission parameters, and a spatial transmission kernel (the relative probability of transmission over some distance) (Morris et al., 2001; Ferguson et al., 2001; Kao, 2001; Tomassen et al., 2002; Keeling et al., 2003a,b; Garner and Beckett, 2005; Tildesley et al., 2006; Ward et al., 2009; Hayama et al., 2013). While these approaches succeed in articulating the spatial-temporal features of an FMD incursion, in an often elaborate ways, they do not provide a ‘global’ optimal solution. These procedures generally only simulate a small number of policy and disease transmission scenarios, thus possibly missing the optimal outcome (Kobayashi et al., 2007).

To find an optimal policy while retaining FMD-epidemic features, a two-step combination of simulations and dynamic optimisation has been proposed by Kobayashi et al. (2007). In particular, the authors estimate transmission parameters using simulations generated by an FMD spread model, and then use these results to find an optimal solution in a dynamic programming setting. The procedure reduces the dimension of the spatial dynamic optimisation problem, making it solvable. Although the authors cannot take into account long-range dispersal patterns, which is crucial in modelling FMD, their simulation-based dynamic optimisation approach does allow for important insights.

Our paper aims to complement the literature in two important ways. First, we consider a specific active surveillance measure for the early detection of FMD, bulk milk testing. We find the optimal level of spending on this measure, considering its cost and its potential benefit in reducing the economic damages that would occur from an FMD incursion in Australia. Second, our optimisation approach takes into account the features of a multi-host, multi-region setting, with both local and long-range dispersal, which are typical in an FMD outbreak. To do so, we combine three techniques: (i) simulations performed on a fully spatial dynamic spread model of FMD for Australia (the AusSpread model); (ii) meta-population modelling; and (iii) spatial dynamic optimisation. That is, the simulation results from the AusSpread are used to estimate transmission parameters, which, in turn, are

¹Studies on optimal surveillance (i.e., search algorithms) can be found for other invasive species with more basic spatial-dynamic processes, e.g. Mehta et al. (2007); Bogich et al. (2008); Hauser and McCarthy (2009); Kompas and Che (2009); Gramig and Horan (2011); Homans and Horie (2011). See Epanchin-Niell et al. (2012) for a review of the literature. The approach largely applied here is an aggregate dynamic optimisation method, which does not take into account spatial heterogeneity. The consequences of this (rather limiting) approach are discussed in detail by Wilen (2007).

fed into in a meta-population model to represent the typical features of an FMD outbreak. Results from this meta-population model are then used for dynamic optimisation. We are thus able to model the typical features of an FMD incursion and spread, while still finding an optimal level of active surveillance against it.

Surveillance for the early detection of FMD and the study area

Passive surveillance

Passive surveillance for FMD is based on notification of clinical symptoms in animals by ‘front-line people’. Front-line people include farmers, meat inspectors and veterinarians. In spite of the serious consequences of any delay in detecting FMD, which may result from the passive system, this approach is generally applied throughout the world, including in key livestock exporting countries, and often without active surveillance measures in place (Bates et al., 2003; Matthews, 2011). There are two inherent problems with this approach, which may likely lead to a delay in detecting FMD in otherwise unaffected countries. First, with visual inspection, it is often difficult to recognise FMD, and it can be easily misdiagnosed as one of a number of other clinically indistinguishable diseases (e.g., bovine viral diarrhea, infectious bovine rhinotracheitis, blue-tongue, and contagious ecthyma) (Bates et al., 2003). The error in diagnosis can also be made worse due to strain and host-specific variations in disease severity and infection (Dunn et al., 1997), as well as from a basic lack of understanding and experience with the disease (McLaws et al., 2009). Second, while it is hoped that farmers take appropriate reporting and biosecurity safeguards under this approach, they may instead delay, and make decisions based on the perceived risk to their own enterprise from a disease incursion (Palmer et al., 2009). In many cases, there is also a basic lack of trust with government institutions and biosecurity regulations, along with issues over the cost of repeated visits by the veterinarian (Palmer et al., 2009; East et al., 2013).

Active surveillance: the bulk milk test

Active surveillance entails frequent and intensive efforts to establish the presence of a disease in an animal or area (Paskin, 1999). This approach can detect recently infected cases that might not otherwise be identified by passive surveillance, at least not until much later in the course of the disease and its spread. Active surveillance can be very expensive and time-consuming. There are many types. Here, we consider bulk milk testing (BMT) as an active surveillance measure for FMD. This test is based on the finding that the milk from FMD incubating cattle may contain an FMD virus for up to 4 days before clinical signs of the disease become evident (Burrows, 1968; Donaldson, 1997). Reid et al. (2006) developed a test using a real-time reverse transcription polymerase chain reaction (rRT-PCR) as a diagnostic tool for detecting FMDV in milk. Not only quicker and more sensitive than virus isolation, an established diagnostic method also suitable for testing FMDV in milk, rRT-PCR is apparently a very cost-effective test since milk samples need to be collected for various tests for food safety purposes in any case (Bates et al., 2003). Furthermore, rRT-PCR also appears to perform much better than other possible approaches to active surveillance, such as sale-yard inspections (Garner et al., 2015).

Study area

Our study area is the state of Victoria in Australia. We choose this area as a case study for three reasons. First, Australia fundamentally relies on passive surveillance against FMD (Matthews, 2011; Garner et al., 2015) throughout the country and in Victoria, and passive surveillance has inherent problems as described above. In particular, the probability of making an appropriate diagnosis by a farmer or a veterinarian, and reporting correctly, are low, resulting in an estimate of between 19 and 35 elapsed days before initially infected farm animals are reported (Higgs et al., 2012). This passive surveillance system is applied in Australia despite it being among the top ten largest livestock producing and exporting countries in the world (USDA, 2014). Indeed, Australia’s agriculture is highly exposed to the world market with farmers exporting around 60% of what they grow and produce, and earning about \$32.5 billion per year from exports in a \$155 billion agricultural industry (National Farmers’ Federation, 2012). Thus, the damage that could be caused by an FMD outbreak to Australia is likely to be very large, with estimates in the range of \$6-50 billion, depending on the size and length of the outbreak (Productivity Commission, 2002; Buetre et al., 2013).

Second, among the 5 states and 3 territories in Australia, Victoria likely bears the highest risk of an FMD introduction, establishment and spread. (East et al., 2013). This is associated with Victoria having higher livestock and human population densities, livestock production being relatively close to high volume air and sea ports and high suitability of environmental conditions for FMD virus survival. Victoria is also Australia’s largest food and fibre exporting state and is the centre of Australia’s dairy production (DEPI 2014). Although occupying only 3% of Australia’s land mass, it has 9.2 % of the national beef cattle population, 63.6% of the dairy cattle population, 24.8% of the pig population and 21.3% of the sheep population (ABARES, 2014).

Finally, the distribution and composition of livestock in Victoria raises both special challenges to the passive surveillance system while offering opportunities for the application of BMT active surveillance. For the former, the range and mix of species (Figure 1) means that FMD could be misdiagnosed as a more common endemic condition, while the large number of sheep in the state could result in delayed detection due to the generally mild symptoms in this species (Kitching et al., 2006). At the same time, pig farms, which bear the highest risk of being exposed and infected to FMDV due to their omnivorous habits of eating both meat and plant products (Matthews, 2011), are scattered throughout the state, thereby making the farms vulnerable to a widespread outbreak. In terms of the opportunities, applying BMT to Victoria, as an active surveillance measure, is natural. Victoria is the main dairy state in Australia, with large concentrations of dairy cattle and extensive bulk milk collection points.

