Causal Analysis of Trade Cost from Pests and Pathogens: A Global Study of Foot and Mouth Disease Impacts on Meat Exports

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Abstract

The highly infectious nature of many animal diseases triggers policy interventions restricting transboundary trade with significant impacts on exports. The impacts are possibly asymmetric; newly infected countries immediately experience a sharp decline in trade while recovering from the disease does not raise the trade to the pre-outbreak level. We identify and quantify the global impacts of FMD outbreaks on meat exports using panel data from 178 WOAH member countries from 1996 to 2016. We adopt a causal inference approach that considers animal disease outbreaks over time as non-staggered binary treatments with the potential for switching in (new outbreak) and out of treatment (recovery) within the sample period. The outcome evolution of switchers and non-switchers identifies the treatment effects. Using a recently proposed dynamic DID estimator robust to group and time heterogeneity, we estimate the treatment effects that decompose into 'joiner' (switch in) and 'leaver' (switch out) effects. We find that the adverse effects of an outbreak on meat exports last for multiple periods after an outbreak. The outbreak decreases meat export by 31,000 to 75,000 tons per year (23% - 56% of mean annual meat export) in the five years following an outbreak, which is brought about by a decline in the joiners' meat exports while the leavers do not recover the export losses even after five years. The average effect is estimated at about 54,000 tons per outbreak, resulting in an export revenue loss of $162 million. The asymmetric post-infection and post-recovery trade costs imply a significant disease burden on the endemic regions.

1. Introduction

Examining the impacts of livestock disease on trade is important for several reasons. Disease incidences in livestock significantly impede people's livelihoods, trade, and food security, especially in agro-pastoral households that rely mostly on livestock production. This implies that eradicating an endemic disease could bring benefits back to such households. Knight-Jones and Rushton (2013) report an annual loss of 6.5-21 billion dollars worldwide due to foot-and-mouth disease outbreaks. Moreover, livestock disease eradication could substantially enhance countries' international trade. Global eradication of Rinderpest provides many insights. For instance, cattle exports from Pakistan to the Middle East almost doubled between 2003 ($2.26 million) and 2006 ($4.32 million) after those countries lifted a ban in 2003 when Pakistan declared provisional freedom from Rinderpest (Roeder and Rich, 2010; FAOSTAT, 2009). Assessing global trade impacts is an important step in addressing the imperfect ability to assess the impacts of animal disease control (Perry et al., 1999). The focus and contribution of the current paper is to econometrically identify and quantify the trade impacts of animal disease, specifically on exports.

Much of the existing literature examines the relationship between trade and the establishment of invasive species in the importing country. For instance, Perrings et al. (2010) use data on animal diseases notified to the World Organization for Animal Health (WOAH) to model the relationship between animal disease outbreaks and imports of risk materials in a panel of 41 countries. Under different model specifications, they find that countries with a higher risk of loss from the disease outbreak, as measured by the level of per capita agricultural GDP, are proportionately more responsive to changes in trade-related risks. Moreover, increasing trade volumes are associated with reduced risk, particularly concerning highly invasive pathogens due to the combined efforts of both the importers (with increased inspection) and the exporters (with increased sanitary and phytosanitary actions). Dalmazzone (2000) reports a positive correlation between merchandise imports and the introduction of invasive plant pathogens in a study of 29 countries. The import duties, on the other hand, were found to deter the introduction of the pathogens.

Various studies have looked at the impact of economic sanctions on trade (e.g., Kaempfe and Lowenberg, 1988; Hufbauer et al., 1997; Caruso, 2003; Yang et al., 2004a, 2004b, 2009). For the target countries, the impacts of such sanctions can include isolation, reduction in trade and investment flows, and deterioration in their overall economic welfare (Yang et al. 2004a). However, few studies have specifically dealt with sanctions imposed due to livestock disease outbreaks. Upton (2001) assesses the impacts of sanitary and phytosanitary (SPS) measures as trade barriers for livestock and livestock products, particularly in low income and least-developed countries.

We depart from this strand of literature to empirically quantify the impact of foot and mouth disease on the export of meat products. Utilizing disease outbreak data from the WOAH across a panel of 178 countries, we econometrically estimate the costs of such an outbreak on the countries' export volume. We use a causal inference framework in identifying the disease effects. To our knowledge, this is the first attempt in the literature that utilizes the disease outbreak data to quantify trade costs associated with pests and pathogens across a wide range of countries. The approach also helps us to quantify the distribution of losses, which is especially important to lower income countries.

Our contributions are several fold. First, we setup a framework from a causal perspective to analyze animal disease impacts on trade. Using a causal inference framework, we apply a recent dynamic DID estimator to measure the impacts of FMD that uses the switching of treatments between periods as the identifying factor and measure the treatment effects on the treated by comparing the outcome evolution of the switchers and the non-switchers pre and post-treatment. Next, we estimate the global impacts of the FMD outbreaks on meat exports using panel data from 178 countries during the period 1996 to 2016. We find a significant decrease in meat export immediately after an outbreak as well as in the subsequent periods. Finally, decomposition of the effect into joiners and leavers effect shows that the negative impacts on meat export are caused by a drop in exports by the newly affected regions. No significance of the leavers' treatment effects implies that the pre-outbreak export market is not recovered after disease mitigation. In fact, no significance of the leavers' dynamic effects over a span of 5 years suggests a long-term effect on trade, which is often overlooked in a benefit-cost analysis of disease cost estimation.

2. Background

Infectious livestock disease outbreak affects livestock production and trade in many ways. Reduced production and trade, loss of production inputs and assets due to livestock morbidity and mortality, and disease control, containment and cleaning costs are all part of the losses incurred due to a disease outbreak. The negative externalities of an infectious disease outbreak on yet-to-be-affected parties rationalize limiting their contact with the infected party and as such, trigger trade restrictions and bans as an immediate response. Therefore, trade losses due to an outbreak comprise a large share of disease losses for a significant exporting country.

Understanding the global burden of animal diseases necessitates measuring disease impacts on trade, including exports. Export loss after an outbreak majorly arises from reduced or non-existent transboundary trade, loss of price premium from losing official disease-freedom status, reduced price from higher supply in the domestic market, and a long-run negative impact from the loss of market share to other competitors (Hennessy and Marsh 2021). The economic literature on disease impacts on trade mostly focuses on an economy's overall trade losses from the sources mentioned above within national boundaries. Few studies span over larger geographic regions as well. However, there is a lack of a truly global estimate of export losses that can be causally attributed to a livestock disease outbreak.

To evaluate the trade costs of pests and pathogens, we consider the case of the Foot-and-Mouth Disease (FMD). FMD is one of the most serious problems in livestock sector in many developing countries. FMD is a highly contagious virus affecting cattle, swine, and other cloven-hoofed animals. Although sometimes fatal to young animals and a cause of abortions, most economic losses of FMD occur through reduced milk production and reduced weight gain (Paalrberg and Lee, 1998). At the farm level, such disease impacts productivity and reproduction and increases cost to households. However, at the country level, FMD stifles economic productivity, disrupts trade, and likely impacts overall economic growth (Tozer and Marsh, 2012; Nogueira et al., 2011). The trade impact stems primarily from trade embargoes imposed by the importing countries on imports of livestock products potentially infected with FMD based on voluntary WOAH guidelines. Overall, the economic consequences of FMD outbreaks are quite large, as demonstrated, for instance, by the estimated £8 billion cost in the UK in the 2001 outbreak (National Audit Office, 2002).

Data on FMD outbreaks reveal that various levels of information on the disease are transpired in the international community. The WOAH is an apex intergovernmental body that takes overall responsibility for animal health worldwide. Established in 1924, WOAH currently has 182 member countries, and each member country undertakes to report the animal diseases that it detects on its territory. The WOAH then disseminates the information to other countries, which can take the necessary preventive action. While some countries completely lack information on the disease, many others do not report the number of outbreaks even after its known incidence. Although the lack of proper data collection mechanism in many developing countries may have contributed to the non-reporting, some of this non-reporting might be deliberate, which may often be part of protectionist policy. Countries may preferably choose not to report the infectious disease outbreaks to avoid potential trade sanctions (Malani and Laxminarayan, 2009). However, the trade-offs of such suppression are that it can increase the likelihood of widespread epidemics as well as preclude medical assistance. Under a game-theoretic framework where a country has private but imperfect evidence of an outbreak, Malani and Laxminarayan (2009) argue that sanctions based on fears of an undetected outbreak rather encourage reporting by reducing the relative cost of sanctions that follow a reported outbreak. Under such circumstances of different levels of information flow on the disease incidence, there might be differential responses from international markets on the import of livestock products from such countries.

