Risk, Arbitrage, and Spatial Price Relationships: Insights from China's Hog Market under the African Swine Fever

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Abstract

We use the 2018 outbreak of African Swine Fever (ASF) in China as a natural experiment to study spatial mechanisms behind the dynamics of market integration. We first apply pairwise price cointegration tests to show that Chinese provincial hog markets were highly integrated before the ASF breakout, became segmented after the government banned live hog shipping across provinces, and re-integrated slowly after the ban was lifted. We build a unique dataset of weekly provincial hog prices and employ a newly developed spatial model to estimate the strength of price co-movement across provinces in different periods around the ASF breakout. Using reduced-form regressions, we explain determinants of the estimated inter-province price co-movement. 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. 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. In addition, the longer a pair of provinces stayed under the ban, the weaker their price link became in the immediate post-ban period. This negative effect, though, turned insignificant in the longer-run. We explain the distance effect by the interplay between arbitrage opportunities and imperfect information. Our findings imply that information transparency is a key factor for the market recovery from the damage caused by the shipping ban to curb animal pandemics like ASF.

Keywords: Market integration, arbitrage, hog market, spatial price relationships, cointegration.

JEL Codes: C22; C23, Q18.

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1. Introduction

Spatial market integration occurs when all arbitrage opportunities are exhausted and the spatial market achieves Pareto efficiency (Barrett and Li, 2006). There exists a large body of literature testing for market integration using time series data (Ravallian, 1986; Wang and Ke, 2005; Shiue and Keller, 2007; Negassa and Myers, 2007; Ge et al, 2010), though not carefully examining spatial relationships which are fundamental to how commodity demand and supply shocks spread over time and space. Dynamics of spatial price relationships are important for today's food markets and agricultural supply chains which face growing uncertainty caused by animal epidemics, extreme weather shocks, human pandemics, and other natural events.

Another gap in the literature on market integration and efficiency is the lack of causal exploration. Most studies on market integration focus on testing whether or not certain markets are integrated. If not, few follow up with identification of the underlying driving forces. Other than transportation costs, which do not affect price cointegration, consumer cultural preferences (Goyat, 2011), which do not apply to generic commodities without place of origin labels, and political barriers, which are mostly limited to the labor market (Fan, 2002), 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 Chinese vegetable markets and caused substantial price volatility (Ruan et al, 2021). Producers may decide to avert risks at the cost of production and profit even without government mandated policies (Sandmo, 1971), which explains, in part, the disruption in market integration facing uncertainty.

The 2018 outbreak of African Swine Fever (ASF) in China provides a chance to incorporate both spatial dimension and risks into the study of market integration. With consumption being concentrated in large cities and production occurring mostly in rural areas, inter-province transportation of live hogs plays a key role in balancing demand and supply of pork across provinces in China. As a result, provincial hog markets had been highly integrated. In response to the ASF outbreak, the central government imposed a ban on inter-province live hog shipments, resulting in significant changes in spatial price relationships across provinces (Zhang et al., 2019a).

We examine the reaction of hog prices to the ASF-induced supply shocks and the shipping ban over time and space and, particularly, the process for the provincial hog market to re-integrate after the ban was lifted. We build a unique dataset of provincial-level weekly hog prices that covers January 1, 2016 through November 10, 2020 (255 weeks) and 29 provinces. Though we have detailed time series data, we lack equally detailed inter-province data (e.g., inter-province trade flows), and thus much of the empirical challenge we face is developing econometric models that allow us to understand the spatial effects of the ban in each period.

To overcome this challenge, our empirical strategy is multi-faceted. First, we conduct pairwise cointegration tests for all provinces to see the extent to which prices co-move in a given period across provinces. These tests reveal a high degree of price cointegration prior to the ban, indicating a high degree of spatial market integration, a near complete lack of cointegration during the ban, and a fairly slow integration recovery after the ban was removed. Second, we use the spatial panel data model recently proposed by de Paula et al. (2018) to estimate the strength of price co-movement across province pairs in each period. This model parameterizes the (unknown) price links between provinces to facilitate estimation of those connections via Generalized Method of Moments (GMM) for high-dimension models – these estimates provide insight into which provinces are most closely linked in hog prices in a given period, while controlling for province- and time-specific factors.

We further use the pairwise provincial price links estimated from the GMM model as the dependent variable in reduced-form regressions designed to explore the correlates of the spatial price relationships, including geographic distances between provinces and the number of weeks that each pair of provinces were under the ban. Results indicate that, in the highly integrated market prior to the ban, longer geographical distances between two provinces did not weaken the strength of their price linkage. Yet, longer distances became a significant obstacle to spatial price linkage in the post-ban periods, implying faster re-integration in hog prices between proximate provinces. In addition, the greater the number of weeks that a pair of provinces stayed under the ban, the weaker their price linkage within the immediate post-ban period. This negative effect became insignificant only after 10 months beyond the lifting of the shipping ban.

Why would provincial markets not re-integrate more quickly after the ban was lifted to eliminate opportunities for arbitrage across provinces? Our empirical findings can be rationalized by a conceptual model of risk-mitigation under imperfect information. We argue that a key obstacle to inter-province trade post-ban is the imperfect information about the ASF spread from public sources, whereby elimination of the ban effectively translates risk mitigation from public to private hands. Empirically, the gap between the number of officially reported ASF cases and the actual loss of hogs is large, indicating such imperfect public information. Thus, even when an area was not under the ban and not reporting ASF cases, firms in other areas had reasons to be suspicious.

In China, live hogs are shipped by truck, often via third-party trucking, and the virus is easily passed between hogs at inspection stations on the highway or attached to trucks at infected slaughtering plants and brought back to farms. With these facts, we model the decision of hog farms by characterizing the interplay between risks of ASF, incomplete information, and arbitrage opportunities. Our model explains why, post-ban, even a risk-neutral hog producer would prefer to trade with slaughtering plants that are closer geographically to avoid mis-information that cannot be verified by his/her local networks and prevent infection due to a relatively long distance travelled by truck (i.e., more opportunities for contamination).