Methods

Our goal is to find the optimal level of spending on BMT active surveillance considering its potential benefit in reducing the economic damages of an FMD incursion in Victoria. To do so, we follow Kobayashi et al. (2007) in feeding simulation-based estimates of spread rates into a dynamic model to overcome the curse of dimensionality, while largely retaining the

spatial heterogeneity of the dynamic process. In addition, following Epanchin-Niell et al. (2012), we use a probabilistic model of FMD dynamics to search for the expected (or ‘steady state’) optimal level of BMT active surveillance. Arguably, the approach of focusing on the steady state may perform poorly in cases where invasions cause relatively slow movements to a new equilibria, or where equilibria are never attained, but for the most part the approach is generally applicable (Finnoff et al., 2010). This is especially the case for FMD since a FMD outbreak is typically short in duration and reaches a steady state quickly. Furthermore, we combine these two approaches with a meta-population modelling technique (Hanski and Gilpin, 1997; Hanski and Gaggiotti, 2004; Keeling and Rohani, 2008). The latter allows us to take into account heterogeneity in FMD spread by host type, and the dependency among regions in FMD spread, both of which are not possible in the model contained in Epanchin-Niell et al. (2012). It also allows us to account for FMDV dispersal over a long spatial range, which too is not possible in the model provided by Kobayashi et al. (2007).

To achieve our goal, we consider two scenarios. The first scenario is to implement an on-going active surveillance program using BMT for detecting FMD, before there is a known or suspected incursion, called ‘BMT-prior’. Since this scenario can be very expensive when the probability of an FMD incursion is low and/or the cost of maintaining the programme is high, we examine a second scenario in which active surveillance using BMT starts only after a known FMD incursion. We call the second scenario ‘BMT-post’. These two scenarios are worth consideration only if their net benefits exceed those under the passive surveillance system. An active surveillance program, if implemented, does not replace on-going passive surveillance, since the latter always exists. Rather, it complements it, and it is assumed that an outbreak will always be detected by the passive surveillance system, if it is not first detected by an active surveillance program.

Epidemiological model: a probabilistic meta-population model of FMD spread

We begin with the epidemiological model. Consider an exotic FMD outbreak, from an outside source, with an arrival probability λ drawn from a Bernoulli distribution. We choose a Bernoulli distribution since the arrival probability of more than one FMD outbreak, over a particular short time period (e.g., a day in our paper), is almost zero. FMD in our model can spread locally and jump over a long range to create multiple local clusters of infected farms. Each local cluster of FMD infected farms is called a colony. An outbreak can have more than one colony and each colony can have more than one infected farm.

We define F as the set of farm types, $F = \{pig, non-pig\}$. Each farm type has its own FMD transmission rate to farms of the same type, β^{ii} , and to the ones of different types, β^{ij} where $i \neq j$ and $i, j \in F$. Our farm classification is based on the fact that pigs get infected and transmit FMDV differently, compared to sheep and cattle. In particular, pigs usually become infected by direct contact with infected animals or by eating FMDV-contaminated material, while sheep and cattle are highly susceptible to a virus infection via aerosol (Grubman and Baxt, 2004). Pigs also excrete large amounts of air-borne virus while other animals do so less (Alexandersen and Donaldson, 2002). Finally, we allow for the fact that different strains may have different impacts on pigs and other animal types (Dunn et al., 1997).

We assume, as commonly thought in Australia, that the FMD outbreak starts from a pig farm (i.e., the *seed* farm) in the first colony since pigs have the highest risk of being exposed to and infected by FMDV (Kitching et al., 2006; Matthews, 2011). This assumption is relaxed in the second colony so that any farm or animal type can get infected with a probability π^s where $s \in F$.

We define L as the set of regions, $L = \{dairy, non-dairy\}$, where the transmission rate of each farm type also depends on local heterogeneity (Kao, 2001). Dairy regions in Victoria are located in the south of Gippsland, the south-east of Barwon South West, and the joint area between Loddon Mallee and Hume (Figure 1). Here, not only are dairy cattle highly concentrated, with a likelihood that FMDV can be transmitted via milk droplets (Grubman and Baxt, 2004), but also the livestock density is particularly high.

We define Φ^l as the number of days it would take for FMD to be detected by passive surveillance, which varies across regions. We define p as the number of possible infected farms in a colony, and ϕ as the colony infection ‘age’, which is measured in days, where $\phi \in [1, 2, \dots, \Phi^l]$. Accordingly, p_ϕ is the number of farms infected in a colony of infection age ϕ . We assume that all farms in the colony of infection age older than Φ^l are ‘stamped out’ according to Australian Veterinary Emergency Plan (AUSVETPLAN) (Animal Health Australia, 2014), while the ones in those of infection age younger than one are susceptible.

We define Q as the set of possible numbers of colonies at each time step, starting from the first day of an outbreak, $Q = \{q_1, q_2, \dots, q_t\}$ where q_t is the number of colonies in day t of an outbreak. We assume that no new colony is established once the outbreak is detected because Australia’s national livestock stand-still policy under AUSVETPLAN will be implemented, preventing all animal movements across the country (Animal Health Australia, 2014).

We define η^{ql} as the probability of a colony being generated in region l , where $l \in L$ and $q \in Q$. For $q = 1$, η^{1l} is the location probability of the first colony and follows a Bernoulli distribution. When $q > 1$, η^{ql} is the probability of a ‘child’ colony being generated in the region l , and is calculated as $\eta^{ql} = \sum_m \eta^{1m} \times \kappa^{ml}$ where $m, l \in L$ and κ is the probability of the location of a ‘child’ colony generated by a ‘mother’ colony.

Following Kobayashi et al. (2007), we assume the local growth of FMD in farm type i with the seed farm s in region l can be described by a logistic function (Verhulst, 1838), and an undetected colony will move to its next age so that the local dynamics of FMD in each colony is given by:

$$p_{\phi+1}^{lsi} = p_\phi^{lsi} + (N^{li} - p_\phi^{lsi}) \sum_j \beta^{lij} \frac{p_\phi^{lsj}}{N^{lj}} \quad \text{for } s, i, j \in F; l \in F; \quad \text{and } \phi \in [1, 2, \dots, \Phi] \quad (1)$$

where N^{li} and N^{lj} are carrying capacities. Likewise, the growth of colonies can also be described by a logistic function, as done in Levins (2007):

$$q_{t+1} = q_t + g \times \frac{(q_{\max} - q_t)q_t}{q_{\max}} \quad (2)$$

where g is a colony growth parameter and q_{\max} is the carrying capacity.

Economic model

The economics for our case is basic and designed to exploit the tradeoff between spending more on early detection and benefiting from avoided losses, compared to the cost of the surveillance program itself. Active surveillance involves upfront investment, but also potentially reduces the size and length of an outbreak. The more one spends on the former, the less needs to be spent on the latter. When the sum of these two expenses are minimised, subject to all of the conditions and constraints in the model, the optimal active surveillance level is reached.

BMT-prior

In the BMT-prior scenario, an on-going active surveillance programme using BMT for detecting FMD is maintained. We denote \mathcal{T}^l as the number of days it takes for FMD to be detected by BMT, where $\mathcal{T}^l < \Phi^l$, and \mathcal{T}^l varies across regions in the same way as Φ^l . We assume that a tanker visits h farms in one trip to collect milk every day, and k is the testing interval of BMT (i.e., one test per k day(s)). The daily cost of this on-going active surveillance program, $C_{\text{bmt}}^{\text{prior}}$, is calculated as :

$$C_{\text{bmt}}^{\text{prior}} = \delta \times \frac{M_{\text{df}}}{k \times h} + E_{\text{daily}} \times M_{\text{fac}} \quad (3)$$

where δ is the unit cost per rRT-PCR milk test; M_{df} is the number of dairy farms; E_{daily} is the daily amortised cost of the testing equipment, which is assumed to be fully depreciated after 10 years; and M_{fac} is the number of milk collection points or factories in Victoria.