Previous studies on FMD have evaluated the economic costs of FMD outbreaks, either ex-post or under a hypothetical scenario. These include, for example, for Australia (Tozer and Marsh, 2012), Canada (Tozer et al., 2015), South-East Asia (Perry et al., 1999), France (Mahul and Durand, 2000), Republic of Korea (Yoon et al., 2006), Mexico (Nogueira et al. 2011), Southern Cone of South America (Rich and Winter-Nelson, 2007), UK (Thompson et al., 2002), and USA (Schoenbaum and Disney, 2003; Zhao et al., 2006; Pendell et al., 2007). Many of these studies focus on evaluating the economic consequences of alternative control strategies of the disease. However, empirical evidence specific to trade is severely limited.

3. Analytical Framework

We adopt a quasi-experimental design based causal analysis approach to the research question. In this approach, an animal disease outbreak can be considered a treatment that applies to different treatment units (e.g., countries) at different periods (e.g., years). As mentioned above, countries respond to an outbreak differently and as such, they differ in recovery time as well. In addition, a country can experience outbreaks multiple times in different years. As such, our research problem fits a multi-period non-staggered treatment design where treatment units receive the treatment at different periods and can switch in and out of the treatment. Given the nature of the treatment, we adopt an identification strategy proposed by de Chaisemartin and d'Haultfoeuille (2020, 2022) where treatment switching is used as the factor identifying the treatment effects on the outcome of interest.

We investigate the impacts of an animal disease outbreak on exports of an outbreak-affected country, an average treatment effect on the treated (ATT). This is defined as:

$$ATT = \frac{1}{N_{treated}} \sum_{i \in \text{treated}, t \in T} Y_{it}(1) - Y_{it}(0)$$

where $N_{treated}$ refers to the number of treated units, $Y_{it}(1)$ and $Y_{it}(0)$ are observed outcomes and potential untreated outcomes of the treated units, respectively.

With the treatment units being allowed to get the treatment and leave it at any given period, we identify a switching effect that decomposes into two parts: the treatment effect of switching in the treatment (joining) and that of switching out (leaving) (de Chiasemartin and d'Haultfoeuille, 2020). They are defined as:

$$ATT_{joiner,t,} = \frac{1}{N_{joiner,t}} \sum_{i \in \text{joiner}} Y_{it}(1) - Y_{it}(0)$$

$$ATT_{leaver,t} = \frac{1}{N_{leaver,t}} \sum_{i \in \text{leaver}, t \in T} Y_{it}(1) - Y_{it}(0)$$

$$ATT_{switcher} = \sum_{t \in T} \left(\frac{N_{joiner,t}}{N_{switcher,t}} \sum_{i \in joiner} ATT_{joiner,t} + \frac{N_{leaver,t}}{N_{switcher,t}} \sum_{i \in leaver} ATT_{leaver,t} \right)$$

$$N_{switchers,t} = N_{joiner,t} + N_{leaver,t}$$

where, ATT_{joiner} and ATT_{leaver} are the treatment effects averaged over the units switching in and out of treatment, respectively. $ATT_{switcher}$ is a weighted average of these two treatment effects.

The switching effect averages the treatment effects on the newly treated units and the previously treated ones (that now left the treatment) and reflects an instantaneous effect of the treatment. However, for a treatment such as a disease outbreak, the effects may linger for multiple periods. As such, we complement the instantaneous effect framework with a dynamic effect framework proposed by de Chaisemartin and d'Haultfoeuille (2022) that uses a similar identification strategy. Instead of simple treatment switching at any given period, we identify dynamic effects of a treatment using only the first-time treatment switching as the identifying factor. For a treatment received or left l periods ago, the joiners' and leavers' effect is defined as:

$$ATT_{joiner,t,l} = \frac{1}{N_{joiner,t,l}} \sum_{i \in F_{join,l}} Y_{itl}(1) - Y_{itl}(0)$$

$$ATT_{leaver,t,l} = \frac{1}{N_{leaver,t,l}} \sum_{i \in F_{leave,l}} Y_{itl}(1) - Y_{itl}(0)$$

where, $N_{joiner,t,l}$ and $N_{leaver,t,l}$ refer to the number of first-time treatment switchers in each category and $F_{join,l}$ and $F_{leave,l}$ refer to the set of treatment units receiving or leaving the treatment for the first-time l periods ago. Thus, the switching effects of these two groups average the differences in potential outcomes of first-time treatment switchers. Similar to the instantaneous effect model, an average switching effect in this design can be defined as a weighted average of the two.

$$ATT_{switcher,l} = \sum_{t \in T} \left(\frac{N_{joiner,t,l}}{N_{switcher,t,l}} \sum_{i \in joiner,l} ATT_{joiner,t,l} + \frac{N_{leaver,t,l}}{N_{switcher,t,l}} \sum_{i \in leaver} ATT_{leaver,t,l} \right)$$

4. Estimation

We adopt a difference in differences (DID) approach in estimating the above-mentioned treatment effects and compare it to a two-way (country-year) fixed effects (TWFE) model. Although a TWFE model is equivalent to a conventional DID estimator (so is a dynamic TWFE model to a conventional event study estimator), given an experimental design where treatment periods vary and the units can join or leave the treatment at different periods during the sample period, i.e., a non-staggered treatment design, the estimated TWFE coefficient may not represent the intended treatment effects. de Chaisemartin and d'Haultfoeuille (2020) argue that this primarily results from the use of a comparison group in these estimators that include previously treated units. Additionally, Goodman-Bacon (2021) points out that in a multiperiod treatment setting, the TWFE estimator may not identify the intended treatment effect when there is group and/or time heterogeneity in treatment effects. Sun and Abraham (2021) extend their result in an event study design and argue that alternative estimators might be required to identify the dynamic treatment effects. Given the treatment design of our study, we use DID estimators proposed by de Chaisemartin and d'Haultfoeuille (2020, 2022) that use treatment switching to identify the treatment effects.

An instantaneous DID estimator compares the outcome evolution of the treatment and control groups before and after the treatment. For any pre and post-treatment periods, there can be observed units that have not been treated in both periods (never treated) or treated in each (always treated). These two groups act as the comparison group in this DID framework and provide estimates of the untreated potential outcomes for the joiners and the leavers, respectively. For a treatment at period t, the instantaneous DID estimators (named DIDM by the authors) are defined as:

$$DIDM_{join,t} = \frac{1}{N_{joiner,t}} \sum_{i \in joiner} Y_{it} - Y_{i,t-1} - \frac{1}{N_{nevertreated}} \sum_{i \in nevertreated} Y_{it} - Y_{i,t-1}$$

$$DIDM_{leave,t} = \frac{1}{N_{alwaystreated,t}} \sum_{i \in alwaystreated} Y_{it} - Y_{i,t-1} - \frac{1}{N_{leaver,t}} \sum_{i \in leaver} Y_{it} - Y_{i,t-1}$$

The DIDM estimators estimate the joiners and leavers effect by comparing their outcome evolution to that of never treated and always-treated units, respectively. Notice that given our hypothesis of the negative impact of disease outbreak on trade holds, $DIDM_{join}$ and $DIDM_{leave}$ estimate negative coefficients. Intuitively, joiner effects can be interpreted as the export loss of new outbreaks while the leaver effects are the export loss avoided by recovering from the outbreaks. As such, the DIDM estimator for the switching effect is defined as the weighted average of the two DIDMs.

$$DIDM = \sum_{t \in T} \frac{N_{joiner,t}}{N_{switchers,t}} DIDM_{join,t} + \frac{N_{leaver,t}}{N_{swichers,t}} DIDM_{leave,t}$$

The two central identifying assumptions, which are partially testable as de Chaisemartin and d'Haultfoeuille (2020) claim, are:

- Existence of a stable group: To identify the joiners' effect, there must be a never-treated group for outcome comparison in the sample and an always-treated group to identify the leavers' effect. This can be tested by observing the data. Our dataset satisfies this condition.

