# Exploring Spatial Price Relationships: The Case of African Swine Fever in China

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**Abstract**

We use a temporary ban on inter-province shipping of live hogs induced by the 2018 outbreak of African Swine Fever (ASF) in China as a natural experiment to study spatial mechanisms behind the dynamics of market integration. With a unique dataset of weekly provincial hog prices, we employ a novel spatial network model to estimate the strength of price co-movement across provinces pre and post the ban. Results indicate that, in the highly integrated national market prior to the ban, longer geographical distances between two provinces did not weaken the strength of their price linkage. The ban broken down spatial integration. Longer distances became a significant obstacle to spatial price linkage in the post-ban periods, implying faster re-integration of hog prices between proximate provinces than remote ones. The negative effect of distance can be rationalized by the interplay between arbitrage opportunities and imperfect information. Our findings highlight information transparency as a key to market integration post shipping bans used to curb animal pandemics like ASF.

**Keywords:** Information transparency, market integration, spatial models, spatial price relationships.

**JEL Codes:** C22; C23, Q18.

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## 1. Introduction

As stated in Barrett and Li (2006), market integration is achieved when all arbitrage opportunities across markets are exhausted, which is often true in free market economies. Studies on market integration using time series data are abundant (Ravallian, 1986; Goodwin and Schroeder, 1991; Wang and Ke, 2005; Shiue and Keller, 2007; Negassa and Myers, 2007; Ge et al, 2010), though most have not carefully examined spatial relationships. Additionally, most existing studies on market integration focus on testing whether certain markets are integrated or not, and if not, few follow up with identifying the underlying driving forces. Other than consumer cultural preferences (Goyat, 2011), which do not apply to generic commodities without place of origin information, political barriers (Fan, 2002), which are mostly limited to the labor market, and processor market concentration (Goodwin and Schroeder, 1991), risks due to animal epidemics may also prevent market integration. For example, the outbreak of BSE (bovine spongiform encephalopathy, or mad cow disease) disrupted the integration of U.S., Canadian, and Mexican beef markets (Sparling and Caswell, 2006), and the most recent COVID-19 outbreak segmented vegetable markets in China (Ruan et al, 2021). These natural disasters bring tremendous market uncertainty, and producers and traders may decide to avert risks at the opportunity cost of reduced production (Sandmo, 1971) and arbitrage, thus breaking the market integration.

The 2018 outbreak of African Swine Fever (ASF) in China provides a natural experiment for us to study the market integration incorporating both spatial dimension and risks. Having the world's largest pork market, Chinese pork consumption is concentrated in large cities in coastal provinces while its production is in rural areas, inter-province transportation of live hogs has been the major form of arbitraging to meet the pork demand with supply, resulting in a rather integrated domestic market. In response to the ASF outbreak, the central government immediately imposed an inter-province shipping ban for live hogs, which affected the spatial price relationships across provinces (Zhang et al., 2019a). The shipping ban was later lifted for any province as it was officially cleared with ASF cases, but the provincial prices did not converge quickly.

In this study, we examine hog price responses to the ASF-induced supply shocks and the shipping ban over time and space and, particularly, the process for provincial hog markets to re-integrate after the ban was lifted. A recently developed spatial panel data model (de Paula et al., 2018) is adopted to estimate the strength of price co-movement between each pair of provinces over time. It parameterizes the price links across provinces to facilitate estimation of those connections via Generalized Method of Moments (GMM) for high-dimensional models – these estimates provide insight into which provincial hog markets are most closely linked in a given period, while controlling for province- and time-specific factors. We then use variables such as the geographic distance and the length of time period under ban for any pair of provinces to explain the slow market re-integration process measured by the price relationships estimated previously. We explain the slow re-integration by producers'/processors' reluctance to reassume the trading with distant partners compared with partners nearby, when the public information of ASF is incomplete.

Our study has important policy lessons, primarily related to the importance of information transparency about contagious animal diseases. A strong policy response may have dramatic economic effects, and the key to quick economic recovery is ensuring producers access to information needed to manage private risks in the recovery stage. The insights are of value to many countries that suffer or may suffer from animal epidemics and human pandemics.

## 2. Background

The Chinese hog market and the situation of ASF breakout in China from 2018 to 2019 are described in this section. Implementation of the inter-province shipping ban on live hogs are also summarized.

### *2.1 Chinese Pork Supply Chain*

China is the world's largest producer and consumer of pork, with pork being the dominant meat in the Chinese diet. Every year, over 600 million hogs, or one-half of the world's total production, are produced and consumed in China. Per capita annual consumption of pork is around 40 kilograms from 2015 to 2018 (Ma et al., 2021) and accounts for 60% of Chinese consumers' total meat consumption (i.e., consumption of pork, poultry, beef, and mutton).

In normal times, or pre-ASF years, the stocks of hogs and sows are around 350 million and 35 million heads, respectively. Figure 1 depicts the monthly stocks from January 2016 to November 2020 and shows the sharp declines in hog and sow stocks caused by the ASF. Within the first year of ASF, the stock of hogs decreased from 321 million to 191 million, a loss of 40.5%, while the stock of sows fell from 31 million to 19 million, or 39.3%. Since the last quarter of 2019, both stocks have been gradually built back. By November 2020, both reached 80% of their pre-ASF levels.

