# The Impacts of African Swine Fever on Vertical and Spatial Hog Pricing and Market Integration in China

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Abstract: This paper investigates the dynamic effects of a disease outbreak on vertical and spatial markets, with an application to the African Swine Fever (ASF) and its impact on Chinese hog markets. Relying on a flexible representation of vertical and spatial price dynamics, we investigate how ASF affected the pork cycle and price transmission across markets. We find that the ASF outbreak had larger long-term effects on spatial prices than on vertical prices, likely reflecting inter-regional trade bans imposed by the government. Our analysis indicates that ASF contributed to shortening the period of the pork cycle. We also provide evidence that the ASF outbreak affected cointegration relations across markets, especially among regional markets.

Keywords: market integration, vertical pricing, spatial pricing, cycles, African Swine fever, China

JEL: C32, Q11

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## 1. Introduction

The last few decades have seen a rise in contagious animal diseases across the globe (Otte et al., 2004; Thornton, 2010). Well-known examples include mad cow disease, foot-and-mouth disease, avian influenza, swine fever, etc. The outbreaks of animal disease not only cause significant production loss but increase human health risk and can trigger public panic. With continuous growth in global meat demand and intensification of livestock production pattern, animal disease outbreaks have imposed an increasingly large economic cost on livestock industry and macroeconomy. For instance, the economic cost of mad cow disease outbreak was estimated to be £50 billion in the UK (Otte et al., 2004), and the total loss of a hypothetical outbreak of foot-and-mouth disease (FMD) in the US was reported to be $2.7-4.1 billion depending on disease situations (Paarlberg et al., 2008). The vast adverse impact of disease outbreaks implies a need to examine how it affects the functioning of markets.

In August 2018, the African Swine Fever (ASF) was first detected in China and spread fast to almost all provinces in the country. As a highly contagious and deadly disease, ASF can cause very high mortality of domestic hogs (Gostard et al., 2013). Since its outbreak, the disease has been spreading speedily and had significant impacts on the Chinese hog sector, generating wide attention to its spread and market response (i.e., quarantine and trade restriction, panic culling, surging prices, etc.). According to the Ministry of Agriculture of China, more than 1.08 million live hogs were slaughtered due to ASF disease control purposes, and the national live hog inventory was reduced by approximately 40 percent[1]. To reduce the spread of the disease, the Chinese government imposed restrictions on interregional live hog transportation. Though effective in controlling disease spread, these interventions triggered complex price changes and market responses in the Chinese hog market. As shown in Figure 1, both vertical and spatial price patterns changed after the disease outbreak. This indicates that ASF had large effects on hog pricing both along its supply chain and across space. The existence of cycles in the pork market makes this issue more complex, indicating a need to develop a joint investigation of market dynamics and cycles in the presence of a major disease shock. How do price cycles differ before and after the disease? What are its impacts on vertical and spatial market integration? This paper investigates these issues and provides answers to these questions.

This is apparently the first paper to investigate the impacts of ASF on Chinese hog pricing and market integration among vertical as well as spatial markets. Our analysis relies on weekly data from 2008 to 2019. We develop a time series representation of the dynamics of vertical as well as horizontal prices, allowing for structural changes. In our case, the structural changes capture the dynamic effects of the ASF outbreak. Our approach generates a flexible representation of changes in vertical and spatial price dynamics caused by the ASF outbreak. Our analysis is applied to price transmission along the supply chain (i.e., two stages of marketing channel) and across space (i.e., seven major regions in China). It investigates how ASF affects the stationarity of prices and the nature of price cycles. Using the error-correction representation of our time series model, we evaluate the disease effects in a multiple-product and multiple-region context, and obtain the cointegration relationships among prices at different stages of the marketing channel as well as across regions. We employ the Singular Value Decomposition (SVD) method proposed by Kleibergen and Paap (2006) to test the nature of cointegration in both the pre-disease regime and post-disease regime. Our econometric analysis provides new and useful information on how a major shock affects the dynamics of vertical and horizontal pricing.