Our study has important policy lessons, primarily related to the importance of information transparency about infectious 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 post-policy. The insights are of value to many countries that suffer or may suffer from animal epidemics and human pandemics.

2. Background

In this section, we provide some information on ASF and its spread in China from 2018 to 2019. We then summarize the policies aimed at controlling ASF at the regional level as well as at the national level.

2.1 African Swine Fever

ASF is a highly contagious animal disease which is spread via the ASF virus. Infected hogs can spread the disease to healthy ones, and so can infected leeches, birds, mice, and contaminated water and feed. The virus is able to stay alive in the air for days and remain active in blood, organs, and droppings of infected hogs for years, and it may spread through carcasses and pre-cut pork parts. Human beings who touch infected hogs or pork cuts may also carry the virus, too (Mason-D'Croz et al., 2020).

China's hog supply chain consists of a large number of producers and processors in all provinces (Zhang et al., 2019b). Major pork consuming provinces and major producing ones do not overlap, creating a need for inter-province hog shipments. Live hogs are transported by processors or logistics firms across provinces, mostly using trailer-trucks.

There are two ways for the ASF virus to spread during the inter-province shipment of hogs. One way 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. Another way the virus might spread during the shipping of live hogs 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

The first confirmed case of ASF was found in a county located in Liaoning Province (Northeastern China) on August 3, 2018. Since then to the end of 2019, over 140 ASF cases have been officially reported in China (see Table A1). In order to prevent ASF from spreading in the province or beyond, two actions were taken shortly after the first case. First, all hogs on any *infected farm* would be culled, and the farm would be thoroughly sanitized. Hogs from any farm located within

3 kilometers from the infected farm would also be culled. 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 hogs in an infected province were not allowed to be shipped to other provinces, and live and slaughtered hogs in an *infected county* were not allowed to be shipped to other counties in its home province 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. On September 11, the government imposed the shipping ban on ten other provinces adjacent to the six infected provinces. Despite these shipping restrictions, the ban was imposed on additional provinces as the virus continued to spread. By December, all mainland provinces except for Hainan, the island province, were under the ban. Almost all provinces had their bans lifted by mid-March 2019.[2]

Not surprisingly, the ban on inter-province shipment of live hogs greatly disrupted market integration, and substantial price divergence appeared across provinces.[3] Specifically, net importing provinces, such as Beijing, Shanghai, and Guangdong, experienced rapid and large price

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[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. News report: http://www.chinanews.com/gn/2019/11-22/9014851.shtml (in Chinese).

[2] For an infected county, the ban remained in effect until no new cases were identified in the county for six weeks in a row (after April 2020, this criterion became three weeks). Once this requirement was satisfied, the local government would do a final examination of the infected county (2-3 days) prior to re-opening its trade with other counties in the province. When all county-level bans in the province were lifted, the province can resume shipping in and out live hogs from and to any other provinces not under a ban.

[3] Carcass shipments across provinces did not maintain market integration for at least three reasons. First, the demand for frozen carcasses from other provinces is limited because of a strong consumer preference for fresh cut pork (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 for net importing provinces. Third, there is insufficient cold chain capacity to ship more frozen or chilled carcasses over a long distance. 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.

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.

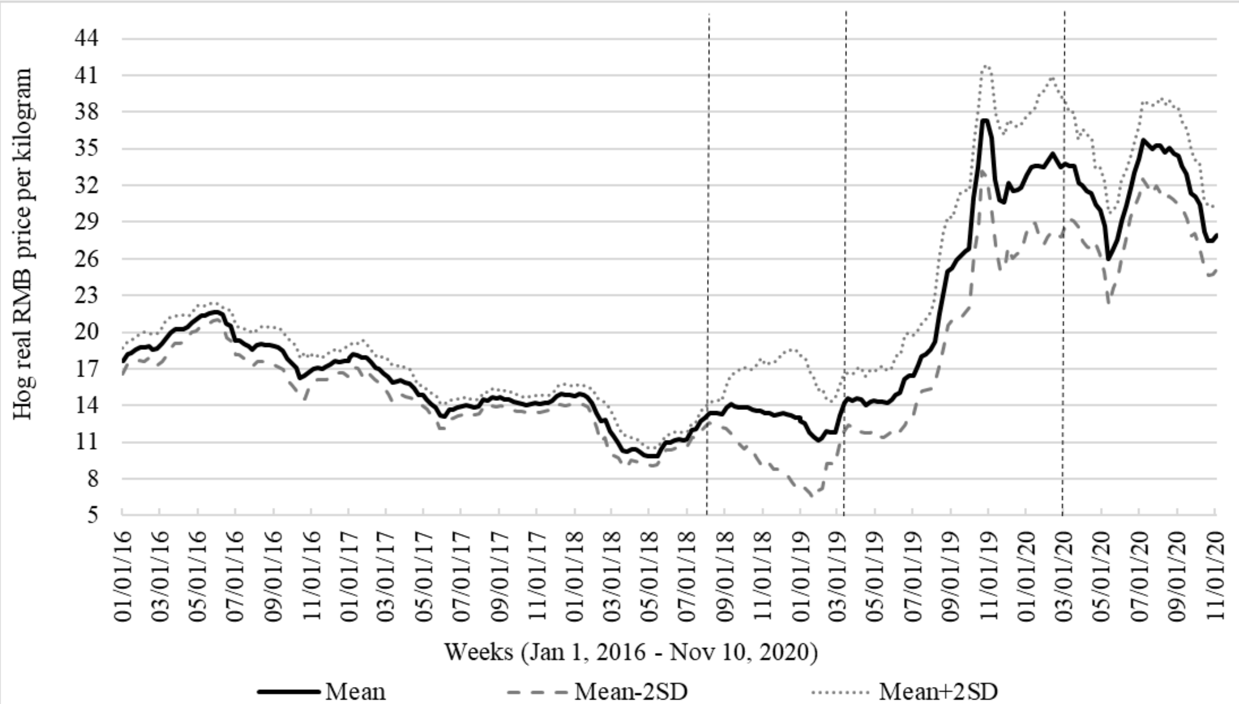

Figure 1. Weekly National Average Hog Price

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

Notes: 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.