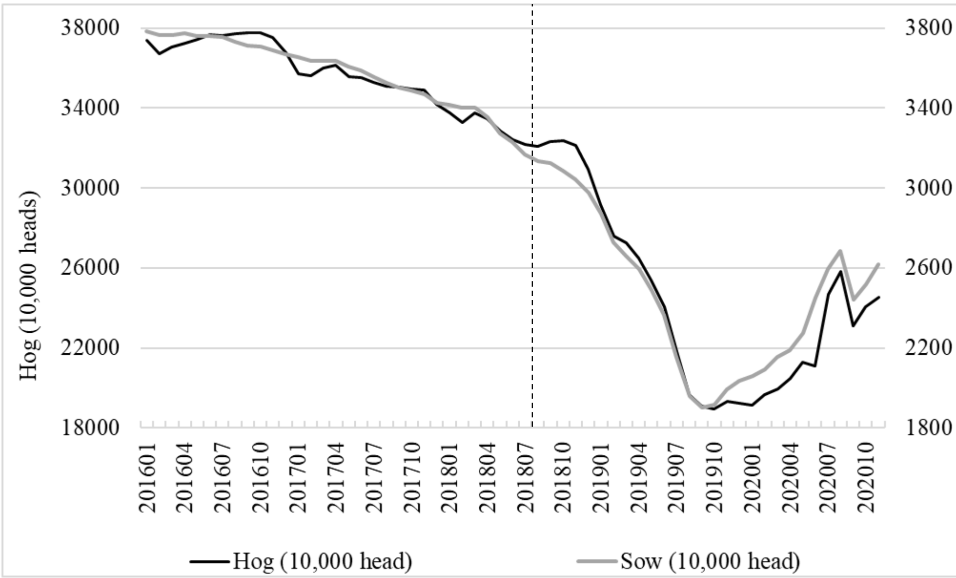


**Figure 1. Hog and Sow Stock in China 2016-2020**

*Source*: Ministry of Agriculture and Rural Affairs of China.

*Note*: The figure covers January 2016 to November 2020. The horizontal axis indicates year and month. For example, 202011 refers to the 10th month of 2020, namely, October 2020. The dotted line indicates August 2018 when the ASF first broke out in China.

For decades, backyard farms had been predominant hog producers in China. In 2002, small farms with an annual output of less than 50 heads accounted for 99% of all hog farms and contributed nearly 73% of the hogs slaughtered (Kuhn et al., 2020). In 2012, the small farms still accounted for 95% of the farms, but only contributed about 30% of the total output. Despite the significant structural transition in hog production from backyard towards industrialized, large-scale farms (Qiao et al., 2016), China's pork supply chain consists of a large number of producers and processors in all provinces (Zhang et al., 2019b) and has much lower concentration ratios in production and processing compared with hog sectors in developed economies. For instance, the collective market share of the largest five slaughtering firms in China was merely 5% in 2018, which is in sharp contrast with the United States where the ratio is 74% (Wen and Liu, 2019).

Pork is produced and consumed in every Chinese province. However, major pork consuming provinces and major producing ones do not overlap. Major consuming provinces include Beijing, Guangdong, Shanghai, and Zhejiang, all of which are most economically advanced and populated in China, while major producing provinces include Henan, Hunan, Shangdong, and Sichuan, which are relatively less developed. Excess demand or excess supply at the province level, coupled with a strong preference for fresh, un-chilled pork (Wang et al., 2018) and underdeveloped cold chains, creates a need for inter-province shipments of live hogs. Large numbers of live hogs are transported by processors or logistics firms across provinces every day, mostly using open-trailer trucks, and processed near the retail markets.

The inter-province shipping of live hogs in trailer-trucks makes the spread of virus easy for two main reasons. One is that trucks from various locations meet at a slaughter plant and may spread the virus to each other if at least one of the trucks carries the virus. In particular, relatively large slaughtering plants often process hogs both from local farms and farms in other provinces. They own or hire trucks to ship in hogs from a number of hog farms. Trucks travelling within and across provinces meet at the slaughter plant frequently. Because trailers are not confined, the virus can easily move from one trailer to another. As trucks travel to load another batch of hogs from local or other provinces, they may spread the virus to those farms. The other way is via animal inspection stations set along inter-province highways. Trucks have to stop multiple times for inspection of various animal diseases at those stations when travelling from one province to another, and the virus may spread during an inspection.

### *2.2 ASF Outbreak in China and Policy Responses*

ASF is a highly contagious disease among swine, wild or domestic, via the ASF virus. Once infected, the death rate is 100%. In addition to being passed among live hogs, the virus can also infect and be passed by leeches, birds, and mice, and can contaminate water and feed. The virus is able to survive in the air for days and remain active in blood, organs, and droppings of infected hogs for years, and it may spread through carcasses, pork cuts, as well as people who touch and carry the virus (Mason-D'Croz et al., 2020).