Our paper obtains three main results. First, it shows how the ASF outbreak affected market dynamics. For example, we present evidence that ASF contributed to shortening the period of the pork cycle, indicating that the shock induced producers to make production decisions in a timelier manner. We document the presence of cyclical patterns in both vertical and spatial price margins and examine how the ASF outbreak affected spatial price margins. Second, we find that ASF had larger long-term effects on spatial prices than on vertical prices, likely reflecting inter-regional trade bans imposed by the Chinese government. The ASF outbreak also had more significant impacts in production regions (as opposed to consumption regions). Third, we provide evidence that ASF affected cointegration relations and had adverse effects on the functioning of implicit markets.

The rest of the paper is organized as follows. Section 2 gives an overview of the economics of contagious animal disease. Section 3 introduces our econometric approach.

After describing the data in section 4, the econometric results are presented in section 5, followed by a discussion of economic implications in section 6. Section 7 concludes.

## 2. Economics of contagious animal disease

The economic analysis of animal disease has been an important topic for academia, policymakers and industry stakeholders (McInerney, 1999; Bennett, 2003; Rich and Nelson., 2007). The outbreaks of animal disease can have significant impacts on livestock production and impose substantial costs to society. Bennett (2003) estimated and compared the economic costs of 30 different endemic animal diseases in Great Britain, concluding that mastitis has the highest costs for cattle with an annual estimate of £137-245 million. Rich and Nelson (2007) built an epidemiological-economic model to study the dynamic and spatial effects of foot-and-mouth disease (FMD) in South America and compared the net present value of six disease control options in the short-run and long-run. Knight-Jones and Rushton (2013) assessed the global impact of FMD, estimating the annual cost of production losses to be in the range of 6.5-21 billion US dollars. The large production impact and economic costs imply a need to understand better how a disease outbreak can affect the functioning of markets.

Previous literature has studied the impacts of animal disease on meat consumption, production, trade and agribusiness. Park et al., (2008) found that the impacts of domestic and oversea animal disease crises on Korean meat markets typically last 13-16 months, and the severity of influence depends on disease type and supply chain. Zongo and Larue (2019) estimated how an animal disease can affect livestock trade flows. Schlenker and Villas-

Boas (2009) evaluated the response of consumer and financial markets to warnings about mad cow disease, finding that the first-time announcement in 2003 triggered pronounced sales reduction and abnormal futures price drops. Henson and Mazzocchi (2002) assessed the impacts on UK agribusinesses of government announcement of human health risk from mad-cow disease; showing heterogenous abnormal returns among meat-related companies. Those studies provide valuable insights regarding the impacts of animal disease outbreaks on various aspects of the livestock market and macroeconomy.

Much attention has focused on the effects of animal disease on market prices. This includes the effects of disease on both vertical and horizontal price transmissions. The economics of price transmission in agricultural markets has been of significant interest (Goodwin and Schroeder, 1991; Frackler and Goodwin, 2001; Barrett and Li, 2002; Abdulai, 2007). For animal disease impact on vertical price transmission, Hassouneh et al. (2010) used a regime-switching vector error correction model to assess the impact of BSE outbreaks on vertical price transmissions; they found that Bovine Spongiform Encephalopathy (BSE) food scares cause price adjustment in producer price but not in consumer price. Serra (2011) evaluated the impacts of a BSE outbreak on price transmission along the Spanish food marketing chain by using an STCC-GARCH model and analyzed the evolution of volatility patterns. For horizontal price transmission, Ihle et al. (2012) explored the occurrence of an animal health crisis on spatial interdependencies of European calf prices; they found that the bluetongue disease induced structural changes in prices with significant short-term adjustments. The literature discussed above provides valuable insights into the price transmission effects caused by animal disease. Though informative, there is a need to investigate the disease effects considering both vertical and horizontal market integration. Doing so is a contribution of this paper.