- Common trends in untreated potential outcomes: The untreated potential outcomes of the treatment and the comparison groups follow a common trend. We use a placebo estimator proposed by de Chaisemartin and d'Haultfoeuille (2020) to test this assumption that uses the outcome evolution of the two groups in pre-treatment periods.

A dynamic DIDM estimator is defined using a similar approach. In each period, there are countries that are disease-free from the start of the panel and there are those who are always disease affected until the final period in the sample. These are called not-yet-treated and not-yet-untreated units and act as the comparison group for the two first-time treatment switchers, the countries that have an FMD outbreak for the first time l periods ago (joiners) and the countries that have recovered from a disease outbreak for the first time l periods ago (leavers), respectively. Comparing the outcome evolution of not-yet-treated units and the joiners between period t and $t - l - 1$ identifies the dynamic effect at period t of a treatment received by the joiners l periods ago. Similarly, a comparison of outcome evolution of the not-yet-untreated and the leavers identify the effect of leaving treatment at $t - l$ period. A weighted average of the two effects (joiners and leavers) proportional to their share in the switching groups constitute a treatment effect from a treatment l periods ago.

$$DIDM_{join,t,l} = \frac{1}{N_{joiner,t,l}} \sum_{i \in F_{join,l}} Y_{it} - Y_{i,t-l-1} - \frac{1}{N_{not-yet-treated,t,l}} \sum_{i \in not-yet-treated,l} Y_{it} - Y_{i,t-l-1}$$

$$DIDM_{leave,t,l} = \frac{1}{N_{not-yet-untreated,t,l}} \sum_{i \in not-yet-untreated,l} Y_{it} - Y_{i,t-l-1}$$

$$- \frac{1}{N_{leaver,t,l}} \sum_{i \in leaver,l} Y_{it} - Y_{i,t-l-1}$$

$$DIDM_{switcher,l} = \sum_{t \in T} \frac{N_{joiner,t,l}}{N_{switcher,t,l}} DIDM_{join,t,l} + \frac{N_{leaver,t,l}}{N_{swichers,t,l}} DIDM_{leave,t,l}$$

Similar to the instantaneous DIDM, the dynamic DIDM estimator relies on two central assumptions:

- Existence of a stable group: To identify the joiners' effect, there must be a not-yet-treated group for outcome comparison in the sample and a not-yet-untreated group to identify the leavers' effect. Our dataset satisfies this condition.
- Common trends in untreated potential outcomes: The untreated potential outcome follows a common trend between the treatment and comparison groups. We use a placebo estimator proposed by de Chaisemartin and d'Haultfoeuille (2022) to test this assumption.

Figure 1 summarizes the identification strategy described above. The estimator does not rely on any assumptions on treatment effect heterogeneity across group and/or time and thus, robust to such heterogeneity. An extension of the estimator to include covariates relies on a weaker common trend assumption. In this case, the identification requires the untreated potential outcomes of the treatment and control groups to follow a common trend conditional on the observed covariates, X_{it}.

4.1 Estimating average total effect

One empirical limitation of this dynamic DIDM estimator is that since the treatment effects are identified using the first treatment switching only, the treatment effects of any subsequent treatment changes between the first switch and period t are not identified. While a simple modification of the estimator can theoretically trace all treatment switches, even for a moderate T, the estimates become imprecise and difficult to interpret. To illustrate, consider three treatment units with the treatment trajectories $\{0, 1, 1, 1, 1, 1\}$, $\{0, 1, 0, 0, 0, 0\}$ and $\{0, 1, 0, 1, 0, 1\}$ respectively. All three units switch their treatment for the first time in the second period. Although the first unit stays in the treatment for the remaining periods, the second unit leaves the treatment in the following period and is never treated again, and the third unit switches in and out of treatment multiple times. For estimating the joiner effect 4 periods after the treatment, all three units are considered joiners in the DIDM estimator and compared to the not-yet-treated units. With a binary treatment, distinguishing and identifying the treatment effects of the joiners with different treatment paths in a sample of 4 post-treatment periods would require estimating $2^4 = 16$ different treatment effects. A similar case is true for the leavers effect.

An implication of this limitation is that the $DIDM_{join,l}$ and $DIDM_{leave,l}$, and consequently $DIDM_{switcher,l}$ are interpreted as the effects of receiving a weakly higher treatment l periods ago than the not-yet-treated, not-yet-untreated and non-switchers, respectively, while the degree of treatment received may vary within groups since then. To complete the analysis, a summary measure is proposed by de Chaisemartin and d'Haultfoeuille (2022) that adjusts the $DIDM_l$ by the estimates of first-switch effects on treatment, i.e., the outcome is replaced by the treatment such that

$$DIDM_{join,t,l}^{D} = \frac{1}{N_{joiner,t,l}} \sum_{i \in F_{join,l}} D_{it} - D_{i,t-l-1} - \frac{1}{N_{not-yet-treated,t,l}} \sum_{i \in not-yet-treated,l} D_{it} - D_{i,t-l-1}$$

where, D_{it} represents the treatment status of unit i at period t. Thus, an average total effect per unit of treatment can be defined as the weighted average of treatment effects adjusted by average treatment level received.

$$DID_{join} = \frac{\sum_L w_{join,,l} DIDM_{join,l}}{\sum_L w_{join,,l} DIDM_{join,l}^{D}}$$

$$w_{join,l} = \frac{N_{join,l}}{\sum_L N_{join,l}}$$

where, L denotes the number of lags considered, and $N_{join,l}$ refers to the number of joiners l periods ago across all time units. DID_{leave} and DID_{switch} can be defined similarly.

5. Data

We use annual meat export data (volume and revenue) for 178 WOAH member countries over the period 1996-2016 from United Nations Food and Agriculture Organization (FAO) database (FAOSTAT). Annual FMD outbreak data is collected from WOAH database. WOAH annual meeting resolutions provide the FMD status of its member countries. The data for control variables are collected from FAOSTAT and world bank data bank. A detailed list of variables is provided in the appendix. Table 1 provides the descriptive statistics for the variables included in our analysis.

Outbreak

There are 103 countries with at least one outbreak during the sample period while on average, 53 countries report at least one outbreak each year (30% of the sample). Asia and Africa have the most outbreak incidence (46% and 45% of the total) while North America and Oceania did not see any outbreak during 1996 - 2016.

Meat exports

We consider meat exports of six cloven-hoofed animals susceptible to FMD: sheep, pigs, cattle, goats, camels and buffaloes. Meat export includes 19 meat products from these six animals[1]. Mean annual meat export is about 133,000 tons. Annual meat exports average about 180,000 tons in the non-affected countries while it is only about 27,000 tons in the affected regions. About 169 countries have some level of meat exports. However, many countries only have a very small level of exports. The global meat export market is highly concentrated with the top 10 exporters' average export volume ranging from 1 million to 3.4 million tons, many times higher than the global average. There are only 69 countries with one-tenth of the mean export (13,000 tons) at least once during the sample period. Averaging over the exporting countries only, mean annual meat exports stands at 176,000 tons. Decomposed by outbreak status, meat exports in the non-affected countries are about 236,000 tons, while it is 36,000 tons in the affected region.

Covariates

We estimate meat export prices from the export revenue and the volume. Global meat price is about $3000/ton and live animal price is about $422/head. As expected, prices are higher in the non-affected regions ($3000/ton and $503/head) than in the affected regions ($2700/ton and $260 head).

[1] A full list of the meat products is provided in the appendix.

Mean agricultural imports and exports are about $5 billion; both are higher in the non-affected regions averaging $5.5 billion. In the affected regions, agricultural imports average at $4 billion while agricultural exports average at $3 billion. Mean GDP is $403 billion in the non-affected regions and $240 billion in the affected ones.