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 (discussed more in the next section). As shown in Figure 1, 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 1 indicate the four periods.

2.3 Regional ASF Management

In January 2019, a special region-level ASF policy was initiated by the central government and carried out by six neighboring provinces in southern China, including Fujian, Guangdong, Guangxi, Hainan, Hunan, and Jiangxi.[4] The six provinces are hereafter referred to as the "Southern region". According to the regional policy, these six provinces aimed to limit shipment of live hogs to/from provinces outside of the region to help eliminate ASF within the region.

The six provinces formed a co-managing agent to conduct actions over ASF and other animal diseases within the region. This regional-level agency started to operate in November 2019. To mitigate the risk of trading with ASF-contaminated farms or processors, the agent performs tests on all farms and processors in the member provinces and certifies their ASF-safe status. In principle, each farm in the region should register their business at the agent, be "matched" with a safe slaughter plant in the region, and try to sustain a long-term trading relationship. The agent ensures timely and accurate information sharing among member provinces and helps farms and

[4] News in Chinese: http://news.southcn.com/gd/content/2019-01/30/content_185007043.htm

processors to find safe trading partners, while exploring arbitrage opportunities in all other provinces in the region.

3. Conceptual Model

The substantial divergence in provincial-level prices post the shipping ban implies obvious arbitrage opportunities across provinces. Once the ban was lifted, one would expect the divergence to be mitigated by arbitrage within a relatively short period of time. Yet the integration of provincial markets was not restored quickly – our cointegration tests (described fully in Section 4.1) suggest that market integration in the first post-ban period is not much different from the ban period. Only by the second post-ban period do we see significant movement towards re-integration, though still quite far from the pre-ban level.

Why did integration in the hog market take so long to recover? For considerable price wedges to persist, arbitrage opportunities must remain unexploited. Despite the lifting of the shipping ban, we argue that a key obstacle for inter-province trade recovery is imperfect information surrounding ASF from public sources. Hog producers in exporting provinces would remain concerned about ASF absent accurate and timely public information about ASF in any importing province, and so would hog processors in importing provinces. Comparison of the officially reported cases and the actual loss of hogs reveals a substantial discrepancy, implying the imperfect public information and possible concerns of under-reporting.[5] Private and anecdotal channels reported many more cases, though most were on relatively small scales than the ones reported officially. Thus, even when a province was not under a ban or reporting zero ASF cases, producers in other provinces were likely to be skeptical about the safety of trade with that province.

[5] The officially reported cases from 2018 to 2019 imply at most 321,830 heads infected by ASF (see Table A1). The reported number of heads culled during the two years is slightly over 1.2 million. However, the actual gross loss of hog and sow stocks from August 2018 to December 2019 was more than 100 million heads (Ma et al., forthcoming).

Bearing in mind the facts described in Section 2.1 about the ASF virus and truck transportation of hogs, we model the decision of a hog farm in an exporting province i by characterizing the interplay between risks of ASF due to incomplete information and arbitrage opportunities. Suppose that the official information on ASF is incomplete, a hog farm expects a risk of infection, θ_{ij}, when selling to a particular slaughter plant located in province j. The risk lies in $(0,1)$ and is exogenous to the hog farm. The risk of infection within the farm's home province is normalized to zero, because sufficient private information can be obtained from local networks of the farm. Throughout the section, we consider a representative farm and a representative processing plant and hence need not index them by subscripts. Both the farm and the plant are assumed risk-neutral. They maximize the expected profits from inter-province trade of hogs facing possible losses caused by ASF infection.

Because the degree of horizontal concentration of hog production in China is low (Qiao et al. 2016), we assume perfect competition among hog farms. All farms are price-takers. In period t, the market price of hogs in province i is p_t. There is a price wedge net transportation costs (normalized to zero), $\delta_{ijt} = p_{jt} - p_{it} \geq 0$, between the exporting province and the importing province j. We assume that the farm ships all its finished hogs (q_t) to one processor. The farm output in period t is predetermined, because its hog stock and outputs result from long-term decisions made months before the shipping takes place.

The farm chooses whether to ship live hogs to province j to capture the arbitrage opportunity or sell locally. If the exported hogs do not catch the virus, the net return of arbitrage equals $q_t\delta_{ijt}$. If hogs of the farm catch the virus in the transaction, two types of loss may occur. First, as the farm ships out live hogs over long distances, hogs may be infected on the way. All hogs on the truck will be culled at inspection stations, and the farm loses opportunity sales in province i of $q_t p_{it}$. Second, if the truck coming from province *j* carries the virus and passes the virus to hogs on the farm, the farm may lose a large number of hogs due to the disease as well as culling requirements set by the government. For simplicity, we focus on the first type of loss. The simplification does not change the core insights of our model.

Comparing expected sales with arbitrage and without arbitrage and the same production costs, we express the net expected return from arbitrage. If the net return of arbitrage is positive, the farm would ship hogs to province *j* where the hog price is higher. Otherwise, it would give up the arbitrage opportunity. The net expected return of the farm is:

$$\Delta E(\pi_{ijt}) = (1-\theta_{ij})q_t\delta_{ijt} - \theta_{ij}q_t p_{it},$$

or equivalently,

$$(1) \qquad \Delta E(\pi_{ijt}) = q_t[p_{jt}(1-\theta_{ij}) - p_{it}].$$

It is easy to see that $\Delta E(\pi_t)$ increases in p_{jt} and decreases in θ_{ij} and p_{it}. The net expected return decreases in p_{it}, because the potential loss tends to be higher when the local price of hogs is higher. In the post-ban periods, even though p_{jt} tends to be much larger than p_{it}, $\Delta E(\pi_{ijt})$ could be non-positive if θ_{ij} is large. The provincial-level prices are exogenous to the farm, while the farm can choose its trading partner and hence change θ_{ij}.