An FMD outbreak is expected to bring economic costs to Australia. Here we focus on the direct costs including the revenue losses and the control costs of an outbreak, following recent studies on the economic impact of an FMD outbreak in Australia (Buetre et al., 2013; Garner et al., 2012; Abdalla et al., 2005; Productivity Commission, 2002). These direct economic costs occur after FMDV is detected. We do not consider the production loss, such as weight loss, milk yield reduction, reduction in fertility and high mortality rates among young animals, since it is deemed negligible due to Australia's 'stamp out' policy of eliminating animals that are infected (Buetre et al., 2013; Garner et al., 2012; Abdalla et al., 2005).

The revenue losses are largely caused by immediate and prolonged export bans to Australia's FMD-sensitive markets and depressed domestic prices (Buetre et al., 2013). The impact of an FMD outbreak on revenues can be long-lasting, and is largest in the first year (Productivity Commission, 2002). Therefore, the expected daily revenue losses which take into account the FMD arrival probability is calculated as:

$$C_r = \lambda \left[c_{r1}(D_{\text{outbreak}}^{\text{prior}} + D_{\text{mkt1}}) + c_{r2}D_{\text{mkt2}} \right] \quad (4)$$

where c_{r1} and c_{r2} is the daily revenue losses in the first and the following years, while D_{mkt1} and D_{mkt2} are the corresponding durations when markets react to an FMD outbreak, inducing revenue losses; $D_{\text{outbreak}}^{\text{prior}}$ is the expected outbreak duration from the day of the first

detection until the day of the last detection, plus the time for culling, ϱ^{bmt} , and the time for quarantine, ς^{bmt} , and therefore, $D_{\text{outbreak}}^{\text{prior}}$ is largely determined by k , \mathcal{T}^l and Φ^l (i.e., $D_{\text{outbreak}}^{\text{prior}}(k, \mathcal{T}^l, \Phi^l)$).

The control costs include the cost of outbreak management and the cost of eradication (which includes expenses on compensation to farms, slaughtering and disposal, as well as decontamination) (FAO, 2002; Doel, 2003; Kompas et al., 2015). The expected outbreak management cost, C_m , which takes into account the FMD arrival probability λ is calculated as:

$$C_m = \lambda \times c_m \times D_{\text{outbreak}}^{\text{prior}} \quad (5)$$

where c_m is the daily operating cost of an FMD disease control centre(s).

There are two things worth noting in equation (5). First, in the formal model, BMT-prior is replaced by the existing passive surveillance system when it fails to detect FMDV earlier than with passive surveillance. Second, C_m is an expectational term, and any colony of age \mathcal{T}^l or older can be detected by BMT at any time with an equal chance during the testing interval k . Here BMT testing efficacy is assumed to be uncorrelated with the testing interval, which is likely given the mechanisation in the milk testing process.

The expected expenses on eradication, C_e , are based on the number of colonies being detected and their farms. As a result, C_e depends on λ (the FMD arrival probability), η^{ql} (the location probabilities of the first colony and a ‘child’ colony), π^s (the probability of a seed farm being a particular farm type), k (the BMT testing interval), as well as \mathcal{T}^l (the number of days it would take for FMD to be detected using BMT). Again, C_e^{prior} is considered in expectational form, and is calculated as:

$$C_e^{\text{prior}} = \frac{\lambda}{k} \sum_l \sum_{t=\mathcal{T}^l}^{\mathcal{T}^l+k-1} \sum_{q=1}^{q_t} \eta^{ql} \sum_s \pi^s \sum_i p_t^{qlsi} c_e^{li} \theta \quad \text{for } l \in L; s, i \in F \quad (6)$$

where c_e^{li} is the unit cost of eradication per farm, which varies across farm types and regions; and θ is the culling ratio which takes into account the pre-emptive culling of susceptible farms.

The objective is to choose the BMT testing interval (k_{prior}^*) that minimises TC^{prior} , which is the sum of on-going active surveillance costs, expected outbreak management costs and expected eradication costs, or:

$$\underset{k}{\text{minimize}} \quad TC^{\text{prior}}(k) = C_{\text{bmt}}^{\text{prior}}(k) + C_r(k) + C_m(k) + C_e^{\text{prior}}(k) \quad (7)$$

There are two things worth noting in equation (7). First, the optimal value of the total cost ($TC^{\text{prior}}(k_{\text{prior}}^*)$) should always be compared with the expected total cost under passive surveillance alone, $\overline{TC}_{\text{ps}}$, since an active surveillance program is recommended if and only if $TC^{\text{prior}}(k_{\text{prior}}^*) \leq \overline{TC}_{\text{ps}}$. Second, a discount rate is not needed in equation (7), as shown in a proof in Appendix A.

The corresponding expected $\overline{TC^{ps}}$ for comparison is calculated as:

$$\overline{TC^{ps}} = \lambda[c_{r1}(D + D_{mkt1}) + c_{r2}D_{mkt2}] + \lambda c_m D + \lambda \sum_l \sum_{q=1}^{q_t} \eta^{ql} \sum_s \pi^s \sum_i p_t^{qlsi} c_e^{li} \theta \quad (8)$$

for $l \in L; s, i \in F, t = \Phi^l$

where $D(t, \Phi^l)$ is the expected outbreak duration, plus the time for culling, ϱ^{ps} , and the time for quarantine, ς^{ps} , under passive surveillance; and other notations are as specified in equations (4), (5) and (6).

BMT-post

The previous scenario, BMT-prior, can be very expensive. Hence, in the second scenario, BMT-post, we consider the case when BMT active surveillance starts only after an FMD incursion. Accordingly, we do not need to consider the FMD arrival probability λ in this scenario.

We ask whether the benefit of reducing the size and length of an FMD outbreak once it happens outweighs the cost of doing so? To answer this question, we also need to choose the BMT testing interval (k_{post}^*) that minimises the total cost of an outbreak, TC^{post} . Being similar to TC^{prior} , TC^{post} also includes four cost items related to surveillance, revenue losses, eradication and outbreak management. While the revenue losses and outbreak management costs are similar for the two scenarios, except with $D_{outbreak}^{prior}$ now being replaced with $D_{outbreak}^{post}$, the other two cost items are slightly different. In particular, the surveillance cost in the BMT-post scenario is calculated as:

$$C_{bmt}^{post} = \delta \times \frac{M_{df}}{k \times h} \times D_{outbreak}^{post} + E_{one-off} \times M_{fac} \quad (9)$$

where $D_{outbreak}^{post}$ is the expected outbreak duration counting from the time FMD is detected by passive surveillance, plus the time for culling, ϱ^{bmt} , and the time for quarantine, ς^{bmt} , minus the time for setting up testing equipment; and $E_{one-off}$ is the one-off cost of the testing equipment; with all other notations as in equation (3).

The eradication cost for an outbreak under BMT-post, C_e^{post} is calculated as:

$$C_e^{post} = \sum_l \sum_{q=1}^{q_\epsilon} \eta^{ql} \sum_s \pi^s \sum_i p_t^{qlsi} \times c_e^{li} \times \theta$$

$$+ \frac{1}{k} \sum_l \sum_{t=\mathcal{T}^l}^{\mathcal{T}^l+k-1} \sum_{q=q_\epsilon+1}^{q_t} \eta^{ql} \sum_s \pi^s \sum_i p_t^{qlsi} \times c_e^{li} \times \theta \quad \text{for } l \in L; s, i \in F \quad (10)$$

where q_ϵ is the number of colonies in day ϵ when equipment is ready for BMT, and other notations are as in equation (6). The first term in equation (10) is the eradication cost of the colonies detected by the passive surveillance system before the testing equipment is available for BMT active surveillance, while the second term is for the colonies detected by BMT

active surveillance afterwards. Equation (10) is used to calculate the eradication cost of an outbreak once it occurs, not the expected eradication cost as in equation (6) and, therefore, as mentioned, it does not need to take into account the FMD arrival probability λ .