The first confirmed case of ASF was reported in a county located in Liaoning Province (Northeastern China) on August 3, 2018. To prevent ASF from spreading in the province and beyond, two actions were taken shortly after. First, all hogs on any *infected farm* and *farms within 3 kilometers* would be culled, and the farms would be thoroughly sanitized. Producers were compensated at 1,200 RMB per hog culled which matched the materials cost of fed hogs. So far, nearly 1.2 million hogs were culled due to ASF.[1]

Second, live and slaughtered hogs in an *infected county* were not allowed to be shipped to other counties in its home province, and live hogs in an *infected province* were not allowed to be shipped to other provinces, starting August 31, 2018. Hereafter, we refer to the ban on inter-province shipments of live hogs as the *ban*. By September 10, six provinces were infected and put under the ban. Ten other provinces adjacent to these six were added to the list a day later. Despite these shipping restrictions, the virus kept spreading and the list kept growing. By the end of 2018, 95 ASF cases were officially reported in China (see Table A1), and all mainland provinces except for Hainan, the island province, were under the ban. However, if an infected country becomes clear of new cases for six weeks, it can be reopened after an inspection, and an infected province can be

[1] The exact amount of compensation can be adjusted by provincial-level governments. The policy on culling hogs was revised in late February 2019, so that hogs on farms within 3 kilometers from the infected farm need not to be culled unless they were tested positive.

removed from the list if all of its counties are cleared. Thus, almost all provinces had their bans lifted by mid-March 2019, albeit the reported cases rose to 144 by the end of 2019.

Not surprisingly, the ban on inter-province shipment of live hogs greatly disrupted market integration, and substantial price divergence appeared across provinces. Specifically, net importing provinces, such as Beijing and Shanghai, experienced rapid and large price increases due to a sharp fall in the supply of live hogs. In contrast, net exporting provinces, such as Henan, Liaoning, and Inner Mongolia, saw large price decreases during the period due to a shift-in of hog demand. See Figure 2, where the mean and +/- two standard deviations of hog prices of from the beginning of 2016 to late 2020 for 29 provincial level regions are shown. These, including all Chinese mainland provinces, municipalities, and minority autonomous regions with the exception of Tibet and Qinghai, are all referred to as *provinces* thereafter. Before the outbreak of ASF, the band around the national average price is narrow, indicating close co-movements of province-level prices. After the bans were lifted, prices began to converge, and markets began to re-integrate. It is clear, however, that this market re-integration is slow. As shown in Figure 2, the weekly two-standard-deviation band of the national average hog price still did not narrow down to pre-ASF levels by November 2020.

Throughout the article, we divide the data from January 1, 2016 to November 10, 2020 into four periods based on the outbreak of ASF and the implementation of the ban. Period 1 lasts from January 1, 2016 to August 5, 2018 and is the pre-ASF period. Period 2 covers the rest of 2018 through March 18, 2019 and is the ban-period. We divide the post-ban period into two segments: the immediate post-ban but pre-COVID period (March 19, 2019 to February 29, 2020) and the post-COVID period. This division of the post-ban period into pre- and post-COVID allows us to isolate any potential confounding market effects of COVID-19. The three dotted vertical lines in Figure 2 indicate the four periods.

Note that carcass shipments, which were allowed, across provinces did not help maintain integration of provincial hog markets for at least three reasons. First, the demand for frozen carcasses from other provinces is limited because of a strong consumer preference for un-chilled, fresh cut pork (Wang et al., 2018; Mason-D'Croz et al., 2020). Second, because local slaughtering capacity was pre-determined to meet the daily demand for fresh pork within the province, net exporting provinces would not be able to process the extra live hogs and produce more carcass for net importing provinces. Third, there is insufficient cold chain capacity to ship more frozen or chilled carcasses over a long distance. Hence, even if additional hogs could be slaughtered in net exporting provinces, the carcasses would not be able to be shipped to net importing provinces in time.