Another strand of literature relates to the cyclical price behavior exemplified in "livestock cycles" (e.g., Rosen et al., 1994; Parker and Shonkwiler, 2014). Rosen et al. (1994) examined the economic rationality of cattle cycles given the underlying dynamics of the breeder herd. In the context of the US pork market, Chavas (1999) documented that price dynamics were related to imperfections in the formulation of price expectations by pork producers. Holt and Craig (2006) used smooth transition autoregressive (STAR) model to analyze the US pork-corn cycles, and provided useful imformation on nonlinearity, regime-dependent behavior, and time-varying parameter change. Parker and Shonkwiler (2014) applied a dynamic unobservable time series model to the German hog-feed price ratio and detected a four-year price cycle with increasing volatility over time. Focusing on China's volatile pork industry, Gale et al., (2014) pointed out that Chinese pork cycles typically last three to four years depending on evaluation situations, and presented a discussion on the government policies attempting to smooth the pork cycles. Zhao and Wu (2015) employed the Threshould Autoregressive (TAR) model to analyze the nolinear dynamics of pork price in China, and characterized the changing process of pork prices into a "mild regime" and a "expansion regime". But how does a major disease outbreak affect market cycles? At this point, the answer to this question is unclear. Addressing this issue is another contribution of this paper. Applied to the ASF outbreak in the Chinese hog market, this paper provides an economic analysis of the dynamic impacts of a disease outbreak on vertical and spatial markets and on hog price cycles.

## 3. Model of Price Dynamics

Consider the markets for $n$ commodities. Let $p_{it} \in \mathbb{R}$ be the market price at time $t$ in the $i$-th market, $i \in N \equiv \{1, \dots, n\}$. We are interested in investigating the determinants of the prices $(p_{1t}, \dots, p_{nt})$. These prices are market equilibrium prices set such that supply equals demand in all markets. In general, we expect prices to evolve over time reflecting the dynamics of supply/demand conditions along with price adjustments across markets. Following Zellner and Palm (1974), many representations of such price dynamics are possible. They include structural models reflecting supply-demand conditions, vector autoregression (VAR) models applied to all prices $(p_{1t}, \dots, p_{nt})$ as well as "final form" models applied to a subset of prices. As discussed in Zellner and Palm (1974), a final form model is a reduced-form model providing a valid representation of price dynamics in selected markets. Our analysis will rely on final form specifications of price dynamics in markets $\{i, j\}, i \neq j \in N$, allowing us to investigate the joint dynamics of $(p_{it}, p_{jt})$. Focusing on two markets at a time will simplify the econometric analysis and facilitate the economic interpretation of the results.[2] As discussed below, we explore price dynamics in all $n$ markets by conducting the analysis for different $(i, j)$ in $N$.

For a given $(i, j), i \neq j \in N$, assume that the determination of market prices $\boldsymbol{p}_t = (p_{it}, p_{jt})$ is given by the equation

$$\boldsymbol{p}_t = \begin{bmatrix} g_i(\boldsymbol{p}_{t-1}, \dots, \boldsymbol{p}_{t-m}, \boldsymbol{x}_t, \boldsymbol{e}_t \\ g_j(\boldsymbol{p}_{t-1}, \dots, \boldsymbol{p}_{t-m}, \boldsymbol{x}_t, \boldsymbol{e}_t \end{bmatrix} = \boldsymbol{g}(\boldsymbol{p}_{t-1}, \dots, \boldsymbol{p}_{t-m}, \boldsymbol{x}_t, \boldsymbol{e}_t) \tag{1}$$

where $m \geq 1$ is the number of lags, $\boldsymbol{x}_t \in \mathbb{R}^k$ are exogenous shifters of $\boldsymbol{p}_t \in \mathbb{R}^2$, $\boldsymbol{e}_t \in \mathbb{R}^s$ is a vector of $s$ i.i.d. random variables representing the effects of unobservable factors and $\boldsymbol{g}$: $\mathbb{R}^{2m} \times \mathbb{R}^k \times \mathbb{R}^s \to \mathbb{R}^2$. Equation (1) reflects market price determination in markets $(i,j)$. The specification in (1) allows for general dynamics in prices $\boldsymbol{p}_t$, exogenous changes captured by $\boldsymbol{x}_t$ as well as stochastic shocks reflected by the random variables $\boldsymbol{e}_t$. It allows for own price dynamics (when $p_{i,t-k}$ affects $p_{i,t}$, $k \in M \equiv \{1, \dots, m\}$) as well as cross price dynamics (when $p_{j,t-k}$ affects $p_{it}$, $j \neq i \in N,\ k \in M$) reflecting economic adjustments across markets.