Average meat production to consumption ratio is 0.97, which is very similar in the disease-affected and the disease-free regions. The number of livestock is higher in the disease-affected regions (about 9.7 million) than that of non-affected regions (about 6.2 million). This is due to China and India being FMD endemic countries, which are among the largest livestock producers in the world.

6. Results

Our identification strategy uses dynamic treatment and control groups that vary each period. Figure 2 summarizes the distribution of different treatment and control groups by year. Additionally, we trace all treatment trajectories of the joiners and leavers used in the dynamic DIDM estimation (Figure 3 & 4). Out of 178 countries, 48 and 41 countries are eventually treated and untreated at least once during our sample period, respectively. For these treatment unit, we have 75 never treated countries and 14 never untreated countries in the sample. This satisfies the first identifying assumption of the DIDM estimator. For a full list of the countries in different groups, see Table A3 in the appendix.

The first row of Table 2 presents the instantaneous DIDM estimates for FMD impacts on meat export both without and with covariates. The estimated disease effect without covariates is -8,382 tons. However, this estimate fails the common trend assumption as the placebo estimate shows (the second row). After accounting for the observed differences in the treatment and comparison groups, the common trends assumption holds and provides a disease effect of -15,339 tons, which is contributed by a significant decrease in exports by 21,188 among the newly disease-affected countries (joiners). The disease-recovered countries (leavers) avoid an export loss of 9,750 tons, although it is not statistically significant. Our estimate closely resembles Bastola (2015), who reports an decrease in export demand following an FMD outbreak by 19,569 tons using a slightly fewer countries and shorter sample period.

The following rows in Table 2 report the dynamic DIDM estimates without and with covariates and Figure 2 plots the dynamic DIDM estimates with covariates. The immediate effect of an outbreak on meat export is negative. Without-covariates estimates show that the meat export volume decreases by about 15,000 tons due to an outbreak, an 11% decrease in the average export. The effect comes from a significant reduction in the exports by the newly affected countries (about a 16% decline) while recovering from an outbreak does not alleviate the export loss. Like the instantaneous DIDM, without-covariates estimates fail to hold the common trends assumption.

With the inclusion of covariates, the estimates satisfy the common trends assumption as the non-significance of the placebo estimates suggests. The immediate effect of an FMD outbreak in this model is estimated at about 31,000 tons, a significantly higher estimate than that of the instantaneous DIDM. It is because the instantaneous DIDM uses a broader sample to identify the treatment effects. In the presence of dynamic effects, the instantaneous estimates, thus, contain residual joiner or leaver effects from treatments received in other periods.

The dynamic estimates show that the negative effects of an outbreak on meat exports last for multiple periods after the outbreak and show an increasingly larger effect in subsequent periods. The outbreak causes a decrease in meat export between 31,000 to 75,000 tons in the 5 years following an outbreak, which amounts to about 23% - 56% of average meat export per year. Again, the impacts are brought about by a decline in meat exports by the newly affected countries, which is estimated between 50,000 tons to 88,000 tons. Recovering from an outbreak does not alleviate the export loss even after 5 years. It implies that once a disease-affected economy loses global market shares due to the trade restrictions following an outbreak, regaining the market share is difficult. Figure 5, 7, and 8 traces the DIDM coefficients of the dynamic effects of FMD outbreaks on the overall sample, as well as the joiners and the leavers.

As mentioned before, the dynamic effects reported here reflect the effects of first switching on meat exports at different intervals from the switching period. The DIDM estimator, however, does not distinguish between the various treatment paths followed by the treatment units in the sample. To mitigate the limitation, we report the average treatment units received in each interval in our analysis. The estimates are equivalent to first-stage switching effects on the treatment status. Figure 6 reports these estimates. The average treatment received by the joiners and leavers ranges from 0.4 to 0.7 units with an overall average of 0.5units, where 1 implies that all treatment-switching units switched treatment in that period. It implies that the treatment timing varies in each interval considered in our analysis, as required by our identification strategy.

The total average effect of each outbreak is estimated at about 54,000 tons. To put it in context, the average meat price is estimated at \$3,000/ton, which implies an export loss of about \$162 million caused by an FMD outbreak. On average, 53 countries report FMD outbreaks each year. This leads to an estimated annual export loss of \$8.6 billion. Thus, the FMD outbreaks cause a significant global economic impact through export losses in addition to a similar level of production and control costs reported by Knight-Jones and Rushton (2013).

6.1 Robustness checks

Table 3 presents DIDM coefficients for a longer time span. The estimated impacts show the negative effects of FMD outbreaks on meat exports over a longer horizon. This shows that the statistical significance of the dynamic effects is not the result of an arbitrary length of the period investigated. However, for each estimated treatment effects further from the actual treatment timing, the estimates become increasingly noisy as there are fewer observations to estimate the ATTs (Table 3 and Figure 8).

Another concern relating to sample period selection might arise due to a long history of global FMD outbreaks. The estimated treatment effects using the initial periods in the sample might be biased by outbreaks before the sample period. De Chaisemartin and d'Haultfoeuille (2022) suggests a subsampling strategy that relies on the assumption that the length of the dynamic effects are known and estimates the treatment effects robust to the initial condition problem. Table 4 and Figure 9 show DIDM estimates on a subsample of countries that switched treatment at least 3 years after the initial sample period (1996). Within this subsample, the dynamic effects are significant for 3 years after the outbreak. The magnitudes are slightly higher than the estimates for the entire sample. The placebo test fails for the period immediately before the outbreak. As de Chaisemartin and d'Haultfoeuille (2022) suggests, common trends assumption still holds because the placebo estimators use a long difference to identify the common trends. The placebo for one period prior to the treatment can be interpreted as an anticipation effect. However, an anticipation effect might not be applicable in this case.

For comparison, we estimated a conventional event study model as well (Table 5). The estimated effects are negative as expected. However, the effects are smaller than the DIDM estimates and not statistically significant. This might be due to a mixed control group in this model. The control group in this model comprises of any untreated unit at the period interval from a given outbreak, regardless of their treatment status before or after the period in question. Thus, the comparison groups in this model might be significantly different from the DIDM estimates and are not directly comparable.

7. Conclusion

We analyze the instantaneous and dynamic trade cost of animal diseases. We observe a statistically and economically significant negative effect of disease events on meat export immediately as well as in the long run. The long-run effect trends downward suggesting that the affected countries lose increasingly larger export revenues over time. This adverse effect is caused by a sharp decline in exports in the newly affected countries, while newly recovered countries do not regain the export losses. In fact, the export loss of the recovered countries remains unmitigated even after 5 years into recovery. This suggests the trade costs of animal disease outbreaks are asymmetric and the trade restrictions following an outbreak causes additional losses on the affected countries which remain unaccounted in the cost-benefit analysis. There are a few limitations of this research. We do not estimate the effects of an outbreak on other commodities or sectors, while the trade restrictions might affect the exports of other commodities. Also, we do not model the exporters' revenue loss from a domestic price drop either from an increase in domestic supply or a perceived or observed quality reduction of meat products. A possible research extension will be analyzing the global costs of animal diseases on domestic trade to complement our findings and to guide global initiatives in animal disease control and mitigation.