The optimisation problem in this scenario is given by:

$$\underset{k}{\text{minimize}} \quad TC^{\text{post}}(k) = C_{\text{bmt}}^{\text{post}}(k) + C_r(k) + C_m(k) + C_e^{\text{post}}(k) \quad (11)$$

Similar to the scenario BMT-prior, the minimum value $TC^{\text{post}}(k_{\text{post}}^*)$ needs to be compared with the corresponding total cost of an outbreak under passive surveillance, TC^{ps} , which is calculated as:

$$TC^{\text{ps}} = [c_{r1}(D + D_{\text{mkt1}}) + c_{r2}D_{\text{mkt2}}] + c_m D + \sum_l \sum_{q=1}^{q_t} \eta^{ql} \sum_s \pi^s \sum_i p_t^{qlsi} c_e^{li} \theta \quad (12)$$

for $l \in L; s, i \in F; t = \Phi^l$

where all notations in equation (12) are the same as in equation (8). The difference between these two equations is that the latter refers to the total cost of an outbreak once it occurs under the passive surveillance system, while the latter refers to the corresponding expected value given the FMD arrival probability λ .

It is worth noting that in this scenario, we focus on the cost of one particular outbreak. As a result, the total cost needs to be discounted as shown in Appendix A. That said, since the outbreak duration is typically short, being less than a year, and the prevalent discount rate in Australia is low, we drop the discount rate for simplicity.

Model parameterization

Table 1 describes parameters and their values. The epidemic parameters are estimated based on simulation outcomes from a spatial model for FMD, i.e., the AusSpread model. This model has been described elsewhere (Garner and Beckett, 2005), and here only a summary is presented. Developed from a Markov chain model and modified to include stochastic elements, AusSpread is a state-transition susceptible-latent-infected-recovered (SLIR) model. It is based on real farm point-location data, and contains detailed information about each farm such as the number and type of animal species and the production type. AusSpread simulates disease spread in daily time steps, allowing for interactions between herds or flocks of different animal species and production type. It accommodates the spread of disease by way of animal movements through sale-yards, wind-borne spread, local spread, as well as by direct and indirect farm-to-farm contact.

AusSpread can be used to simulate an outbreak in two phases, including pre-detection and post-detection. In the pre-detection phase, FMD can spread with the normal pattern of animal movements and other forms of interactions while in the post-detection phase, policies described in AUSVETPLAN or customised measures can be configured once the disease has been confirmed. Model outputs include a range of maps and information describing the geographic extent of the outbreak, its duration, the number of infected herds or flocks,

tracing information to identify dangerous contacts (DC) and premises, contiguous (CP) to infected premises (IP), and so on, at each time step. Since the model is run in a series of random iterations, their simulation outcomes form a set of random data, which can be used to estimate parameters for each epidemic.

To obtain data for estimating the parameters for an epidemic, we simulate an outbreak and its spread under two setups. Both setups have the current passive surveillance in place, but one also has BMT. The number of simulations is 322 for the former and 222 for the latter, for an event where an outbreak is randomly introduced into a pig farm of less than 500 pigs. This event is the most likely since, as mentioned, pigs have the highest risk of getting infected by FMD, and small farms tend to have less stringent biosecurity measures (Hernández-Jover et al., 2012).

Using non-linear methods, we fit equations (1) and (2) to the simulation data to obtain estimates for FMD local transmission rates (β^{ii} and β^{ij}), the long distance transmission rate (g) and the maximum carrying capacity of colonies (q_{\max}). The maximum carrying capacities of each farm type in each region are then calculated by using the number of farms of that type in that region divided by the estimated $\widehat{q_{\max}}$. Details on estimation are in Appendix B. All estimates, except the ones for the local transmission rates of pig farms to farms of other type, are statistically significant at 1% level and have expected signs (Table 1). The statistical insignificance and ‘wrong signs’ of estimates for the local transmission rates of pig farms to farms of other type is not surprising due to the fact that pig farms account for less than 1% of the total number of farms in Victoria. Therefore, we drop these parameters from our estimation, and set their values to zero in the model.

Other parameters for an epidemic, including detection time, the culling ratio, the probability of being a seed farm, and the location probabilities of colonies are drawn from the average values of the simulation data. Last, but not least, the FMD arrival probability, λ , is estimated using the information on the past FMD incursions in Australia. Since there were four FMD incursions over the last 200 years (Productivity Commission, 2002), we assume the FMD arrival probability is 2 outbreaks/100 years.

Parameter values for the economic model are estimates from the literature and drawn from expert opinion. In particular, the daily costs of revenue losses due to an FMD outbreak are \$5.4 and \$0.807 billion in the first year and the following 9 years, respectively. These estimates are based on the average revenue losses of \$6.21 billion for a small FMD outbreak in Victoria, controlled using a ‘stamp-out’ policy estimated by Buetre et al. (2013), and the assumption of 87% of these revenue losses being incurred in the first year (Productivity Commission, 2002). The unit cost of eradication per farm and the daily operating cost of an FMD disease control centre(s) is based on Garner et al. (2012) and Abdalla et al. (2005).

With regard to BMT specifically, Garner et al. (2015) discuss in detail the possibility of implementing BMT and its costing in Australia, noting that BMT is not yet commercially available. Accordingly, a typical milk tanker of 20,000 litres can collect milk from about 5 farms since the average size of an Australian dairy herd is 225 cows and the average yield is 17 litres/cow/day. With 7590 dairy farms in Victoria, and tankers visiting 5 farms/trip, there will be 552,552 (i.e. $(7590/5) * 52$ (weeks) $* 7$ (days)) milk samples to test on a daily

basis. The efficacy of bulk milk testing is not sensitive to the testing interval (Garner et al., 2015). Testing at the tanker level could allow detection of a small number of infected cows since rRT-PCR is able to detect FMDV in milk being diluted 10,000 fold (Reid et al., 2006). For milk rRT-PCR to have an analytical sensitivity of $10^{-2.5}$ or 10^{-3} , we need 2 to 4 infected cows per farm and at least one infected farm contributing to a tanker. In this model, we use the farm level threshold of 3 infected cows for detection ($\sim 10^{-2.6}$). The diagnostic sensitivity of milk rRT-PCR is 95%. We assume a delay of two days from when milk is tested until FMDV is confirmed to allow for the trace back of individual farms and confirmation on investigations and testing. The cost per bulk milk test and testing equipment is estimated based on expert opinion (at conservative values). All values are in Australian Dollars in 2014 unless otherwise specified.

Results

Results for our paper are obtained using Fortran and the software R (R Core Team, 2014, version 3.1.1). In particular, we use packages **sensitivity** (Pujol et al., 2014), **triangle** (Carnell, 2013), **lhs** (Carnell, 2012), **reshape** (Wickham and Hadley, 2007), **maptools** (Bivand and Lewin-Koh, 2015), **sp** (Pebesma and Bivand, 2005; Roger S. Bivand, 2013), **rgeos** (Bivand and Rundel, 2014), **ggplot2** (Wickham, 2009), **Plotrix** (J, 2006), **RColorBrewer** (Neuwirth, 2014), and **tikzDevice** (Sharpsteen and Bracken, 2015).

BMT-prior

The expected total cost of an FMD outbreak per day under the BMT-prior scenario is presented against passive surveillance alone in Figure 2. For illustrative purposes only, the total expected cost of an outbreak is calculated for a case where an FMD detection relies solely on active surveillance using BMT (the dashed-dotted red line). This case is not realistic since passive surveillance always exists. However, in this unrealistic case, a clear trade-off can be seen between the cost of active surveillance versus revenue losses and the costs of eradication and outbreak management. The earlier an outbreak is detected, the less damage it would bring about, but then the more costly is the program. Given this trade-off, the expected total cost is minimised at the BMT testing interval of 9 days as seen by the large red dot. Nonetheless, this total expected cost of an outbreak under BMT without passive surveillance in place is always higher than its counterpart under passive surveillance (the solid blue line), suggesting that FMD detection using BMT is less cost-effective than simply using the current passive surveillance.