Let $\boldsymbol{P}_{t-1} = (p_{i,t-1}, \dots, p_{i,t-m}; p_{j,t-1}, \dots, p_{j,t-m})$. For the $i$-th market, assume that $g_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_t)$ in (1) takes the form

$$g_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_t) = \alpha_i + \beta_i\, \boldsymbol{P}_{t-1} + \gamma_i\, h_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) + s_i(\boldsymbol{e}_t). \tag{2}$$

Equation (2) is linear in the parameters $\delta = (\alpha, \beta, \gamma)$. For a given specification of $h_i$ and conditional on $(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$, the parameters $\delta$ in (2) can be consistently estimated using standard regression. Equation (2) provides a flexible way to investigate empirically the determination and evolution of mean prices in the $n$ markets. Importantly for our analysis, the parameters $\gamma_i$ in (2) capture possible structural changes (when $h_i$ depend on $\boldsymbol{x}_t$) as well as changing dynamics (when $h_i$ depend on $\boldsymbol{P}_{t-1}$).

Given $\boldsymbol{P}_{t-1} = (p_{i,t-1}, \dots, p_{i,t-m}; p_{j,t-1}, \dots, p_{j,t-m})$, equations (1) and (2) can be alternatively written as

$$\begin{bmatrix} g_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_t) \\ p_{i,t-1} \\ \vdots \\ p_{i,t-m+1} \\ g_j(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_t) \\ p_{j,t-1} \\ \vdots \\ p_{j,t-m+1} \end{bmatrix} = \begin{bmatrix} \alpha_i + \beta_i\, \boldsymbol{P}_{t-1} + \gamma_i\, h_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) + s_i(\boldsymbol{e}_t) \\ p_{i,t-1} \\ \vdots \\ p_{i,t-m+1} \\ \alpha_j + \beta_j\, \boldsymbol{P}_{t-1} + \gamma_j\, h_j(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) + s_j(\boldsymbol{e}_t) \\ p_{j,t-1} \\ \vdots \\ p_{j,t-m+1} \end{bmatrix}$$

$$= \boldsymbol{G}(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t, \boldsymbol{e}_t) \qquad (3)$$

Equation (3) is a difference equation of order $2m$ that provides a representation of price dynamics in markets $(i, j)$. Under differentiability, the effects of lagged prices at time $t$ in (3) are given by the $(2m \times 2m)$ matrix $DG(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) = \frac{\partial \boldsymbol{G}}{\partial \boldsymbol{P}_{t-1}}(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$. For given $(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$, let $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_{nm})$ be the Eigenvalues (or roots) of $DG(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$, where $\lambda_1$ is the dominant root. First, consider the case of a linear model where all roots are constant for any $(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$. In this case, the dynamic system is globally stable if $|\lambda_1| < 1$: when the dominant root has a modulus in the unit circle, then all prices converge to unique long run equilibrium (Simon and Blume, 1994). As such, according to Katok and Hasselblatt (1997), price dynamics would follow an exponential path toward the long run equilibrium when $\lambda_1$ is real and positive, an oscillatory path when the root $\lambda_1$ is real and negative, and cyclical patterns when $\lambda_1$ is complex ($\lambda_1 = a_1 + b_1\sqrt{-1}$) with a cycle of period $[2\,\pi/\arctan(\frac{b_1}{a_1})]$. Alternatively, having $|\lambda_1| > 1$ means that price dynamics is unstable: there is no long run equilibrium and $\log(|\lambda_{1,t}|)$ measures the rate of divergence of prices along a forward path.

Second, consider the case where $\gamma \neq 0$ in (2)-(3) and the roots $\boldsymbol{\lambda}_t = (\lambda_{1,t}, \ldots, \lambda_{nm,t})$ depend on $(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$. In this case, the above results still hold locally in the sense that a linearized version of (3) can approximate price dynamics in the neighborhood of the evaluation point. Then, having $|\lambda_1(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)| < 1$ means that prices tend to converge along a forward path in the neighborhood of $(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$. Alternatively, having $|\lambda_1(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)| > 1$ means that price dynamics is locally unstable, $\ln(|\lambda_{1,t}|)$ measuring the rate of divergence of prices along a forward path in the neighborhood of $(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t)$. Below, we test empirically whether $|\lambda_1|$ is statistically different from one. It is well-known that this "unit root" test does not have a standard asymptotic distribution (Hamilton, 1994; Enders, 2014). On that basis, our unit-root test relies on bootstrapping.