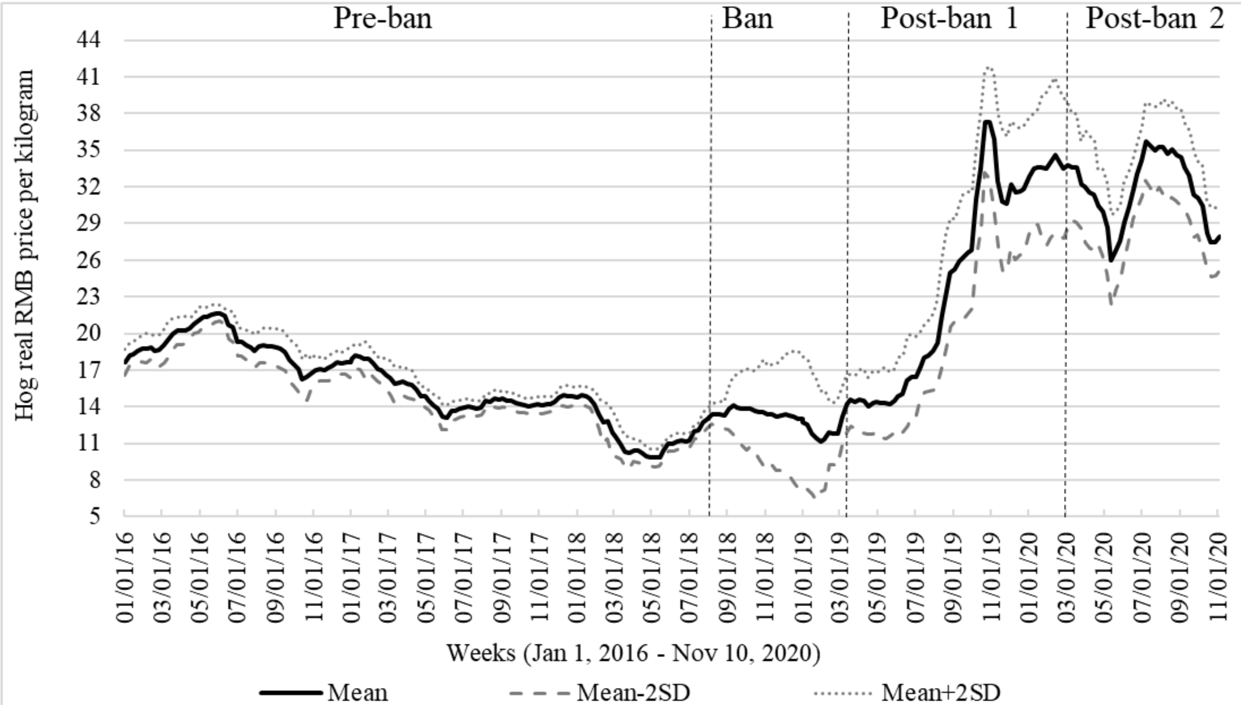


**Figure 2. Weekly National Average Hog Price**

*Source*: http://www.zhujiage.com.cn

*Note:* The dotted curves represent the two-standard-deviation bands of the national average hog price (real RMB/kilogram). Each observation on the upper dotted curve represents the mean price plus two times the corresponding standard deviation, and each observation on the lower dotted curve represents the mean price minus two times the corresponding standard deviation. The horizontal axis represents all weeks from January 1, 2016 to November 10, 2020. From left to right, the three dotted vertical lines indicate the end of Period 1, the end of Period 2, and the end of Period 3, respectively.

## 3. Econometric Approaches

We construct two econometric models in this section. First, we will identify the spatial connectivity among provincial markets through their price relationships in each period. Second, we will identify factors affecting the spatial market relationships.

### *3.1 Spatial Model*

To develop the spatial regression model, we define a standard panel-data spatial regression structure as:

(1) $$p_{it} - \overline{p_t} = \rho \sum_{j=1}^{n} w_{ij}(p_{jt} - \overline{p_t}) + v_i + \mu_t + \varepsilon_{it},$$

where the index, $i = 1,2, \ldots, n$, references provinces, and $t = 1,2, \ldots, T$ represents weeks. The variable $(p_{it} - \overline{p_t})$ on the left-hand-side of the equation denotes the price deviation in the hog price time series where $p_{it}$ is the hog price for province $i$ in week $t$, and $\overline{p_t}$ is the average price across all provinces in week $t$.[2] In the model, this price deviation is explained by the weighted average of all its spatial lags, $\sum_{j=1}^{n} w_{ij}(p_{jt} - \overline{p_t})$, where $w_{ii} = 0$. The model is applied to each of the four periods defined in the second section, respectively.

Stationarity tests between the price series and price deviation series confirms appropriate use of the price deviation series in our regression models: the price series is not stationary, but the price deviation series is stationary. Variable $v_i$ is a province-specific effect that may be unobserved (a province-level fixed effect), $\mu_t$ is a potentially unobservable month-specific seasonal effect (a month-level fixed effect), and $\varepsilon_{it}$ is the regression error.

As is standard spatial regression formulation, $w_{ij}$ are the elements of an $(n \times n)$ proximity matrix, $W$, whereby each element represents the pairwise spatial link among provinces $i$ and $j$; the spatial links are constant over weeks within each period. The diagonal elements of $W$ are constrained to be zero, so that each province's own price deviation is not used to explain itself on the right-hand-side. Thus, for any province $i$, $\sum_{j=1}^{n} w_{ij}(p_{jt} - \overline{p_t})$ captures the spatially weighted

[2] In the model, we use the price deviation instead of price level itself to stabilize the price time series, as co-movement in the untransformed price series renders estimation challenging.

average of hog price deviations of all other provinces. Then the parameter $\rho$ is the coefficient for the spatially weighted sum of hog price deviations of the province's trading partner provinces, and it captures the effect of the price deviations in other partner provinces on each province's price deviation series: the larger the value of $\rho$, the more closely related are the price deviation series across provinces.

In traditional spatial models, the elements of $W$ are assumed to follow a pre-specified spatial structure; for instance, proximate, contiguous neighbors (Florkowski and Sarmiento, 2005; Tian et al., 2010; Wetzstein et al., 2021). Estimation then amounts to estimating $\rho$ while accounting for the fixed effects, and is typically done using maximum likelihood. Econometric consistency hinges, in particular, on accurate specification of the spatial structure. Indeed, in many empirical settings, the investigator likely does not know the exact spatial structure and merely imposes a particular structure based on geographic location. In our case of hog prices with a shipping ban, no prior knowledge about spatial relationships is available and, to make things more complex, the ban was imposed and then lifted.

In the newly developed de Paula et al. (2018) model, the elements of $W$ are treated as parameters to be estimated. The primary advantage of this generalized spatial modeling approach is that one needs not pre-specify a fixed spatial structure, instead allowing for data-driven detection of spatial links (which may be constrained to be binary or allowed to be continuous, or ranging within 0 to 1 as in our study). Estimation of the spatial structure is a novel and robust way of determining the extent to which different hog prices are correlated across provinces.

It is worth pointing out that, distinct from traditional spatial econometric models, an alternative spatial-temporal approach would be a spatial transition model (see Fackler and Goodwin, 2001 for a review of that literature), in which one would estimate a temporal transition probability or transition rate at which the province moves from one price regime to another. There is an important difference between our approach and this transition approach, that is we are not required to specify price regimes as transition models do. The price connectivity among provinces is hence not constrained to fall between a small set of (specified) regimes. The data driven approach allows for minimal structural assumptions on price connectivity, which ensures a more robust and likely more accurate estimation of spatial price relationships.