The more realistic case we consider is BMT implemented on top of the current passive surveillance system. That is, FMD infected farms not detected earlier under BMT-prior are assumed to be detected by passive surveillance. In this case, given the parameter values in Table 1, the expected total cost of an FMD outbreak is a monotonically diminishing function, having no optimal point. The reason for the non-existence of an optimum is twofold. First, the annual cost of an active surveillance programme, C_{bmt}^{prior} , is very large compared with revenue losses (C_r) and the expected costs of eradication (C_e^{prior}) and outbreak management (C_m), given the low FMD arrival probability (λ). Second, the difference in the time it

would take for FMD to be detected under BMT-prior and under passive surveillance is not particularly large; on average, 5 and 2 days for dairy and non-dairy regions, respectively (Table 1). Consequently, as the cost of active surveillance falls when the BMT testing interval increases, more infected farms are likely to be detected by passive surveillance rather than by active surveillance. To this end, revenue losses and the costs of eradication and outbreak management do not increase quickly enough to create an optimum, which results in a monotonic fall of the expected total cost of an FMD outbreak as the BMT testing interval increases. Finally, in addition to not having an optimum, the expected total cost of an FMD outbreak is always higher for BMT-prior than under passive surveillance, making BMT-prior non-economic.

When would BMT-prior be economically worthwhile to be implemented? Put differently, we ask when an optimum exists, or at these optimal points, is the total expected cost of an outbreak under BMT-prior less than that under passive surveillance? Those optimal points are represented in Figure (3), corresponding to varying values of the unit cost per bulk milk test and the FMD arrival probability. The FMD arrival probability varies from 1 to 30 outbreaks per 100 years, while the value of unit cost per bulk milk test varies from \$1 to \$50. As can be seen, no optimal points are obtained where the FMD arrival probability is small and the unit cost per bulk milk test is large (the top left region). Optimums are achieved only for a BMT testing interval in the range of 1-5 days. This result is plausible since FMD can be detected, on average, 1-5 days earlier by BMT active surveillance than by passive surveillance (Table 1), and FMDV is contained in milk for up to 4 days before clinical signs of the disease become evident (Burrows, 1968; Donaldson, 1997).

Figure (3) is also revealing in several other ways. First, if the probability of an FMD incursion is 2 outbreaks/100 years as assumed in this paper, it is not cost effective to implement on-going surveillance using BMT unless the unit cost per bulk milk test is \$2 or lower. While our estimated unit cost per bulk milk test is \$36, it seems likely that BMT may be much less expensive when it is commercially available and efficiently combined with other milk tests for food safety purposes. Second, if the unit cost per test remains \$36, then the probability of FMD incursion needs to be roughly 4 outbreaks/100 years for on-going surveillance using BMT to be cost-effective. There are, in fact, good reasons to believe that the FMD arrival probability could be much higher than our assumed 2 outbreaks/100 years, in spite of Australia's good record of preventing FMD. Indeed, over the last 50 years, FMD has occurred more regularly in FMD previously-free countries due largely to increasing globalisation and international trade. That, combined with the risk that goes with increases in FMD prevalence in now two-thirds of the world (Knight-Jones and Rushton, 2013; Kompas et al., 2015), suggests that probability calculations based on data from a century or more ago are no longer truly reliable. The recent outbreak from an unknown source in Japan, also an island country with strict quarantine regulations, serves as a good warning for Australia (Muroga et al., 2012).

BMT-post

In this scenario, active surveillance using BMT only starts after an FMD outbreak occurs, and also operates on top of the existing passive surveillance system as in BMT-prior. As

seen in Figure (4), the total cost of an outbreak under passive surveillance alone is above BMT-post for any BMT testing interval of less than 100 days (or more). Furthermore, the optimal point is achieved when BMT is implemented every single day. These results are clearly in contrast with those for BMT-prior. The reason for these results is that the cost for BMT active surveillance (C_{bmt}^{post}) becomes relatively small in comparison with the revenue losses and the control cost of an FMD outbreak, since the latter are known, and no longer considered as expected values. In fact, revenue losses and the control costs now become very high, with certainty, generating substantial benefits for each extra day that an outbreak is shortened. Overall, our result suggests that using bulk milk testing as a means of active surveillance is much more cost-effective than merely relying on passive surveillance.

Given this result, we check to see how sensitive it is to parameter values. To do so, we focus on the ratio of the total cost under the BMT-post and the total cost under passive surveillance alone. Starting at the optimum (when the ratio is much smaller than 1), with all parameter values specified as in Table 1, we vary estimated coefficients within \pm of their standard deviations. Since the culling rate, θ , can be high due to possible delay in the culling process which, in turn, can increase the number of IP, CP and DC farms, we let it vary in the range [-10%,+30%] of its value. We vary the number of farms that a tanker can visit in one go (h) by $\pm 20\%$ of its value. The unit cost per BMT could fall substantially when it becomes commercially available; we therefore vary its value in the range [-90%, +10%]. With regard to revenue losses, since the main difference in these losses under the BMT-post and passive surveillance alone rests on the differences in the corresponding outbreak duration, we focus on the losses caused by outbreak durations. This avoids revenue loss dominating other parameters in this exercise. We also exclude from our sensitivity analysis some parameters that are basically fixed, given actual data, such as the number of milk factories, the number of dairy farms and the cost of testing equipment, along with protocols such as the quarantine duration and restrictions on animal movements. All other coefficients are varied within $\pm 10\%$ of their values.

Following (Thomas et al., 2011; Nguyen et al., 2015), our sensitivity analysis is based on a standard combination of Latin Hypercube Sampling (LHS) for efficient sampling of the parameter space (McKay et al., 1979), and the multivariate Partial Rank Correlation Coefficient (PRCC) analysis (Campolongo et al., 2000; Marino et al., 2008). In particular, we randomise coefficients using a triangle distribution with Latin Hypercube Sampling. We then calculate PRCCs, where values with magnitudes close to one are most important, and the sign is the correlation. Based on 3000 runs, this sensitivity analysis suggests that our result is most sensitive to culling time and detection time, and to a lesser extent, daily revenue loss and the unit cost of a bulk milk test (see Figure 5). This makes good sense since culling time and detection time play a pivotal role in determining the size and length of an outbreak, while daily revenue loss and the unit cost of a bulk milk test are key determinants for the potential costs and benefits of a policy intervention.

Conclusion

This paper has examined whether active surveillance using BMT against FMD is economically justified. We investigate two scenarios. For BMT-prior, an on-going active surveillance regime using BMT for detecting FMD is implemented while in BMT-post, the testing only starts after an FMD incursion. In both scenarios, BMT active surveillance operates on top of the existing passive surveillance system.

We find that BMT-prior is generally justified when FMD is expected to occur much more frequently than 2 outbreaks/100 year and the unit cost per BMT is much cheaper than \$36, or roughly \$2 per test. Indeed, if the unit cost per BMT remains unchanged, BMT-prior is not economical unless the FMD incursion probability is seen to be 4 outbreaks/100 years or higher. Our result also suggests the need for a more affordable BMT. For example, for an unit cost of \$10, BMT-prior is well justified when FMD is expected to occur every 12 years or more frequently. Since bulk milk testing is not yet commercially available, perhaps a partnership between the public and private sectors is worth exploring to reduce the cost of this testing method.

On the other had, we have shown that BMT is highly suited to active surveillance after an FMD incursion. The result is relatively insensitive to model parameter values, except for parameters especially crucial to the size and the cost of an FMD outbreak. As a result, BMT-post is recommended for active surveillance against FMD to shorten the length and size of an outbreak, even at the current estimated cost of the test in Australia, as well as testing for post-outbreak proof of FMD-free status. In short, it offers an important biosecurity measure to at least partially offset the otherwise devastating effects of an FMD incursion.