The value of θ_{ij} is affected by a few factors. First, farm managers can obtain private information about ASF through personal networks. The more accurate information the smaller θ_{ij}, because the farm can choose to trade with a safe processor located in the province with lower probability of catching ASF, *ceteris paribus*. Because it tends to be more costly to collect information of slaughtering plants located farther away, θ_{ij} is likely to increase with distance between the farm and the plant.

Second, with the same amount and quality of information, θ_{ij} is affected by the number of inspection stations that the truck has to go through to reach the slaughtering plant. To see why, consider a common positive probability of ASF infection, , $\theta \in (0,1)$, in any station. If there are K stations from the farm in province i to the slaughter plant in province j, the aggregate probability of catching the virus is:

$\theta_{ij} = 1 - (1 - \theta)^K$.

Everything else the same, the larger number of stations, the larger is θ_{ij}. The number of stations increases with the distance travelled from province i to j (i.e., D_{ij}); K is a function of the inter-province distance and $\frac{\partial K(D_{ij})}{\partial D_{ij}} > 0$. Again, θ_{ij} tends to increase with the distance between the farm and the plant, namely, $\frac{\partial \theta_{ij}}{\partial D_{ij}} > 0$.

Because the risk of catching the ASF virus increases with the distance of shipping, the net expected return to arbitrage between the home province *i* and the destination province *j* decreases as the farm and the slaughtering plant move farther apart. Hence, a farm is more likely to trade with a slaughter plant located in a nearer province than one farther away. For all farms and processing plants in the pair of provinces, the intensity of trading on average tends to be lower for two provinces located relatively far away, leaving prices in the two provincial markets less cointegrated. Similarly, we can show that a slaughter plant is more likely to trade with hog farms located in a nearer province than farther, and the derivation is omitted here.

Furthermore, as discussed in Section 2.3, the Southern region established a region-level information sharing channel that ensures timely and accurate information of ASF at the farm/processor level, after the shipping ban was removed. Everything else is the same, farms and processors within the region are likely to face lower risk of infection and hence tend to exploit arbitrage opportunities within the region than with outside provinces. We hence propose two testable hypotheses as follows.

Hypothesis 1: the intensity of trading, and thus co-movement of prices, tends to be weaker for two provinces located relatively far away from each other, after the shipping ban is lifted.

Hypothesis 2: the intensity of trading, and thus co-movement of prices, tends to be stronger for two provinces located in the Southern region, after the shipping ban is lifted.

4. Empirical Models

We construct three econometric models in this section. Each model focuses on one dimension of the data, and together they can provide us a comprehensive understanding of spatial integration of provincial hog markets in China before and after the outbreak of ASF.

4.1 Preliminary Testing for Temporal and Spatial Patterns

The first step in our empirical strategy is to pre-test for temporal and spatial patterns. For an initial gauge of the degree of price integration in hog markets across provinces, we conduct pairwise cointegration tests between each pair of provinces using the Johansen (1988) approach (details in Appendix 2). The tests are performed separately for each period. The tests give us a glimpse into the evolution of the market price integration: the extent to which different provinces have cointegrated prices in the pre-ban period, the extent to which this cointegration is disrupted by the ban, and the speed at which this cointegration recovers post-ban.

4.2 Spatial Regression Models

Recognizing that the cointegration approach is not conditional on any control variables, our primary empirical approach is a combination of spatial regression estimation and reduced-form estimation aimed at parsing patterns in spatial connectivity in the temporal price series. To develop the spatial regression approach, we define a standard panel-data spatial regression structure as:

$$p_{it_m}^m - \overline{p_{t_m}^m} = \rho^m \sum_{j=1}^n w_{ij}^m \left(p_{jt_m}^m - \overline{p_{t_m}^m}\right) + v_i^m + \mu_{t_m}^m + \varepsilon_{it_m}^m,$$

where the index $m \in \{1,2,3,4\}$ denotes the four periods, each covering $i = 1,2,\ldots,n$ provinces and $t_m = 1,2,\ldots,T_m$ weeks per period. Variable $(p_{it_m}^m - \bar{p}_{it_m}{}^m)$ on the left-hand-side of the equation denotes the price deviation in the hog price time series where $p_{it_m}^m$ is the hog price for province i in week t_m in period m, and $\overline{p_{t_m}^m}$ is the average price across all provinces in week t_m in period m. In the model, this price deviation is explained by the spatial lag of price deviation, $\sum_{j=1}^n w_{ij}^m \left(p_{jt_m}^m - \overline{p_{t_m}^m}\right)$.

In these models, we use the price deviation to stabilize the price time series; co-movement in the (untransformed) price series renders estimation challenging. 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^m is a province-specific effect that may be unobserved and heterogeneous across the m periods, $\mu_{t_m}^m$ is a potentially unobservable month-specific effect that is allowed to vary across periods, and $\varepsilon_{it_m}^m$ is the regression error.

As is standard spatial regression formulation, w_{ij}^m are the elements in an $(n \times n)$ proximity matrix, W^m, whereby each element represents the pairwise spatial link among provinces i and j; here, this term is superscripted by m in order to allow the spatial structure to vary across periods, though the spatial links do not vary by week. The diagonal elements of W^m are constrained to be zero, so that each province is not its own spatial neighbor. Thus, for any province i, $\sum_{j=1}^n w_{ij}^m \left(p_{jt_m}^m - \overline{p_{t_m}^m}\right)$ captures the spatially weighted sum of hog price deviations of the province's trading partner provinces. Then the parameter ρ^m 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 ρ^m, the more closely related are the price deviation series across provinces.