Equation (2) is expressed in terms of price levels. It can be equivalently written in terms of first differences. To see that, let $\boldsymbol{p}_{t-k} = \begin{bmatrix} p_{i,t-k} \\ p_{j,t-k} \end{bmatrix}$ and $\boldsymbol{h}(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) = \begin{bmatrix} \boldsymbol{h}_i(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) \\ \boldsymbol{h}_j(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) \end{bmatrix}$. Then equations (1)-(2) can be written as

$$\boldsymbol{p}_t = A + \sum_{j=1}^{m} B_j\, \boldsymbol{p}_{t-j} + K\, \boldsymbol{h}(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) + S(\boldsymbol{e}_t), \tag{7a}$$

where $A, B_1, \dots, B_m$ and $K$ are conformable matrices of parameters. Equation (7a) can be equivalently expressed as

$$\Delta\boldsymbol{p}_t = A + \Pi\, \boldsymbol{p}_{t-1} + \sum_{j=1}^{m-1} \Gamma_j\, \Delta\boldsymbol{p}_{t-j} + K\, \boldsymbol{h}(\boldsymbol{P}_{t-1}, \boldsymbol{x}_t) + S(\boldsymbol{e}_t), \tag{7b}$$

where $\Delta\boldsymbol{P}_t = \boldsymbol{p}_t - \boldsymbol{p}_{t-1}$, $\Delta\boldsymbol{p}_{t-j} = \boldsymbol{p}_{t-j} - \boldsymbol{p}_{t-j-1}$, $\Pi = \sum_{j=1}^{m} B_j - I_n$ and $\Gamma_j = -\sum_{k=j+1}^{m} B_j, j = 1, \dots, m-1$. When $K = 0$, equation (7a) is a standard vector autoregression (VAR) model (Hamilton, 1994; Enders, 2014). And when $K = 0$, equation (7b) is a vector error-correction model (VECM) frequently used in the presence of a "unit root". In this context of linear dynamics, the effects of $\boldsymbol{p}_{t-1}$ on $\Delta\boldsymbol{P}_t$ in (7b) are captured entirely by the matrix $\Pi$ and the cointegration (long term) relationships among

$(p_{1,t}, \ldots, p_{n,t})$ are associated with a reduced rank of $\Pi$ (Engle and Granger, 1987; Johansen, 1995). But when $K \neq 0$, price dynamics would depend on the evaluation point.

Our analysis will rely on the specification and estimation of equation (7a) applied to both vertical and spatial commodity markets. The case of vertical markets arises when $(p_i, p_j)$ are commodity prices at different stages of a marketing channel (e.g., producer price versus retail price). Then, the investigation would involve examining the nature of dynamic price transmission in a marketing channel. The case of spatial markets arises when $(p_i, p_j)$ are commodity prices in different regions. Then, the analysis would focus on the dynamic determination of spatial prices for a given commodity. But what happens to the price determination process if the markets exhibit significant structural changes? This is a key question addressed in this paper. As shown below, our analysis provides new and useful information on how vertical and spatial markets adjust in the presence of a disease shock.

Our econometric analysis will rely on the specification and estimation of the VAR model given in (7a). In the absence of serial correlation in the error terms, this provides consistent estimates of the parameters (Hamilton, 1994; Enders, 2014). This includes unit root processes where prices are nonstationary. In this case, it is useful to consider the equivalent vector error-correction model (VECM) given in (7b). The VECM allows us to distinguish between the short run and long run adjustments across markets. For active markets of a standard commodity, we can expect prices $(p_i, p_j)$ to be cointegrated. Indeed, under nonstationary, the long run difference between $p_i$ and $p_j$ may reflect the presence of arbitrage between the two markets (with arbitrage cost being processing cost in vertical markets and transportation cost in spatial markets). In this case, the prices $(p_i, p_j)$ would have a long run cointegration relationship that would reduce the rank of the $\Pi$ matrix in (7b) (Engle and Granger, 1987; Johansen, 1995). In situations where $rank(\Pi) = 1$, there would be a single cointegration relationship between $p_i$ and $p_j$, with $|p_i - p_j|$ being stationary and the $\Pi$ matrix reflecting the arbitrage cost between these markets.