To this end, we recognize that in a complex trading environment, of which Chinese inter-province hog trading is a good example, it is unlikely that spatial price connectivity follows a straightforward geographic-oriented spatial structure or is confined to a known and small set of regimes. In the event that the drivers of spatial connectivity is multivariate – perhaps stemming from geographical proximity, road/rail accessibility, provincial or regional trade policies, and established supply chain infrastructure – a pre-specified $W$ or transition model – that does not account for these factors or assign appropriate relative weights will be mis-specified and leads to bias. Using the de Paula et al. (2018) approach allows us to avoid this type of bias. Of course, the econometric consistency properties derived by de Paula et al. (2018) ensures that this method is able to recover a variety of spatial patterns, whether simple or complex, and in light of evidence of a complex spatial connectivity structure, we can develop a deeper analysis of the estimated spatial links to better understand the nature of the price connectivity across Chinese provinces.

It is important to acknowledge that the parameterization of the spatial connectivity matrix leads to a large number of parameters to be estimated. After imposing the (necessary) diagonal constraint that each province is not able to directly influence itself, there remains $n(n-1)$ parameters to estimate. One might further choose to impose a symmetry constraint that the influence of province $i$ on province $j$ is equivalent to $j$'s influence on $i$ in order to reduce the number of remaining parameters to $n(n-1)/2$ parameters. Regardless, there are still a large number of parameters to estimate – large meaning greater than $n$. Fortunately, we follow de Paula et al. (2018) and deploy recently developed GMM methods designed for estimating econometric models with a high-dimensioned parameter vector. The estimator is solved numerically, and so to ensure robustness of the numerical solution we follow a multiple starting value approach, initially setting the starting values of spatial connectivity to be in the set 0, 0.25, 0.5, 0.75, and 1. We then use an Akaike information criterion for each optimization set to determine the optimal solution.

### *3.2 Reduced-Form Econometric Model*

We construct reduced-form regressions to identify factors affecting the spatial relationships found from equation (1). We propose as the dependent variable the estimated inter-province price links, $w_{ij}^m$, which measures the degree to which province *i*'s hog price follows the partner-province *j*'s hog price. Superscript *m* is added to denote the weights are for the $m^{th}$ period, *m* =1, …, 4 for the four periods defined in Figure 2 with pre-ASF as period 1 and so on. The goal is to test if $w_{ij}^m$ depends on the distance between provinces *i* and *j* and the number of weeks that the pair of provinces stayed under the ban, controlling for the average price of the partner province in the period (i.e., $ln\left(\overline{p_{Jm}}\right)$).

The distance variable is denoted by $D_{ij}$ and is constant over time. To estimate the impact of the shipping ban, we use variable $\Gamma_{ij}$ to measure the total number of weeks that at least one of provinces of the pair was under the ban. Additional exogenous variables are included in the regression. The provincial level hog output and province trading status pre-ASF are included in the baseline regression and denoted by vector $\Omega_j$ for province *j*. The period-specific specification is expressed as:

(2) $ln\left(w_{ij}^{m}\right) = c^{m} + \alpha^{m}\, ln\left(D_{ij}\right) + \beta^{m}\, ln\left(\overline{p_{Jm}}\right) + \varphi^{m}\Gamma_{ij} + \omega^{m}\Omega_{j} + F_{i} + e_{ij}^{m}, m = 1, \ldots, 4$

where $F_i$ is the fixed effect of the home province, and $e_{ij}^{m}$ is the error term. The fixed effect captures any effect that is province-*i*-specific, including province $i$'s average hog price in the period. Because the error term may be correlated among multiple observations related to the same home province, we cluster $e_{ij}^{m}$ at the province level. When estimating the effect for the second to the fourth periods, we also add pre-ban estimated $\ln\left(w_{ij}^{1}\right)$ as a control variable to account for potential path-dependence of the trading relationship. Taking logarithm on the weight, right-hand-side coefficients can be interpreted as percentage change in *w* brought by one unit change is corresponding variables.

**4. Data**

Data used in this study come from various sources and include hog prices and production, provincial-level trade status, geo-distances among provinces, and time and province of shipping bans. In this section, we explain how the data were collected and processed, and present key summary statistics.

Daily county-level hog price data are obtained from http://www.zhujiage.com.cn/, for the period between January 1, 2016, and November 10, 2020. They are then aggregated to the provincial level by a simple average as the focus of our study is on inter-province trade and market integration. Before 2018, there are missing days in a fairly large number of weeks, and so we take the simple average of prices across all available days in each week to generate the weekly price.

The raw dataset contains 31 provinces of China. Two provinces, Qinghai and Tibet, are excluded because their hog prices are not reported for 80% and 90% of the weeks, respectively. All other provinces are observed for at least 252 weeks, except for Ningxia (209 weeks), Shanghai

(221 weeks), Hainan (230 weeks), and Guizhou (245 weeks). A linear interpolation is used to back out for the missing weeks of the 29 provinces.

Real prices measured as RMB per kilogram are obtained by deflating the nominal prices with the monthly Consumer Price Index (CPI) reported by the National Bureau of Statistics of China (http://www.stats.gov.cn). Setting January 2018 as the base month with a value of 100, the CPI series starts with a value of 96.2 in January 2016 and ends at 105.2 in November 2020. The finalized price dataset is a panel of 29 provinces and 255 weeks. Summary statistics of the price data are displayed on the top four rows in Table 1. Average prices in the post-ban periods are considerably higher compared with earlier periods due to the sharp reduction in hog supply caused by ASF.