In traditional spatial models, the elements of W^m are assumed to follow a pre-specified spatial structure; for instance, proximate, contiguous neighbors. Estimation then amounts to estimating ρ^m while accounting for the fixed effects, and is typically done using maximum likelihood. In the de Paula et al. (2018) model, the elements of W^m are treated as parameters to be estimated. To manage the number of parameters, we deploy GMM methods that are capable of estimating parameter models with high-dimensionality.[6] The primary advantage of the de Paula et al. (2018) 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). 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 in the traditional approach – that does not account for these factors or assign appropriate relative weights will be mis-specified and leads to bias. The de Paula et al. (2018) approach avoids this bias.

Of course, being generally consistent, the de Paula et al. (2018) approach is capable of recovering simple patterns of spatial connectivity if those patterns best fit the data. In the event that the de Paula et al. (2018) produces evidence supporting the hypothesis of more complex spatial

[6] The GMM parameters are solved numerically, using multiple starting values for the spatial parameters in the matrix, including 0, 0.25, 0.5, 0.75, and 1. The best solution was selected via the Akaike information criterion.

processes, we can statistically analyze the estimated spatial weighting structure so as to understand what factors drive the apparent spatial links.

4.3 Reduced-Form Econometric Model

In order to better understand the spatial price patterns estimated using the de Paula et al. (2018) approach, we construct reduced-form regressions aimed at providing evidence supporting the hypotheses derived from the conceptual model. Following 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 in a period *m*. For each of the 29 provinces in our sample, there are 28 partner provinces, leaving us with $29 \times (29 - 1) = 812$ estimated w_{ij}^{m} in each period.

According to the hypotheses, we test if w_{ij}^{m} tends to be larger for province *i* and province *j* with a shorter in-between distance, controlling for the average price of the partner province (i.e., $ln\left(\underline{p_{jm}}\right)$). The distance variable is denoted by D_{ij} and is constant over time. Indicator S_{ij} is also included and equals one if two provinces are both located in the Southern region. Hypothesis 2 suggests that provinces within the region tend to form stronger price links in the post-ban period.

We add a few other variables in the regression. To estimate the impact of the shipping ban, we use variable Γ_{ij} to measure the total number of weeks that at least one of province *i* and province *j* was under the ban. The provincial-level hog output in 2017 and province trading status in 2016 are included in the baseline regression and denoted by vector Ω_j for province j. The period-specific specification is expressed as:

(2) $$ln\left(w_{ij}^{m}\right) = c + \alpha\, ln\left(D_{ij}\right) + \beta\, ln\left(\underline{p_{jm}}\right) + S_{ij} + \Gamma_{ij} + \Omega_j + F_i + e_{ij}^{m},$$

where c is a constant, 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.

5. Data

Our dataset contains information on hog prices, shipping bans, hog production, provincial-level trade status, and distances among provinces. Various data sources are used. In this section, we explain how the data were collected and processed and present key summary statistics.

5.1 Hog Price Data

We extract daily county-level hog price data from the website, http://www.zhujiage.com.cn/, for the period starting on January 1, 2016 to November 10, 2020. Because the focus of our study is on inter-province trade of hogs, we aggregate the county-level data to the provincial-level by taking a simple average. 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 provincial-level average 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). For the missing weeks of the remaining 29 provinces, we use a linear interpolation to back out the values of missing points.

We deflate the price data covering 58 months using 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 baseline 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. Throughout this article, prices are measured in real-RMB per kilogram. The finalized price dataset is a panel of real prices of 29 provinces and 255 weeks. Summary statistics of the price data are displayed 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 outputs	2.42	1.90	0.11	6.58	10 mil heads
Province importer (0,1 with 1=yes)	0.55	0.50	0.00	1.00	-
No. weeks province under ban	25.16	4.64	12	34	-
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

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

5.2 Other Data

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 when the ban was lifted for a 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.

We add two major control variables to the reduced-form econometric model. First, provincial-level hog output is reported by the National Bureau of Statistics. 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".[7] 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 contains a summary of these additional data.

6. Empirical Results

In this section, we present empirical outcomes from three econometric models: the cointegration tests, estimation of the spatial matrices, and the reduced-form regressions. We find supporting evidence for the hypotheses proposed in Section 3.

6.1 Cointegration Tests

As our first step, we test the hog price series for cointegration across provinces and periods. In total, we perform $\frac{29\times28}{2}$= 406 tests. Figure A1 shows that 81.3% of the price pairs are cointegrated

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

in the pre-ban period, while only 13.1% of the price pairs are cointegrated in the ban period. The statistics confirm the observed price divergence in Figure 1. Cointegration of the hog market becomes much weaker in the ban period as inter-province price arbitrage opportunities between importing and exporting provinces are not all taken. Somewhat surprisingly, only 23.2% of the pairs are cointegrated in the first post-ban period. Re-integration of the market is slow: in the second post-ban period the ratio rises to 57.9%, though still far below the pre-ban level. The outcomes suggest that the enlarging price divergence across provinces was not merely a result of rising transportation costs due to ASF-related supervision or sanitization activities; the price co-movement was significantly weakened after the ban was imposed.

6.2 Spatial Regression Models

The estimated price links form the GMM model are reported in Table 2. The absolute value of the estimated price links are difficult to interpret directly, and their relative magnitudes lead to more insights. It is important to 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 pre-ASF and in the final post-ban period. 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	Unit
Estimated w_{ij} in Period 1	0.16	0.14	0.00	0.98	-
Estimated w_{ij} in Period 2	0.27	0.25	0.00	1.00	-
Estimated w_{ij} in Period 3	0.51	0.31	0.00	1.00	-
Estimated w_{ij} in Period 4	0.32	0.14	0.00	0.84	-
Geographic D_{ij}	1.31	0.70	0.11	3.46	1000km
Economic D_{ij}	0.56	0.24	0.11	1.57	Real 2018 RMB/kg

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

To complement our estimated spatial-links model, we consider two alternative definitions of spatial connectivity, based on traditional spatial proximity designs. The first is the most traditional specification: we measure the linear distance between the capital cities of any two provinces in units of 1,000 kilometers. This distance is fixed, given that provincial boundaries do not change, and is taken as exogenous to hog prices.