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Appendix A: Discounting factor

The purpose of this appendix is to clarify whether a discount factor is needed in optimisation equations (7) and (11). Without the loss of generality, we simplify our problem and notation. An FMD outbreak can happen at any given day with a probability of λ and last for T days from the day of incursion until the day when an FMD-free state is declared. Since BMT active surveillance can reduce outbreak duration, T is a function of k (i.e. $T(k)$) where k is the BMT testing interval.

A daily cost, $C(a, k)$, incurs during $T(k)$ and consists of eradication and management expenses where a is the length of an outbreak. Please note that a is defined in a similar fashion as the age of colonies ϕ , as before, but refers now to the length of the whole outbreak. We need a to distinguish different outbreaks over time.

In the context of the BMT-prior scenario, we define the daily cost of BMT active surveillance as $S(k)^{prior}$ which is a function of k . The daily expected total cost which includes expenses on active surveillance, eradication and management is calculated as follows:

$$DC(k) = S(k)^{prior} + \lambda \sum_{a=1}^{T(k)} C(a, k) \quad (13)$$

On any given day, an FMD outbreak can occur. Our objective is to minimise the sum of all daily expected total costs counting from day 1 to day ∞ as follows:

$$\begin{aligned} \min_k TC^{prior} &= \min_k \sum_{t=1}^{\infty} \frac{DC(k)}{(1+\rho)^t} \quad \text{where } \frac{1}{1+\rho} \text{ is a discount factor} \\ &= \min_k DC(k) \times \rho^{-1} \quad \text{since } t \rightarrow \infty \text{ and } DC(k) \text{ does not depend on } t \end{aligned} \quad (14)$$

Therefore,

$$\min_k TC^{prior} \Leftrightarrow \min_k \left[S(k)^{prior} + \lambda \sum_{a=1}^{T(k)} C(a, k) \right] \quad (15)$$

where the term on the right hand side of equation (15) is a simplified version of equation (7). To this end, optimising equation (15) is equivalent to optimising equation (7). This approach has been used in a similar way by Epanchin-Niell et al. (2012).

In the context of the BMT-post scenario, active surveillance starts only when FMD is detected. We define the daily cost of BMT active surveillance as $S(k)^{post}$ which incurs from the day when BMT testing equipment is ready for testing. We define the cost of management and eradication as $C(a, k)^{post}$. Our objective is to minimise the total cost of an outbreak once it occurs. The optimisation equation is as follows:

$$\min_k TC^{post} = \min_k \left[\sum_{d=D}^{\Pi(k)} \frac{S(k)^{post}}{(1+\rho)^d} + \lambda \sum_{a=1}^{\Pi(k)} \frac{C(a, k)^{post}}{(1+\rho)^a} \right] \quad (16)$$

where D is the day when BMT testing equipment is ready for active surveillance; $\Pi(k)$ is the outbreak duration under BMT-post. The key difference between equation (16) and equation (14) is that the time horizon of the former is the outbreak duration, not ∞ as in equation (14) for the case of the BMT-prior. Therefore, the series $\sum_{d=D}^{\Pi(k)} \frac{1}{(1+\rho)^d}$ and $\sum_{a=1}^{\Pi(k)} \frac{1}{(1+\rho)^a}$ of equation (16) are finite, not converging to ρ^{-1} as in equation (14). To this end, the optimisation in equation (14) needs to take into account the discount factor. However, we choose to drop the discount factor for simplicity because: (a) the time horizon is likely to be relatively short (i.e., in the order of 3 to 6 months, plus 3 months of quarantine); and (b) the prevailing discount rate in Australia is low.

Appendix B: Estimation results

Non-linear estimation is used in estimating transmission parameters. In particular, using the simulation data with 663 observations and equation (2) gives the following estimate of the long distance transmission rate (g) and the maximum carrying capacity of colonies (q_{\max}):

$$\widehat{q_{t+1} - q_t} = \underset{(0.00431)}{0.0709} \times \underset{(1.38)}{\frac{(19.01 - q_t)q_t}{19.01}}$$

Likewise, using the simulation data and equation (1) gives the following estimates of the local transmission rates to farms of the same type (β^{ii}):

Estimation of local transmission rates to farms of the same type

Parameter	Dairy		Non-dairy	
	Pig	Others	Pig	Others
β^{ii}	0.109	0.0455	0.0852	0.0369
SE	(0.00916)	(0.00137)	(0.00532)	(0.00158)
Number of observations	118	2440	166	1466

Using the simulation data and equation (1) gives the following estimates of the local transmission rates to farms of the different type (β^{ij}):

Estimation of local transmission rates to farms of different types

Parameter	Dairy		Non-dairy	
	Pigs to others	Others to pigs	Pigs to others	Others to pigs
β^{ij}	0.00	0.00129	0.00	0.000963
SE		(0.000106)		(0.000127)
Number of observations		2440		1466

The maximum carrying capacities of each farm type in each region is calculated by using the number of farms of that type in that region divided by the estimated $\widehat{q_{\max}}$.

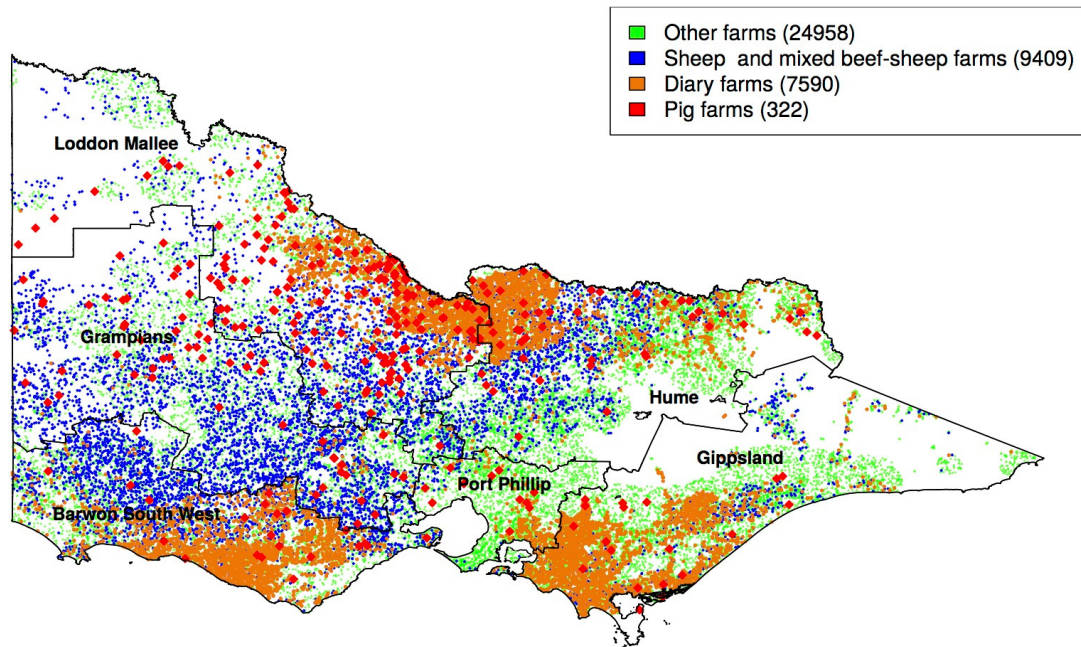
Table 1: Table of Parameter Values and Descriptions