**Table 1. Summary Statistics of Additional Variables**

| Variables | Mean | SD | Min | Max | Unit |
|---|---|---|---|---|---|
| Province hog price in Period 1 | 15.81 | 0.34 | 15.11 | 16.69 | RMB/kg |
| Province hog price in Period 2 | 13.05 | 1.56 | 10.45 | 16.71 | RMB/kg |
| Province hog price in Period 3 | 24.56 | 1.53 | 20.98 | 27.04 | RMB/kg |
| Province hog price in Period 4 | 31.71 | 1.59 | 28.79 | 35.73 | RMB/kg |
| Distance $D_{ij}$ | 1.31 | 0.70 | 0.11 | 3.46 | 1000km |
| Province hog outputs | 2.42 | 1.90 | 0.11 | 6.58 | 10 mil head |
| Province net importer (0,1 with 1=yes) | 0.55 | 0.50 | 0.00 | 1.00 | - |
| Number of weeks province under ban | 25.16 | 4.64 | 12 | 34 | Week |

*Source*: Authors' calculation. *Note:* The number of observations is 812. Statistics are weighted by observations.

The linear distance between the capital cities of any pair of provinces is collected from geodesic distance computed via the *Imap* package in R and measured in units of 1,000 kilometers. This distance is fixed, given that provincial boundaries do not change. The Ministry of Agriculture and Rural Affairs of China (http://www.moa.gov.cn/gk/yjgl_1/) has reported officially confirmed

ASF cases since the outbreak. We collect information regarding ban imposition, cross-checked with news reports to pin down the starting week of the ban for each province. Yet, there is hardly any news on ban lifting time for each province. We define the ending week of a ban for a province as the week when the ban on the last reported case in the province was lifted, confirming each ending week with an official announcement claiming that almost all bans on inter-province hog shipment were lifted by April 2019. Except for Hainan, all mainland provinces were under the ban for some weeks during the ban period, with the number of ban weeks per province ranging from 12 to 34.

Provincial-level hog output is reported by the National Bureau of Statistics of China. We use hog output in 2017 as a control variable in the econometric models as a proxy for the regular production scale of the province. The production scale may affect trade relationships among provinces. Second, according to industry reports, some provinces are net importers and some are net exporters of pork in "normal times".[3] We add the provincial-level importer/exporter status in 2016 as another control variable to account for the impact of trade directions on trade relationships. Table 1 also presents the summary of statistics for these additional variables.

## 5. Empirical Results

Empirical results from the spatial model and the reduced form model are presented and discussed in this section.

[3] Information in Chinese: http://pg.jrj.com.cn/acc/Res/CN_RES/INDUS/2018/11/19/0699a384-c292-461e-aa98-74a0a019ec7d.pdf

*5.1 Spatial Regression Outcomes*

For each of the 29 provinces in our sample, there are 28 partner provinces, leaving us with 29× (29-1) =812 estimated $w_{ij}$, or $\widehat{w_{ij}}$, in each period. The summary of statistics of the estimated price links from the GMM model are reported in Table 2, instead of the 812×4=3248 estimates. It is important to be clear that $w_{ij}$ measures the relative strength of the connection between provinces $i$ and $j$. For instance, one might interpret the strength of ties relative to the mean, median, or maximum strength, or, as in our case, seek to understand drivers of the strength of connection via reduced form regressions.

To gain preliminary insight, we can see, for instance, that the standard deviation of the links is lowest in Periods 1 and 4, indicating a greater degree of similarity in estimated spatial links in the pre-ASF and final post-ban periods. The higher standard deviations in Periods 2 and 3 indicate periods with more heterogeneity in links across provinces.

**Table 2. Summary Statistics of Estimated Spatial Matrices and Distances**

| Variables | Mean | SD | Min | Max |
|---|---|---|---|---|
| Estimated $w_{ij}$ in Period 1, $\widehat{w_{ij}^1}$ | 0.16 | 0.14 | 0.00 | 0.98 |
| Estimated $w_{ij}$ in Period 2, $\widehat{w_{ij}^2}$ | 0.27 | 0.25 | 0.00 | 1.00 |
| Estimated $w_{ij}$ in Period 3, $\widehat{w_{ij}^3}$ | 0.51 | 0.31 | 0.00 | 1.00 |
| Estimated $w_{ij}$ in Period 4, $\widehat{w_{ij}^4}$ | 0.32 | 0.14 | 0.00 | 0.84 |

*Source*: Authors' calculation. Note: The number of observations is 812. Statistics are weighted by observations.

*5.2 Reduced Form Regressions*

Regression results of equation (2) are summarized in the left four columns of Table 3. R-squared is fairly high across periods, suggesting the good fit of our model. A few patterns can be recognized. First, before ASF, the distance between two provinces does not have any significant impact on the co-movement of their prices. During the ban, the distance does not matter in a significantly way, either, as inter-province shipping was not allowed for any province near or far.

In the post-ban periods, provinces that were under the shipping ban for a relatively large number of weeks tend to have a significantly weaker price link in Period 3. If the two provinces were under the ban for one more week, strength of their price link would fall by 2%. It is likely because that the ban temporarily broke some of the original trading relationships across provinces. The longer two provinces stayed under the ban, the more likely that original trader partners had to build new trade relationships. Thus, the longer two provinces were under the ban, the more of their trading relationships broke and the less their prices connected. In Period 4, the number of weeks under the ban no longer has any significant negative impact on the price link, suggesting some recovery of the original trading relationships.