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Tables and Figures

Table 1: Descriptive Statistics

Variables	Obs	Mean	Std	min	median	max
Meat export (volume)	3,660	133,210	452,003	0	644	4,624,810
Live animal export (volume)	3,539	336,453	1,141,748	0	1,189	13,416,950
Outbreak	3,694	0.30	0.46	0.00	0.00	1.00
FMD status = 0	3,694	0.60	0.49	0.00	1.00	1.00
FMD status = 1	3,694	0.34	0.48	0.00	0.00	1.00
FMD status = 2	3,694	0.05	0.22	0.00	0.00	1.00
Meat price	2,772	0.00	0.00	0.00	0.00	0.03
Live animal price	2,388	0.00	0.00	0.00	0.00	0.09
Agricultural import	3,657	4,987	12,851	8	900	156,055
Agricultural export	3,657	4,790	12,982	0	500	153,003
GDP	3,513	352,287	1,311,982	122	27,134	17,040,896
Meat consumption ratio	3,328	0.97	0.65	-0.50	0.96	6.82
Animal stock	3,673	7,245,962	20,107,331	65	1,612,125	174,988,084

Table 2: DIDM estimates of FMD impacts on meat export

	Overall	Join	Leave	Overall	Join	Leave
DIDM (instantaneous)	-8382*	-12184*	-4674*	-15339*	-21188*	-9750
DIDM (placebo)	-2993*	-4989	-1047	-4278	-4354	-4215
DIDM (dynamic)						
-5	34562*	39472*	31986	98720	70062	118799
-4	26431*	26418	26672	53519	15281	98839
-3	17408	13838	21131	18674	-12127	69280
-2	15174*	15563*	14804	18907	8477	36775
-1	20443*	29033*	10446	21124	16835	27645
0	-19242*	-29841*	-6957	-31210*	-49197*	-10671
1	-24748*	-37300*	-10524	-43133*	-74863*	-12536
2	-25452*	-30652*	-19526	-56169*	-81891*	-29753
3	-27012*	-28099*	-25765	-65273*	-88454*	-42592
4	-25460*	-23953	-27058	-53777	-58175	-49862
5	-31128*	-23907	-39491	-75868*	-72377	-79187
DIDM (average)	-45959*	-61499*	-34461	-53988*	-83694*	-33678
Covariate	no	no	no	yes	yes	yes

* Parameters are significant at 5% significance level The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

Table 3: DIDM estimates of FMD impacts on meat export (all lags and leads)

	Overall	Join	Leave	Overall	Join	Leave
DIDM (dynamic)						
-9	39985*	56456*	484	-20319	-20319	0
-8	29031*	64870*	-373	-7971	-15591	760
-7	24018*	60791*	-841	-11140	-17211	2340
-6	19386*	55867*	296	-6764	-27013	1096
-5	34562*	39472*	31986	98720	70062	118799
-4	26431*	26418	26672	53519	15281	98839
-3	17408	13838	21131	18674	-12127	69280
-2	15174*	15563*	14804	18907	8477	36775
-1	20443*	29033*	10446	21124	16835	27645
0	-19242*	-29841*	-6957	-31210*	-49197*	-10671
1	-24748*	-37300*	-10524	-43133*	-74863*	-12536
2	-25452*	-30652*	-19526	-56169*	-81891*	-29753
3	-27012*	-28099*	-25765	-65273*	-88454*	-42592
4	-25460*	-23953	-27058	-53777	-58175	-49862
5	-31128*	-23907	-39491	-75868*	-72377	-79187
6	-26642	-24931	-28521	-82847*	-104767	-61290
7	-30736*	-36006	-24738	-101660*	-147763*	-51505
8	-35479*	-47047	-22709	-113617*	-179165*	-45865
9	-33231*	-46329	-18731	-111060*	-184913	-38863
10	-38143	-51760	-23753	-161205*	-289067*	-51699
11	-50905*	-71529	-28580	-150212*	-272648*	-57313
12	-54197	-72985	-31961	-206604*	-347359*	-70015
13	-62135*	-86995*	-30998	-221419*	-397294*	-59793
14	-72284*	-92099*	-43351	-239733*	-371375	-92611
15	-54522	-92787	3572	-207567	-358822	-4741
16	-69625*	-122503*	8118	-118258	-251144	-438
17	-73980*	-139968*	7433	-211761	-928732	8509
18	-71172*	-139127*	7216	-234232	-741944	-24561
19	-97917*	-190764*	4963	-47319	-178798	-9575
DIDM (average)	-77065*	-130988*	-35747	-124412*	-233842*	-40286
Covariate	no	no	no	yes	yes	yes

* Parameters are significant at 5% significance level The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

Table 4: DIDM estimates of FMD impacts on meat export (3 initial periods removed)

	Overall	Join	Leave	Overall	Join	Leave
DIDM (dynamic)						
-5	23140*	52192*	-1971*	-9524	-15200	1618
-4	13546*	42341*	-2372*	-11692	-18525	2290
-3	8999*	29213*	-983	994	-671	1296
-2	17410*	11275	20938	48641	28970	54742
-1	24059*	34785*	14879	47812*	72643*	29901
0	-25120*	-39129*	-9631	-29493*	-42012*	-10833
1	-31519*	-43542*	-18498	-37585	-50525	-18817
2	-32774*	-28521*	-36570	-79236*	-66146*	-97635
3	-36910*	-22715	-49784	-111983*	-89019*	-150370
4	-34913	-14057	-55069	-90641	-54843	-155260
5	-40810	-11254	-72701	-92797	-64240	-125050
DIDM (average)	-68188*	-68701*	-69065	-105488*	-143683*	-93073
Covariate	no	no	no	yes	yes	yes

* Parameters are significant at 5% significance level The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

Table 5: Additive dynamic TWFE estimates for FMD impacts on meat export

Dependent variable	Meat export volume
t = -4	-24,583.469
	(2.10)**
t = -3	-17,244.714
	(2.25)**
t = -2	-10,213.832
	(1.37)
t = -1	-5,926.660
	(0.91)
t = 0	-12,231.056
	(1.21)
t = 1	-2,597.709
	(0.20)
t = 2	-6,891.555
	(0.84)
t = 3	-160.480
	(0.02)
t = 4	-4,157.169
	(0.48)
Meat price	-1,981,244.638
	(1.18)
Live animal price	5,804,899.872
	(0.65)
Meat consumption ratio	63,797.906
	(1.77)*
GDP	0.221
	(2.50)**
Animal stock	0.016
	(1.54)
FMD status =1	25,257.114
	(0.98)
FMD status = 2	24,345.548
	(0.71)
R^2	0.23
N	1,226

* p<0.1; ** p<0.05; *** p<0.01

The values in the parentheses report t-statistics.