The second measure is a construction of the economic distance between provinces using the average price gaps between hog price in province *i* and price in province *j* over the 2016 to 2017 interval. Economic distance, according to the definition of market integration, reflects the average arbitrage cost, including but not limited to the transportation cost, between a pair of provinces as long as their price series are cointegrated during the period. Cointegration tests confirm that the economic distance is a valid measurement of inter-province arbitrage costs for most pairs of provinces in the pre-ban period. Assuming that transportation and other arbitrage costs do not change too much in the post-ban periods, we may use the economic distance as an alternative measurement of inter-province distance.

Table 2 provides a comparison with the two constructed inter-province distance measures (geographic and economic distance). To see how the estimated price links correlate with constructed geographic and economic distance measures, we report correlation coefficients among these six variables in Table A2. There is little correlation between the estimated links and the constructed distance measures, and that the correlations of estimated links of the four periods are weakest in the fourth period.

6.3 Reduced Form Regressions

Relying on equation (2), our reduced-form estimation outcomes using the geographic distance and the economic distance are summarized in Tables 3 and 4, respectively. Using the two distance variables result in similar estimates. We interpret the model based on the geographic-distance estimates.

Each column corresponds with a specific period. R-squared is fairly high across periods, suggesting the good fit of our model. A few patterns stand out in columns (1) through (4). First, before ASF, the geographic distance between two provinces does not have any significant impact on the co-movement of their prices, which echoes the high degree of cointegration of the hog market pre-ASF as discussed in Section 6.1. During the ban, the distance does not matter in a significantly way, because inter-province shipping was not allowed.

In the post-ban periods, the inter-province distance has a significant impact on the price link, supporting our first hypothesis. 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 co-movement rate drops by 1%. In period 4, the negative effect of D_{ij} continues to be significant and larger; if the distance increases by 10%, the co-movement rate drops by 3%. 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.

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, their link would fall by 2%. As suggested by the second hypothesis, province pairs within the Southern region enjoy a 40% stronger price link on average compared with province pairs outside the Southern region, supporting the second hypothesis. This positive effect reflects the value of providing trustworthy public information of ASF cases. In the fourth period, the number of weeks under the ban no longer has any significant negative impact on the price link.

The positive impact of the Southern region is also gone, probably indicating enhanced information in provinces outside the region after 10 months into the post-ban period.

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 using our conceptual model. Similarly, a negative coefficient of the partner-province's price can be rationalized by the arbitrage behavior of hog importers or processing plants using the model. 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 as control variables via the alternative specification:

$$ln\left(w_{ij}^m\right) = c + \alpha\, ln\, ln\left(D_{ij}\right) + S_{ij} + \mathit{\Gamma}_{ij} + F_i + F_j + e_{ij}^m,$$

where S_{ij} and $\mathit{\Gamma}_{ij}$ are defined in equation (2).

Estimates from this alternative specification are displayed in columns (5) to (8) in Table 3. As expected, the R^2 increased 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. In these models, the (previously positive) coefficient of S_{ij} is insignificant. This is not too surprising, because the fixed effect of each pair of provinces is likely to have largely absorbed the effect of the Southern region indicator, which makes the effect of S_{ij} weaker. For a final comparison, we also estimate a regression with control variables for both provinces, but no fixed effects. The general patterns identified in Table 3 remain robust.

Table 3. Inter-Province Estimated Price Links and the Determinants using the Geographic Distance

	(1) Pre-ban	(2) Ban	(3) Post-ban 1	(4) Post-ban 2	(5) Pre-ban	(6) Ban	(7) Post-ban 1	(8) Post-ban 2
Distance between	0.08	0.07	-0.10*	-0.27***	0.09	-0.12	-0.19***	-0.26***
provinces *i* and *j*	(0.10)	(0.12)	(0.05)	(0.09)	(0.10)	(0.09)	(0.06)	(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)
South-south (1, yes)			0.40**	-0.04			0.15	-0.04
			(0.15)	(0.10)			(0.13)	(0.12)
Province *j* average price	6.29*	-1.27***	-1.29**	-0.98*				
in the period	(3.16)	(0.45)	(0.51)	(0.57)				
Pre-ban $\widehat{w_{ij}}$	NO	YES	YES	YES	NO	YES	YES	YES
Province *j* controls	YES	YES	YES	YES	YES	YES	YES	YES
Province *i* FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.57	0.48	0.64	0.36	0.59	0.60	0.67	0.42
# observations	812	812	812	812	812	812	812	812

Notes: Standard errors in parentheses and *p*-values in the square brackets. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10. "South-south" is an indicator which equals 1 if both provinces *i* and *j* are in the Southern region. "Province *j* controls" include hog outputs in the partner province and an indicator whether the partner province is a net importer of pork.

Table 4. Inter-Province Estimated Price Links and the Determinants using the Economic Distance

	(1) Pre-ban	(2) Ban	(3) Post-ban 1	(4) Post-ban 2	(5) Pre-ban	(6) Ban	(7) Post-ban 1	(8) Post-ban 2
Distance between	0.18	0.22	-0.09*	-0.13	0.11	-0.17	-0.13**	-0.10
provinces *i* and *j*	(0.14)	(0.14)	(0.05)	(0.08)	(0.16)	(0.11)	(0.06)	(0.09)
	[0.19]	[0.14]	[0.10]	[0.12]	[0.50]	[0.12]	[0.04]	[0.27]
#weeks under the ban		-0.02*	-0.02**	-0.02*		-0.04***	-0.02***	-0.03*
provinces *i* and *j*		(0.01)	(0.01)	(0.01)		(0.01)	(0.00)	(0.02)
South-south (1, yes)			0.43**	0.08			0.27	0.16
			(0.17)	(0.09)			(0.18)	(0.10)
Province *j* average price	5.05*	-1.53**	-1.15**	-1.02				
in the period	(2.68)	(0.55)	(0.49)	(0.80)				
Pre-ban $\widehat{w_{ij}}$	NO	YES	YES	YES	NO	YES	YES	YES
Province *j* controls	YES	YES	YES	YES	YES	YES	YES	YES
Province *i* FE	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.57	0.48	0.64	0.36	0.59	0.60	0.66	0.41
# observations	812	812	812	812	812	812	812	812

Notes: Standard errors in parentheses and *p*-values in the square brackets. Standard errors are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.10. "South-south" is an indicator which equals 1 if both provinces *i* and *j* are in the Southern region. "Province *j* controls" include hog outputs in the partner province and an indicator whether the partner province is a net importer of pork.