More interestingly, the inter-province distance has a significant impact on the price link post the ban. Within the first 10 months after the ban was lifted (i.e., Period 3), inter-province distance has a significant and negative impact on the co-movement of prices in two provinces. When the distance increases by 10%, the strength of price connectivity drops by 1%. In period 4, the negative effect of $D_{ij}$ continues to be significant and enlarges to a 3% drop for each 10% increase in distance. It suggests that the newly formed trade relationships among nearby provinces in Period 3 were strengthened. There seems evidence of path-dependence in developing new trading relationships, after an integrated market fell segmented.

The negative effect of inter-province distance is likely to be driven by the lack of public information on ASF, after the ban was lifted. Recall that Table A1 suggests a considerably larger number of ASF cases than that was officially announced. A farm manager who decides whether to ship live hogs from the home province to another province has to weigh the potential gain from arbitrage and the potential loss due to catching ASF. The gain depends on the price spread between the two provinces which the farm takes as given and known to all. The loss is determined by the risk of catching ASF. Without accurate public information, the farm manager has to rely on his/her own information sources to evaluate the risk.

The risk of catching ASF tends to increase in the distance of shipping for two major reasons. First, the more accurate the information the lower the risk, because the farm can choose to trade with a safe processor located in the province, *ceteris paribus*. Farmers obtain private information about ASF through personal networks. Because it tends to be more costly to collect information of slaughtering plants located farther away, the risk of catching ASF tends to be higher when trading with farther away provinces. Second, with the same amount and quality of information, the risk simply grows in the number of inspection stations that the truck has to go through to reach a slaughtering plant. As a result, inter-province arbitrage opportunities are less likely to be taken by farms and slaughtering plants located in relatively far away provinces during the post-ban periods, leaving corresponding inter-province price links weaker.

Controlling for the fixed effect of province $i$, the average hog price of province $j$ has a significant effect on the co-movement of prices both before and after the ASF shipping ban. In Period 1, a positive coefficient of the partner-province price suggests that inter-province trade is intensified if the hog price in the partner province increases. This can be rationalized by the arbitrage behavior of hog farms that export hogs. Similarly, a negative coefficient of the partner-province's price can be rationalized by the arbitrage behavior of hog importers or processing plants. In terms of the magnitude, effects of partner-province prices on $w_{ij}^{m}$ is considerably lower in the post-ban periods compared with Period 1. This indicates that, prior to the ASF, inter-province trade is more strongly motivated by arbitrage opportunities among provinces, while other incentives such as risks may have weakened the effect of price signals in leading inter-province trade of hogs in later periods.

One possible concern may be that the control variables defined for province *j* in the baseline regression may not have captured all the province-specific characteristics that affect the number of weeks that two provinces were under the ban and their price links. To address this possible concern, we add fixed effects for both provinces ($F_i$ and $F_j$) as control variables via the alternative specification (2').

(2') $ln\left(w_{ij}^m\right) = c^m + \alpha^m\, ln\left(D_{ij}\right) + \varphi^m \Gamma_{ij} + \omega^m \Omega_j + F_i + F_j + e_{ij}^m$, $m = 1, \ldots 4$.

Estimates from this alternative specification are displayed in columns (5) to (8) in Table 3. As expected, the R-squared increases relative to the previous model, suggesting that some unobservable factors of province *j* help explain the estimated inter-province price links. The coefficients of inter-province distance and the number of weeks under the ban stay robust in terms of both statistical significance and magnitude.

**Table 3. Inter-Province Estimated Price Links and the Determinants**

| | Without fixed effects for province *j* | | | | With fixed effects for province *j* | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Pre-ban | Ban | Post-ban 1 | Post-ban 2 | Pre-ban | Ban | Post-ban 1 | Post-ban 2 |
| Distance between | 0.08 | 0.07 | -0.12** | -0.26*** | 0.09 | -0.12 | -0.21*** | -0.25*** |
| provinces *i* and *j* | (0.10) | (0.12) | (0.06) | (0.08) | (0.10) | (0.09) | (0.07) | (0.08) |
| | [0.42] | [0.56] | [0.05] | [0.00] | [0.39] | [0.22] | [0.00] | [0.00] |
| #weeks under the ban | | -0.02* | -0.02** | -0.01 | | -0.03** | -0.01*** | -0.02 |
| provinces *i* and *j* | | (0.01) | (0.01) | (0.01) | | (0.01) | (0.00) | (0.01) |
| Province *j* average price | 6.29* | -1.27*** | -1.02** | -1.04* | | | | |
| in the period | (3.16) | (0.45) | (0.39) | (0.53) | | | | |
| | | | | | | | | |
| Pre-ban $\widehat{w_{ij}}$ | NO | YES | YES | YES | NO | YES | YES | YES |
| Province *i* fixed effect | YES | YES | YES | YES | YES | YES | YES | YES |
| Province *j* controls | YES | YES | YES | YES | NO | NO | NO | NO |
| Province *j* fixed effect | NO | NO | NO | NO | YES | YES | YES | YES |
| $R^2$ | 0.57 | 0.48 | 0.63 | 0.38 | 0.59 | 0.60 | 0.66 | 0.42 |
| # observations | 812 | 812 | 812 | 812 | 812 | 812 | 812 | 812 |

*Note:* *** $p$<0.01, ** $p$<0.05, * $p$<0.10. Standard errors in parentheses and $p$-values in the square brackets. Standard errors are clustered at the province level. "Province *j* controls" include hog outputs in the partner province and an indicator whether the partner province is a net importer of pork.