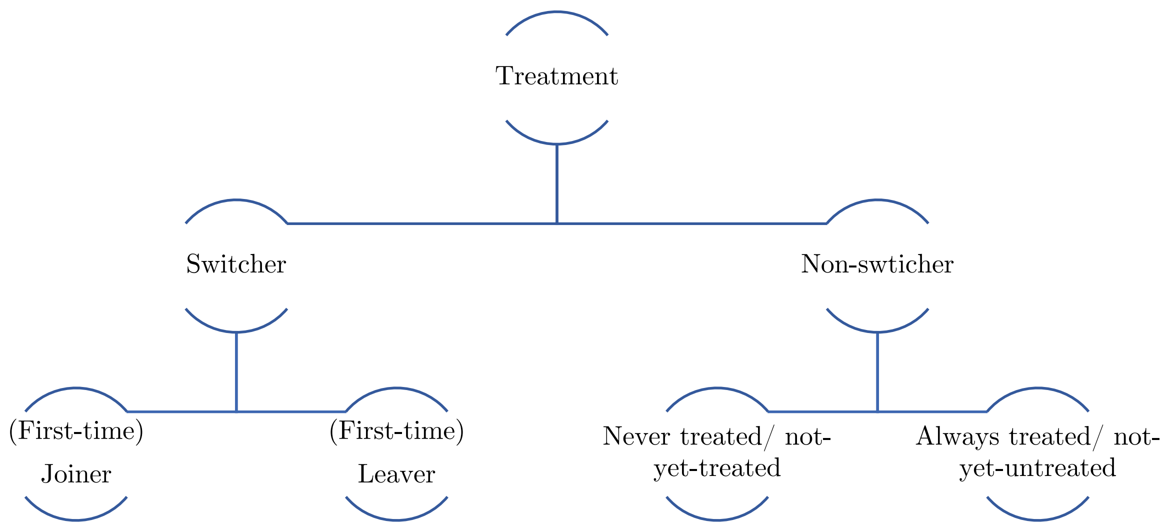

Figure 1. Identification strategy

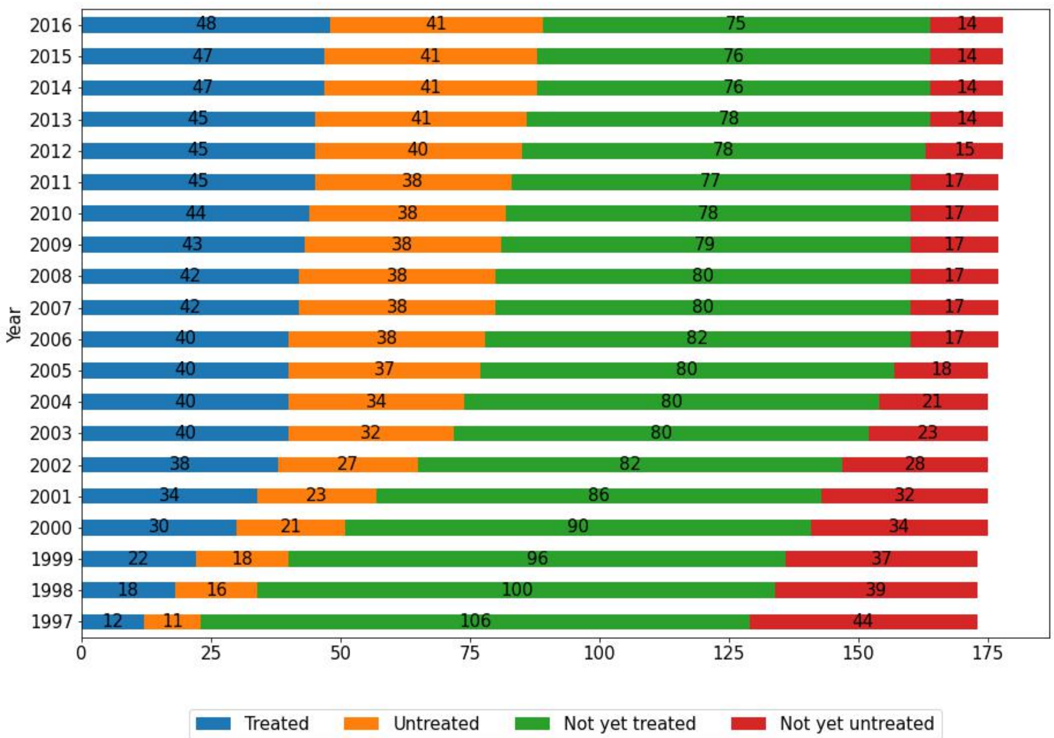

Figure 2: Distribution of treatment and control groups by year

Figure 3: Event plot of joiners' treatment trajectories. The treatment units are sorted in ascending order by their first treatment switching years.

Figure 4: Event plot of leavers' treatment trajectories. The treatment units are sorted in ascending order by their first treatment switching years.

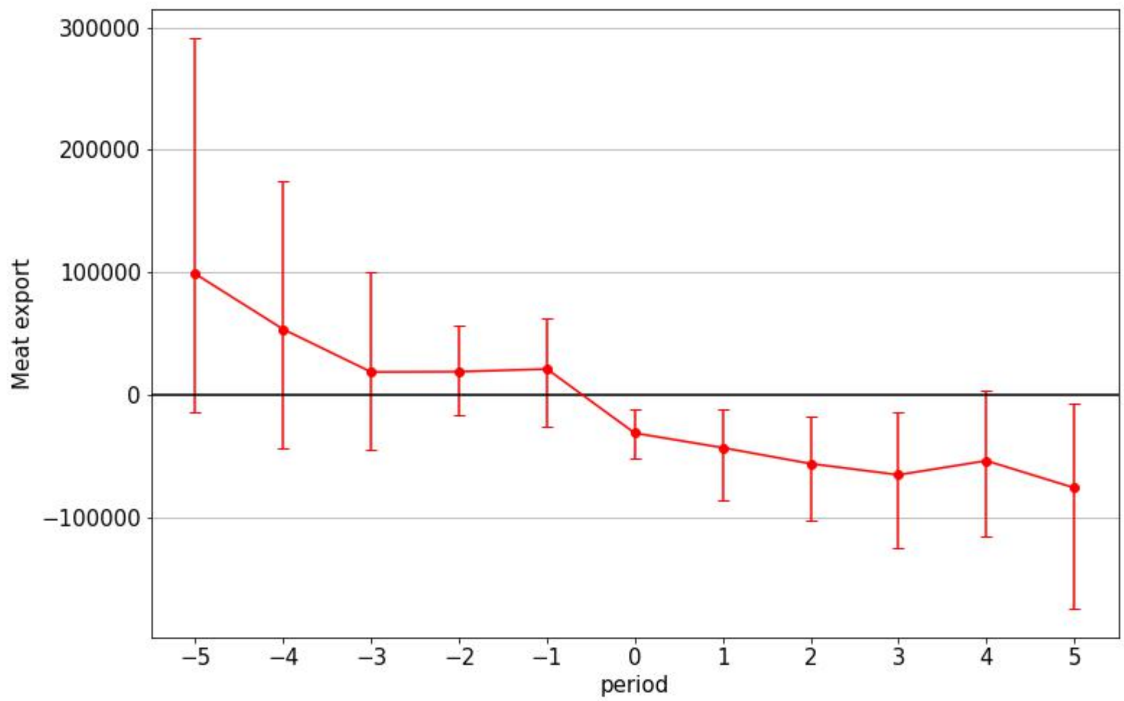

Figure 5: Dynamic effects of FMD outbreak on meat exports. The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