7. 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., forthcoming). In addition to necessary culling, 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.

Our analysis demonstrates the empirical effects of this shipping ban on market price 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 a combination of cointegration tests, GMM spatial panel data estimation, and reduced-form regressions to analyze the spatial connectivity in live hog price series across provinces. All the three empirical models confirm similar results: 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. Market re-integration began relatively early in the Southern region of China where information transparency was greatest given the regional initiatives designed to provide information as well as facilitate inter-province safety and trade. 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. The value of providing high-quality public information not only applies to China or animal epidemics, but also to a context of human epidemics involving travel within and across countries.

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.

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Appendix 1. 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/.

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

Appendix 2. Cointegration Tests

We test the cointegration of hog price series. As conintegration only applies to nonstationary time series data, we first perform augmented Dickey-Fuller (ADF) tests on the unit root of all price series in each period. Both price levels and first-differenced prices are tested. All price series in all periods turn out to be integrated with degree 1, except for Shandong, Shaanxi, and Xinjiang in the ban period. These three prices may be integrated at higher degrees. Thus, we claim that the price series of Shandong/Shaanxi/Xinjiang does not co-integrate with any other series in the second period.

Under the Johansen test, we rely on Akaike Information Criterion (i.e., AIC) to choose the optimal number of lags for a given period. The test is conducted using the *vecrank* package in STATA with one lagged term. For each pair of provinces, if we cannot reject the null hypothesis that the rank of their vector error-correction model is 1, we conclude that the pair of series are cointegrated. The pairwise outcomes under the Johansen test are presented in Figure A1. Tests suggest that the hog market was highly integrated in the pre-ban period, the integration largely broke down in the ban period, the integration failed to restore in the first post-ban period, and the integration level is considerably higher in the second post-ban period.

prv	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1		1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1		1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1		0	1	0	0	1	0	1	0	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	0	1	1
4	1	1	0		0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1
5	1	1	1	0		0	1	1	0	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	0	1	0	1	1
6	1	1	0	1	0		1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0
7	1	1	0	1	1	1		1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1
8	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
9	0	0	0	1	0	0	0	1		1	1	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0
10	1	1	1	1	1	1	1	1	1		0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
11	0	1	0	1	1	1	1	1	1	0		0	0	0	0	0	1	1	1	1	0	1	1	1	0	1	1	1	1
12	1	1	1	1	1	1	1	1	0	0	0		1	1	1	1	0	0	1	1	0	1	1	1	1	1	1	1	1
13	1	1	1	1	1	1	1	1	0	0	0	1		1	1	0	0	0	1	1	1	1	1	1	1	1	0	1	1
14	1	1	1	1	1	1	1	1	0	0	0	1	1		1	1	0	0	1	1	1	1	1	1	1	1	0	1	1
15	1	1	1	1	0	1	1	1	0	1	0	1	1	1		1	0	0	1	1	1	1	1	1	0	1	1	1	1
16	1	1	0	1	0	1	1	1	1	1	0	1	0	1	1		0	0	1	1	1	1	1	1	0	1	1	1	1
17	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0		1	1	1	0	1	1	0	0	1	1	1	1
18	1	1	0	1	1	1	1	1	1	1	1	0	0	0	0	0	1		1	1	0	1	1	0	0	1	1	1	1
19	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1	1
20	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	0	0	1	1		1	1	1	1	1	1	1	1
22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1	1
23	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1	1	1
24	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	1	1	1		1	1	1	1	1
25	1	1	1	0	0	0	0	1	0	0	0	1	1	1	0	0	0	0	1	1	1	1	1	1		1	0	1	1
26	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1
27	1	1	0	0	0	1	1	1	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1		0	0
28	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0		1
29	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	

(a) Pre-ban period

prv	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1		0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	1	0	1	0	1	0	0	0
2	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0
3	0	0		1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1		0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0
5	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0		0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
7	0	0	0	0	0	0		0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
8	0	0	1	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
9	0	0	1	0	0	1	1	0		1	1	1	1	1	0	1	0	0	1	1	0	0	0	1	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
11	0	0	0	0	0	0	0	0	1	0		0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0
12	1	0	0	0	0	0	0	0	1	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
13	0	0	0	1	0	0	0	0	1	0	0	0		0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0
14	0	0	0	1	0	0	0	0	1	0	0	0	0		0	0	0	0	0	1	0	0	0	0	0	0	0	1	1
15	1	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	1	0	0	0
16	1	0	0	1	0	0	0	0	1	0	0	0	1	0	0		0	0	1	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	1	0	0	0	0	0	0	0	0	1	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		1	0	0	0	0	0	0	0	0	1	0
19	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1	1		0	0	0	0	1	0	1	0	0	0
20	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0		0	0	0	0	0	0	0	1	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0
22	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0
24	1	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0		0	1	0	1	1
25	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0
26	1	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0		0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0
28	0	1	0	1	0	1	1	0	0	1	1	1	1	1	0	0	1	1	0	1	0	0	0	1	0	0	0		0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	