Parameter	Description	Dairy		Non-dairy		Unit	
		Pig	Others	Pig	Others		
β^{ii}	FMD local transmission rate to farms of the same type ^(a)	0.109*	0.0455*	0.0852*	0.0369*	per day	
β^{ij}	FMD local transmission rate to farms of different types ^(a)	0.00	0.00129*	0.00	0.000963*	per day	
N	Farm carrying capacity ^(a)	6	859	11	1347	farm	
c_e	Unit cost of eradication per farm ^(b)	0.439	0.194	0.456	0.149	\$ mil	
π^s	Probability of being a seed farm ^(a)	0.607	0.393	0.607	0.393		
		From dairy → dairy → non-dairy		From non-dairy → dairy → non-dairy			
κ	Probability of the location of a ‘child’ colony generated by a ‘mother’ colony ^(a,e)	0.702	0.298	0.332	0.668		
		Dairy		Non-dairy			
η^{1l}	Probability of the location of the 1st colony ^(a)	0.352		0.648			
Φ	Detection time by passive surveillance ^(a)	21		23		day	
\mathcal{T}	Detection time by active surveillance ^(a)	16		21		day	
		For the whole outbreak					
λ	FMD arrival probability ^(c)	~ 0.000055					per day
θ	The culling ratio ^(a)	3.74					
g	Colony growth rate ^(a)	0.0709					per day
q_{\max}	Colony carry capacity ^(a)	19					colony
δ	Unit cost per bulk milk test ^(d)	36					\$

	Description	For the whole outbreak	Unit
c_m	Daily operating cost of an FMD disease control centre(s) ^(b)	0.475	\$ Mil
c_{r1}	Daily revenue loss in the first year ^(c)	14.8	\$ Mil
c_{r2}	Daily revenue loss in the 9 following year ^(c)	0.246	\$ Mil
ϱ^{ps}	Culling time for a colony under passive surveillance	16	day
ϱ^{bmt}	Culling time for a colony under BMT-post and BMT-prior	16	day
ς^{ps}	Quarantine time under passive surveillance	90	day
ς^{bmt}	Quarantine time under BMT-post and BMT-prior	90	day
h	Number of farms visited by a milk tanker in one trip ^(d)	5	farm
ϵ	Testing equipment set-up time ^(d)	7	day
M_{df}	Number of dairy farms ^(a)	7,590	farm
E_{daily}	Amortised cost of testing equipment ^(d)	50,000/365	\$
$E_{one-off}$	One-off cost of testing equipment ^(d)	500,000	\$
M_{fac}	Number of milk factories ^(d)	25	factory

Values are in Australian Dollar 2014; (*): statistically significant at 1% level; (a): Estimated from AUSSPREAD simulations and explained in detail in Appendix B; (b): Calculated based on Abdalla et al. (2005) and Garner et al. (2012); (c): Approximately 2 outbreaks/100 years, based on Productivity Commission (2002) and Buetre et al. (2013); (d): (Garner et al., 2015) and expert opinion; (e): $\eta^{ql} = \sum_m \eta^{1l} \kappa^{ml}$ when $q > 1$ and where $m, l \in L$.

Figure 1: Farm distribution in Victoria State



Farm distribution is based on AusSpread Model (Garner and Beckett, 2005)

Figure 2: BMT-prior: expected total cost of an FMD outbreak versus BMT testing intervals

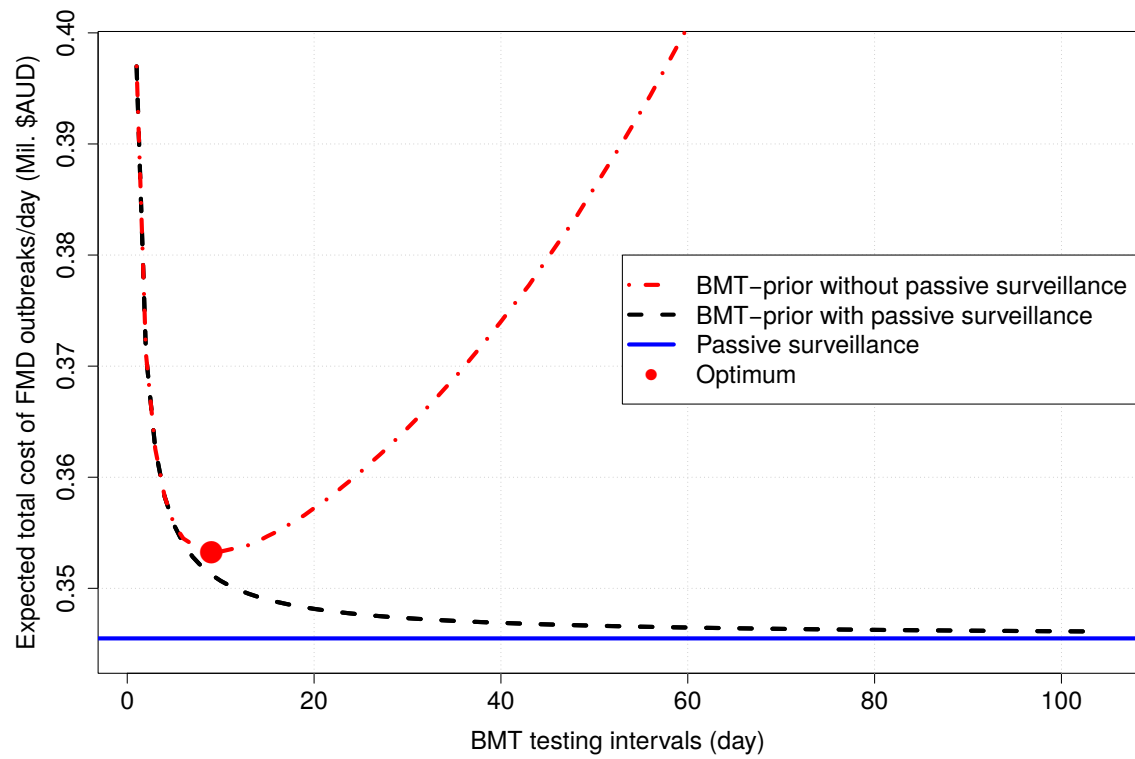
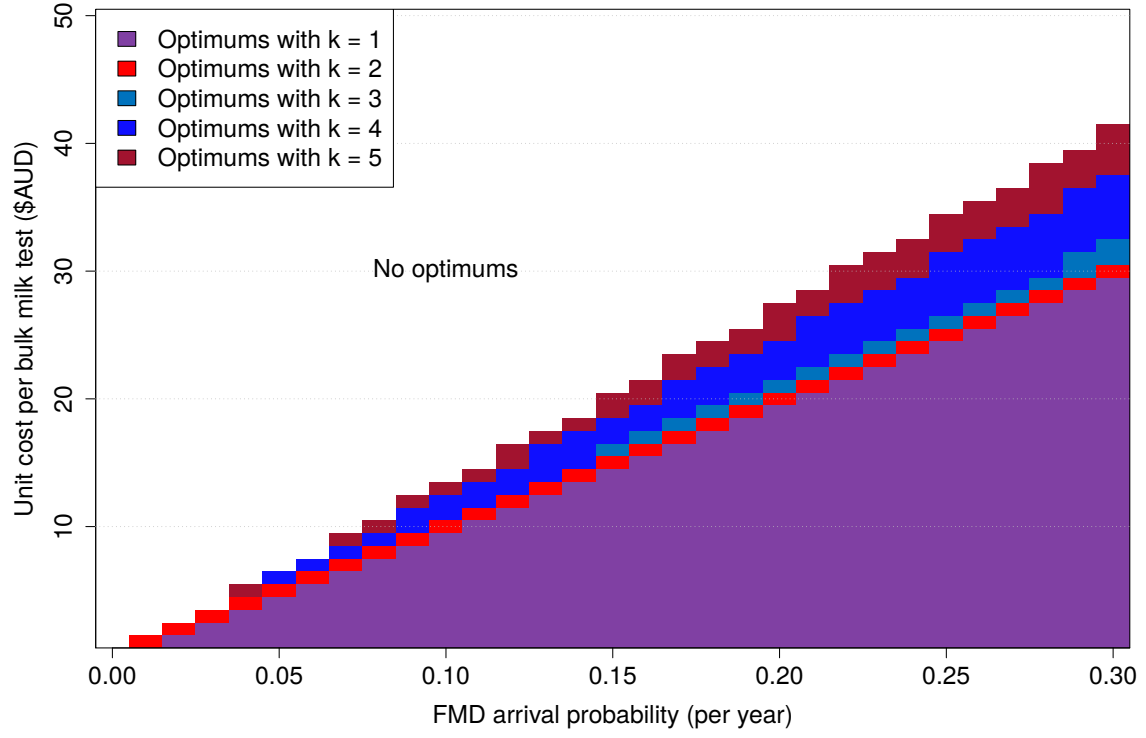


Figure 3: BMT-prior: surveillance frontier



k is the BMT testing interval; step sizes for y-axis and x-axis are \$1 and 0.01, respectively.