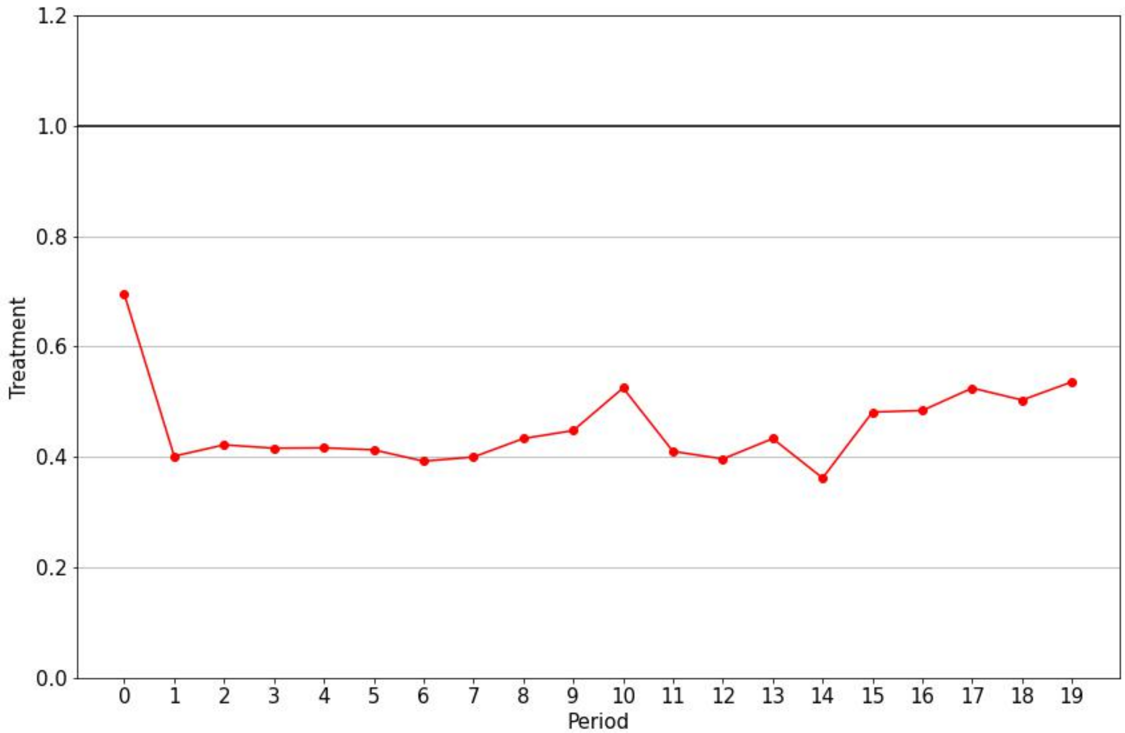

Figure 6: Average treatment received in each period

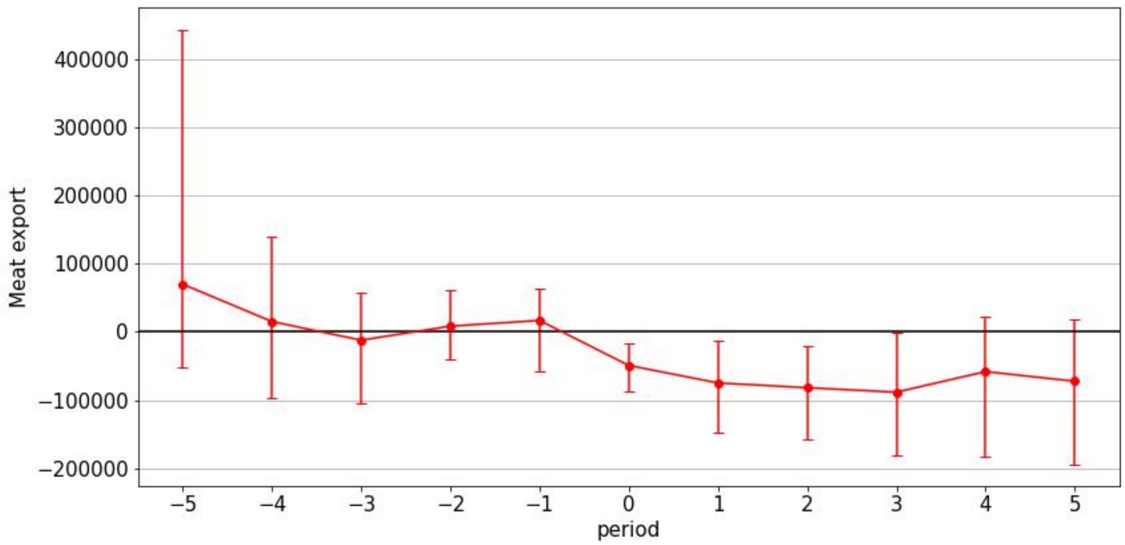

Figure 7: Dynamic effects of FMD outbreak on joiners' meat exports. The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

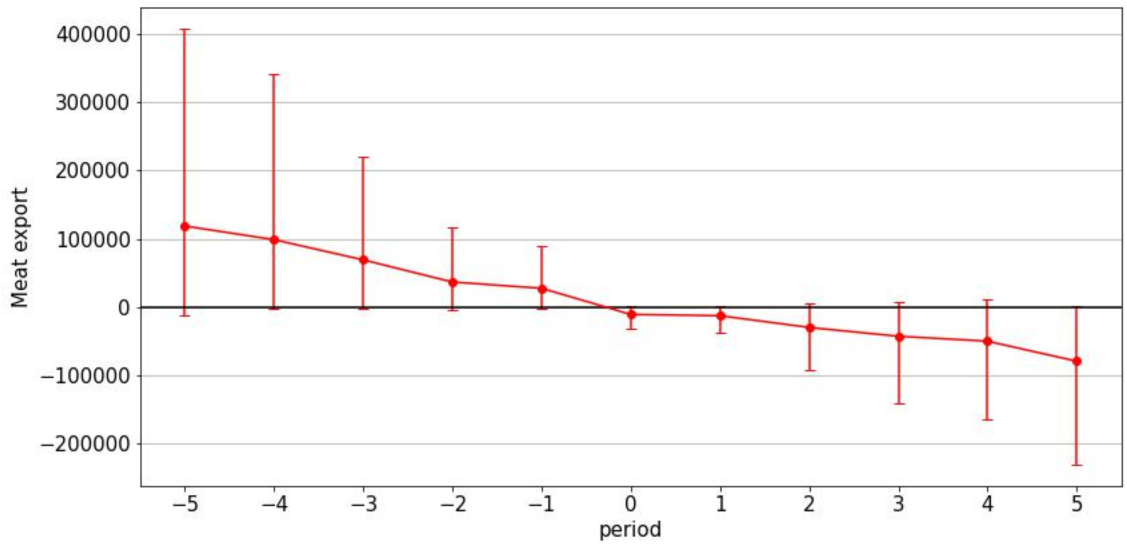

Figure 8: Dynamic effects of FMD outbreak on leavers' meat exports. The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

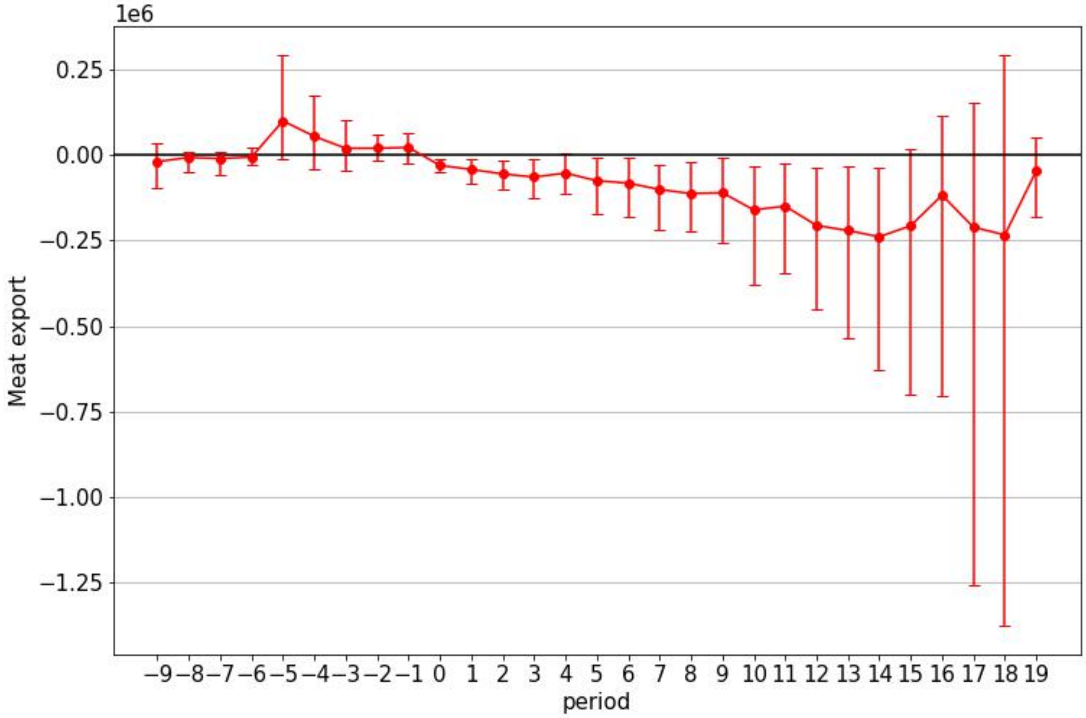

Figure 9: Dynamic effects of FMD outbreak on meat exports (all lags and leads included). The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