## 6. Policy Implications and Conclusion

The outbreak of ASF in China has caused a drastic shock to the hog market with a supply shortage reflected by considerable price jumps (Li and Chavas, 2020; Ma et al., 2021). In addition to necessary culling of infected hogs, the inter-province shipping ban broke up the market integration and resulted in high prices in net consuming provinces and low prices in net producing provinces, a clear social welfare loss for the whole country.

We apply a novel method in studying spatial price transmission among trading partners by harnessing recently developed methods in spatial econometrics and network analysis that, itself, makes use of recent advances in GMM estimation. Our analysis demonstrates the empirical effects of this shipping ban on market integration, and the speed and manner at which markets re-integrate following a lifting of the ban, but in a setting in which uncertainty of information regarding the spread of the virus persists. We use the combination of the GMM spatial panel data model and reduced-form regressions to analyze the spatial connectivity in live hog price series across provinces. These empirical models confirm the observations that the once highly integrated live hog markets across Chinese provinces quickly fractured under the ban, and were slow to recover after the ban was lifted.

One reason for this relatively slow recovery is a difference between public and private information about the spread of ASF, leading to uncertainty for producers and processors. The uncertainty in ASF information, absent the public mandate, leads to privately borne ASF risk for private operators. An immediate policy lesson from our analysis is that the government should strive to maintain certainty and transparency in information regarding the disease outbreak if it wants to maintain safe trade within the region.

Another implication is that cold chain logistics may be an effective measurement to limit live hog shipping from production regions to consumer centers where the slaughtering plants are located. Many contagious animal diseases have happened in recent years, including the blue ear disease, swine flu, hoof and mouth disease, and now ASF in China. Although viruses can survive in carcasses, the survival period and rate are much shorter and lower than in live animals. With the fast development of the modern retail sector and home cold storage in emerging economies, cold chain logistics form the last link to close the meat distribution system. The existing slaughter facilities near consumer centers may be an obstacle to the cold chain development.

Given the slow recovery of market integration in the post-ban periods, it is likely that welfare losses were incurred; expanded use of cold chain logistics might be a way to minimize such losses in future disease-outbreak cases both within China and in other emerging economies beyond China. Besides, our methodological approach has application beyond the current Chinese hog market context for studying spatial price transmission.

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## Appendix. Officially Reported ASF Cases in China

Table A1 summarizes the numbers of officially reported ASF cases in 2018 and 2019 by province in mainland China. The number of hogs affected is the reported number of hogs on all directly infected farms. Hogs raised on nearby farms may be culled as well.

**Table A1. Officially Reported Cases of African Swine Fever**

| Province | No. cases 2018 | No. cases 2019 | No. cases | No. hogs affected |
|---|---|---|---|---|
| Anhui | 8 | 0 | 8 | 10981 |
| Beijing | 3 | 0 | 3 | 14050 |
| Chongqing | 2 | 1 | 3 | 423 |
| Fujian | 3 | 0 | 3 | 22247 |
| Gansu | 0 | 3 | 3 | 586 |
| Guangdong | 3 | 0 | 3 | 6167 |
| Guangxi | 0 | 5 | 5 | 27619 |
| Guizhou | 4 | 4 | 8 | 1666 |
| Hainan | 0 | 6 | 6 | 1238 |
| Hebei | 0 | 1 | 1 | 5600 |
| Henan | 3 | 0 | 3 | 260 |
| Heilongjiang | 5 | 1 | 6 | 74649 |
| Hubei | 4 | 3 | 7 | 2026 |
| Hunan | 7 | 1 | 8 | 13443 |
| Inner Mongolia | 5 | 1 | 6 | 995 |
| Jilin | 4 | 0 | 4 | 1458 |
| Jiangsu | 2 | 1 | 3 | 69066 |
| Jiangxi | 3 | 0 | 3 | 463 |
| Liaoning | 16 | 0 | 16 | 35342 |
| Ningxia | 0 | 4 | 4 | 465 |

**Table A1 (continued)**

| Province | No. cases 2018 | No. cases 2019 | No. cases | No. hogs affected |
|---|---|---|---|---|
| Qinghai | 1 | 1 | 2 | 101 |
| Shandong | 0 | 1 | 1 | 4504 |
| Shanxi | 5 | 0 | 5 | 8379 |
| Shaanxi | 3 | 2 | 5 | 11857 |
| Shanghai | 1 | 0 | 1 | 314 |
| Sichuan | 5 | 3 | 8 | 1608 |
| Tianjin | 2 | 0 | 2 | 1000 |
| Tibet | 0 | 1 | 1 | N/A |
| Xinjiang | 0 | 3 | 3 | 1124 |
| Yunnan | 4 | 7 | 11 | 1919 |
| Zhejiang | 2 | 0 | 2 | 2280 |
| All | 95 | 49 | 144 | 321,830 |

*Source*: Authors' summarize from http://www.moa.gov.cn/gk/yjgl_1/yqfb/.

*Note:* "No. hogs affected" is the total number of hogs on the infected farms in the reported cases.