Figure 4: BMT-post: total cost of an FMD outbreak versus BMT testing intervals

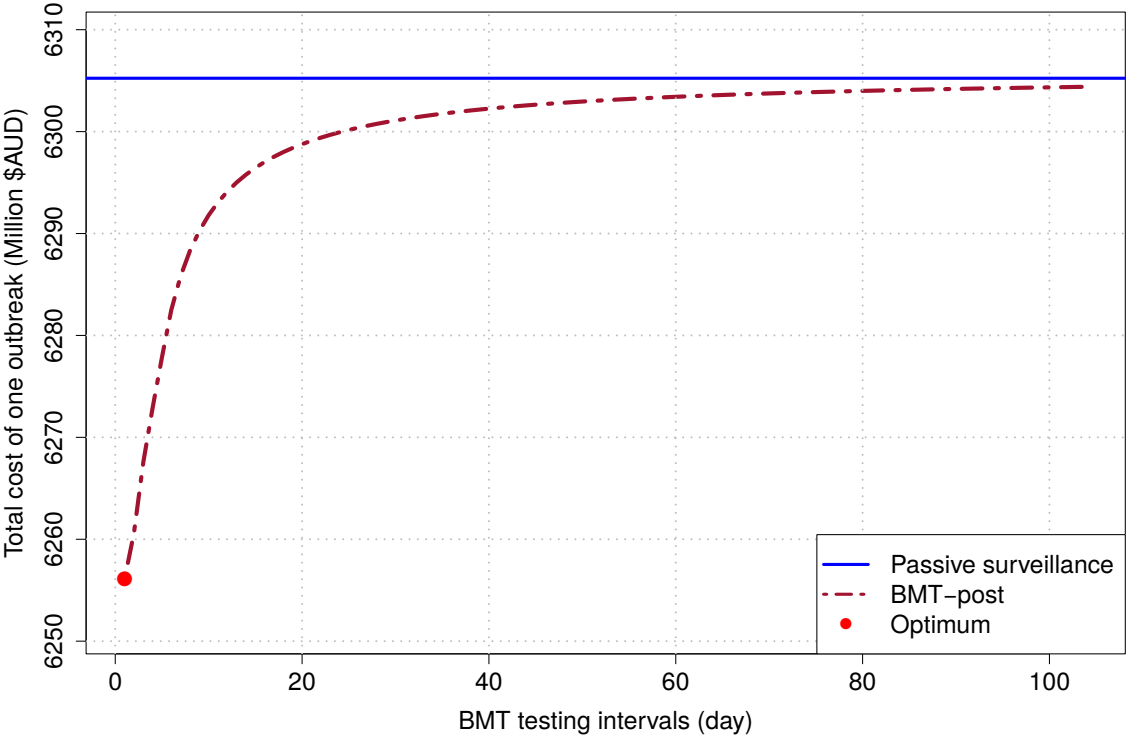
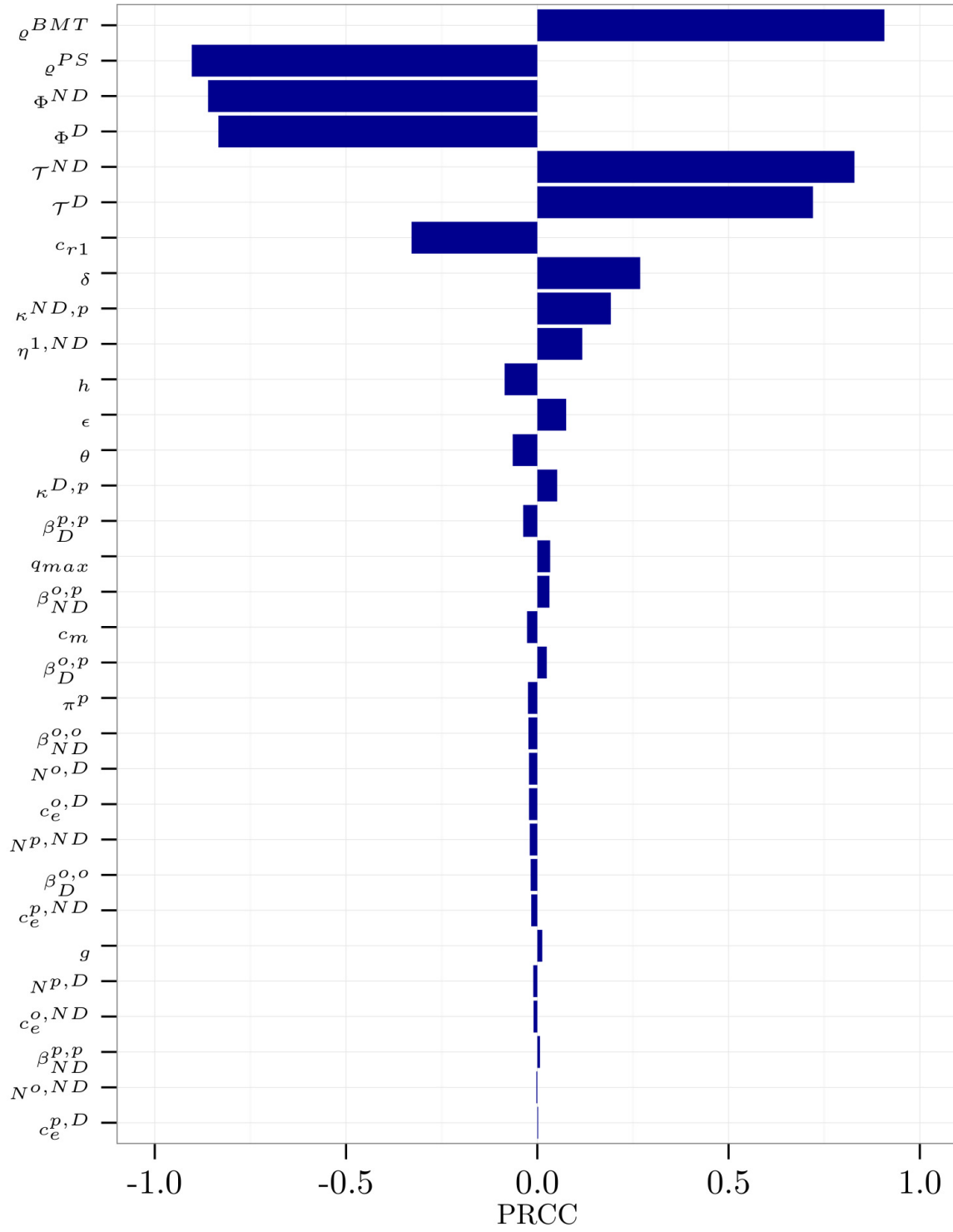


Figure 5: BMT-post: sensitivity analysis



Parameters are defined in Table 1. PRCC: Partial rank correlation coefficient; D: Dairy region; ND: Non-dairy region; p: pig farms; o: other farms