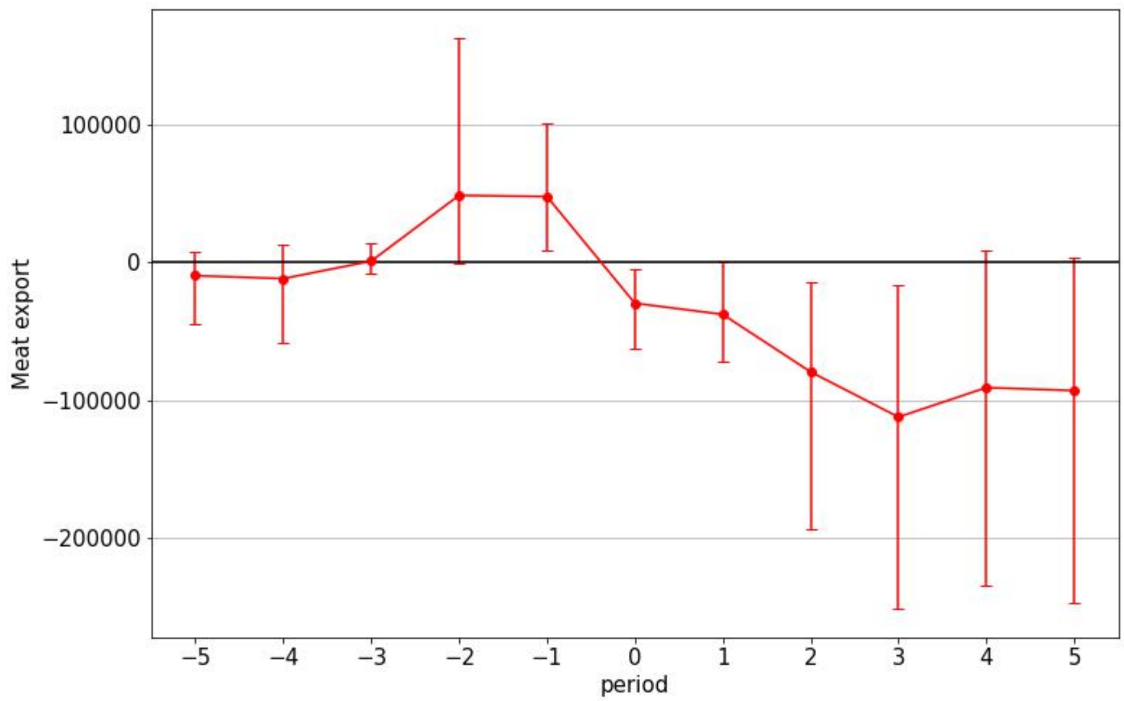

Figure 10: Dynamic effects of FMD outbreak on meat exports (adjusted for initial outbreaks). The 95% confidence intervals are generated using 200 replications of bootstrap samples clustered at the country levels.

Appendix

Table A1: Variable description

Variable	Description	Units	Source
Meat export (volume)	Total meat export quantity	tonnes	FAO
Meat export (value)	Total meat export value	million $	FAO
Outbreak	Outbreak indicator	0 = No outbreak 1 = Outbreak	WOAH
FMD Status	Official WOAH status	1 = FMD free with/without vaccination 2 = Partially FMD free with/without vaccination 0 = Otherwise	WOAH
Agricultural export	Total value of agricultural export	million $	FAO
Agricultural import	Total value of agricultural import	million $	FAO
Meat production to consumption ratio	(Domestic supply + Export - Import)/ Domestic supply		Calculated
GDP	Gross Domestic Product	millions, constant 2010 $	WB
Animal	Number of buffaloes, cattle, goat, camels, pig and sheep in cow equivalent and region standardized unit	head	FAO

Table A2: List of meat products included in the outcome variable

Meat, cattle, boneless (beef & veal)	Meat, beef, preparations
Meat, pig	Bacon and ham
Tallow	Lard
Meat, cattle	Fat, pigs
Meat, pork	Fat, camels
Meat, sheep	Offals, sheep, edible
Offals, edible, cattle	Meat, goat
Offals, pigs, edible	Meat, beef and veal sausages
Meat, pig sausages	Fat, cattle
Meat, pig, preparations	

Table A3: List of countries in different treatment and control groups

Eventually treated	**Eventually untreated**	**Never treated**	**Always treated**
Algeria	Afghanistan	Australia	Benin
Angola	Albania	Austria	Bhutan
Argentina	Armenia	Bahamas	Burkina Faso
Bolivia (Plurinational State of)	Azerbaijan	Barbados	Cameroon
Botswana	Bahrain	Belarus	Ethiopia
Burundi	Bangladesh	Belgium	Ghana
China	Belgium	Belize	India
China, Taiwan Province of	Brazil	Bosnia and Herzegovina	Myanmar
Comoros	Bulgaria	Brunei Darussalam	Nepal
Cyprus	Cambodia	Cabo Verde	Oman
Democratic People's Republic of Korea	Central African Republic	Canada	Thailand
Democratic Republic of the Congo	Chad	Chile	Turkey
Egypt	Colombia	Congo	Uganda
Eswatini	Côte d'Ivoire	Costa Rica	United Republic of Tanzania
France	Ecuador	Croatia	
Gambia	Eritrea	Cuba	
Guinea	Georgia	Czechia	
Guinea-Bissau	Greece	Denmark	
Iraq	Iran (Islamic Republic of)	Djibouti	
Ireland	Israel	Dominican Republic	
Japan	Jordan	El Salvador	
Lao People's Democratic Republic	Kazakhstan	Equatorial Guinea	
Libya	Kenya	Estonia	
Malawi	Kuwait	Fiji	
Mauritius	Kyrgyzstan	Finland	
Mongolia	Lebanon	Gabon	
Morocco	Luxembourg	Germany	
Mozambique	Malaysia	Guatemala	
Namibia	Mali	Guyana	
Netherlands	Mauritania	Haiti	
Nigeria	Montenegro	Honduras	
Paraguay	Niger	Hungary	

Republic of Korea	North Macedonia	Iceland
Russian Federation	Pakistan	Indonesia
Rwanda	Peru	Italy
Somalia	Philippines	Jamaica
South Africa	Qatar	Latvia
South Sudan	Saudi Arabia	Lesotho
Sri Lanka	Senegal	Liberia
Sudan	Serbia	Lithuania
Syrian Arab Republic	South Sudan	Luxembourg
Tajikistan	United Arab Emirates	Madagascar
Togo	Venezuela (Bolivarian Republic of)	Maldives
Tunisia	Viet Nam	Malta
Turkmenistan	Zambia	Mexico
United Kingdom of Great Britain and Northern Ireland	Zimbabwe	Micronesia (Federated States of)
Uruguay		Montenegro
Yemen		New Caledonia
		New Zealand
		Nicaragua
		Norway
		Panama
		Papua New Guinea
		Poland
		Portugal
		Republic of Moldova
		Romania
		Saint Lucia
		Sao Tome and Principe
		Serbia
		Seychelles
		Sierra Leone
		Singapore
		Slovakia
		Slovenia
		Spain
		Suriname
		Sweden
		Switzerland
		Timor-Leste

	Trinidad and Tobago
	Ukraine
	United States of America
	Uzbekistan
	Vanuatu

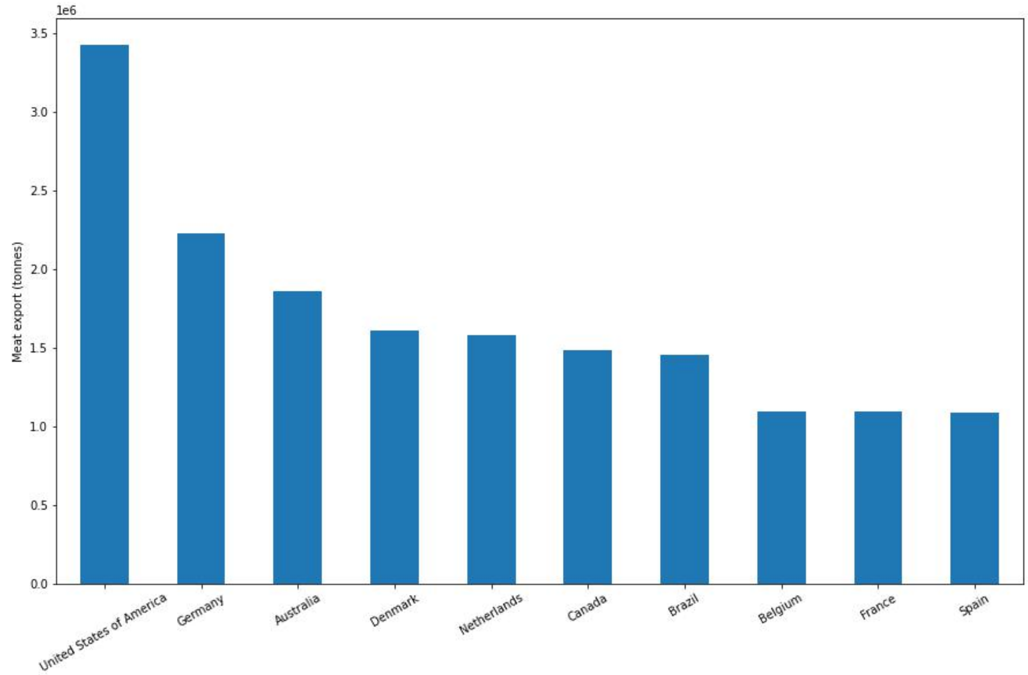

Figure A1: Top 10 meat exporters