(b) Ban period

prv	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1		0	1	0	0	0	0	1	0	0	0	1	1	0	1	0	0	0	0	1	0	1	1	0	0	0	0	0	0
2	0		0	1	0	1	0	0	0	1	1	1	0	0	1	1	1	1	0	1	1	0	1	1	0	1	0	0	1
3	1	0		0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
4	0	1	0		0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	0	1	0	0	1
5	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
6	0	1	0	0	0		1	0	1	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	0	0	0	0	0
7	0	0	0	0	0	1		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	1	0	1	0	0	0	0		0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	1	0	0		0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
10	0	1	0	0	0	0	0	0	0		1	0	0	0	0	0	0	0	1	1	0	1	1	1	0	0	0	0	0
11	0	1	0	0	0	0	0	0	0	1		0	0	0	0	0	1	0	1	1	1	0	1	1	0	0	0	0	0
12	1	1	0	0	0	0	0	0	0	0	0		1	0	1	0	0	0	0	1	0	1	1	0	0	0	0	0	0
13	1	0	0	0	0	0	0	1	0	0	0	1		0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	1	0	0	0	0	0		0	1	0	0	0	1	0	1	0	0	0	0	0	0	0
15	1	1	0	1	0	1	0	0	0	0	0	1	1	0		0	0	0	0	1	0	1	1	1	0	0	0	0	1
16	0	1	0	1	0	1	0	0	0	0	0	0	0	1	0		0	0	0	1	0	1	0	0	0	0	0	0	1
17	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0		1	1	1	0	0	0	0	0	0	0	0	0
18	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1		0	1	0	1	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	0		1	0	1	0	1	0	0	0	0	0
20	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1		1	1	1	1	0	1	1	0	1
21	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1		1	0	0	0	0	0	0	0
22	1	0	0	1	0	1	0	0	0	1	0	1	1	1	1	1	0	1	1	1	1		1	1	0	0	1	0	1
23	1	1	0	0	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	1	0	1		1	0	0	0	0	0
24	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	1	1	0	1	1		0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0
26	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0		0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0		0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0
29	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	0	0	0	0	

(c) Post-ban Period 1

prv	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1		1	0	1	0	1	1	1	1	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1
2	1		0	0	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0	0	0	1
3	0	0		0	1	0	1	1	1	0	1	1	1	0	0	0	0	0	1	0	0	0	1	1	0	1	0	0	1
4	1	0	0		0	1	1	0	1	1	1	1	0	1	1	1	1	1	0	0	1	1	0	1	0	1	0	0	1
5	0	1	1	0		0	1	1	1	1	0	0	1	1	1	0	1	1	1	0	1	0	1	1	1	1	0	1	1
6	1	0	0	1	0		0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1
7	1	0	1	1	1	0		1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0	1	0	1
8	1	1	1	0	1	0	1		1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	0	1	1
9	1	1	1	1	1	0	1	1		1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
10	0	1	0	1	1	0	1	1	1		1	0	1	1	1	0	0	0	1	0	0	0	1	0	1	1	0	0	1
11	1	1	1	1	0	0	1	1	1	1		1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	0	1	1
12	0	1	1	1	0	0	1	1	1	0	1		1	1	1	0	0	1	1	0	1	0	0	0	1	1	0	0	1
13	0	1	1	0	1	0	1	1	1	1	1	1		1	1	0	1	1	1	0	1	0	1	1	1	1	0	1	1
14	1	1	0	1	1	0	1	1	1	1	1	1	1		1	1	1	1	1	0	1	0	0	1	0	1	0	0	1
15	1	1	0	1	1	0	1	1	1	1	1	1	1	1		1	1	1	1	0	1	0	0	1	0	1	0	0	1
16	0	1	0	1	0	1	1	1	1	0	1	0	0	1	1		0	0	0	0	0	0	0	0	1	1	0	0	1
17	0	1	0	1	1	0	1	1	1	0	1	0	1	1	1	0		0	1	0	0	0	1	0	1	1	0	0	1
18	0	1	0	1	1	0	1	1	1	0	1	1	1	1	1	0	0		1	0	0	0	1	1	1	1	0	0	1
19	0	1	1	0	1	0	1	1	1	1	1	1	1	1	1	0	1	1		0	1	0	1	1	1	1	0	1	1
20	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	1	1	0	0
21	0	1	0	1	1	0	1	1	1	0	1	1	1	1	1	0	0	0	1	0		0	1	1	1	1	0	0	1
22	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0
23	0	1	1	0	1	0	1	1	1	1	1	0	1	0	0	0	1	1	1	0	1	0		1	1	1	0	0	1
24	0	1	1	1	1	0	1	1	1	0	1	0	1	1	1	0	0	1	1	0	1	0	1		1	1	0	0	1
25	1	1	0	0	1	0	1	1	1	1	1	1	1	0	0	1	1	1	1	0	1	0	1	1		0	0	0	1
26	1	0	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0		1	1	1
27	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1		0	0
28	0	0	0	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0		1
29	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	0	1	

(d) Post-ban Period 2

Figure A1. Pairwise Outcomes of Johansen Cointegration Tests for 29 Provinces

Source: Authors' calculation.

Notes: Number "1" in a cell and color green indicate that the corresponding two price series are cointegrated, while "0" and color red mean that they are not. Province numbers are ranked alphabetically with their names are found in Table A1.

Appendix 3. Correlation Coefficients of Key Variables

The table displays correlation coefficients of estimated price links and two measures of the inter-province distance.

Table A2. Correlation Coefficients of Key Variables

Variables	Estimated w_{ij} in Period 1	Estimated w_{ij} in Period 2	Estimated w_{ij} in Period 3	Estimated w_{ij} in Period 4	Geog. D_{ij}	Econ. D_{ij}
Estimated w_{ij} in Period 1	1.00					
Estimated w_{ij} in Period 2	0.20	1.00				
Estimated w_{ij} in Period 3	0.29	0.21	1.00			
Estimated w_{ij} in Period 4	0.08	-0.10	0.09	1.00		
Geographic D_{ij}	-0.19	-0.01	-0.20	-0.32	1.00	
Economic D_{ij}	0.01	0.17	0.02	-0.16	0.54	1.00

Source: Authors' calculation.

Notes: The number of observations is 812.