Note that cointegration relationships can become more complex in the presence of differentiated products. Indeed, under differentiated products, we expect long run commodity prices to reflect the shadow prices of the underlying product characteristics (Rosen, 1974; Chavas and Kim, 2005). In this context, the number of cointegration relationships would be the number of product characteristics in active markets. This indicates several possible scenarios for the rank of $\Pi$ in (7b): 1/ $rank(\Pi) = 0$: the markets $i$ and $j$ are not cointegrated and there is no active arbitrage between the two markets; 2/ $rank(\Pi) = 1$: markets $i$ and $j$ are cointegrated (e.g., the commodity is standard and there is active arbitrage between the two markets); and 3/ $rank(\Pi) = 2$: markest $i$ and $j$ are cointegrated and there are two cointegration relationships reflecting product differentiation and long run linkages with the shadow pricing of the underlying product characteristics). Which scenario is likely to develop? We see the relevance of each scenario to be largely an empirical issue (as the nature of cointegration can depend on the markets being analyzed). Our discussion also raises the question: Could a large shock affect the long run relationship between prices (and thus the nature of their cointegration)? These questions are being addressed in the analysis presented below.

Alternative approaches have been used in the investigation of cointegration relationships (Johansen, 1988, 1991; Kleibergen and Paap, 2006). In this research, our analysis of cointegration relationship and of the $rank(\Pi)$ relies on a rank test proposed by Kleibergen and Paap (2006, KP hereinafter). The KP test relies on a Singular Value Decomposition (SVD) of the matrix $\Pi$ in (7b). Under non-stationarity, Kleibergen and Paap (2006) showed that the limiting distribution of the KP rank statistic is identical to that of the Johansen trace statistic. We relied on the KP rank test instead of the conventional Johansen test for three reasons. First, our analysis involves regime-switching together with complex interactions of disease and price dynamics, which makes it harder to test the $rank(\Pi)$ using the indirect "concentrating out" approach proposed by Johansen (Johansen, 1988, 1991). Second, the KP approach can accommodate the presence of market cycles (as there is strong evidence of market cycles in the hog market). Third, as discussed below, our model of price dynamics reflects both short-term and longer-term dynamics, which is more difficult to capture using the Johansen approach. All those arguments point to the more straightforward SVD-based KP test to test the $rank(\Pi)$ in our cointegration analysis.

Our cointegration test proceeds using a two-step procedure. In step one, we obtain consistent estimates of the VAR model in (7a) and the associated $\Pi$ matrix in (7b). In a second step, we use a singular value decomposition of $\Pi$ and its two eigenvalues $(E_1, E_2)$ satisfying $|E_1| \geq |E_2|$. In this context, we have $rank(\Pi)$ equals 2 if $|E_1| \geq |E_2| > 0$, equals 1 if $|E_1| > |E_2| = 0$, and equals 0 if $|E_1| = |E_2| = 0$. We use the KP approach to test $|E_1| = 0$ and $|E_2| = 0$, estimating the standard errors using bootstrapping obtained from resampling 500 times from the sample data. This allows us to evaluate the $rank(\Pi)$ and its implications for the cointegration among prices. As discussed below, we use this approach to investigate how a large shock (due to disease outbreak) can affect the nature of cointegration relationships in both vertical and horizontal markets.

## 4. Data

The study investigates the effects of a major ASF outbreak in 2018 on pricing and market integration in the Chinese pork market. China is the largest pork producer and consumer in the world, with its self-sufficiency rate higher than 96 percent.[3] Our analysis relies on weekly price data over the period from January 2008 to June 2019. The data were obtained from the Department of Market and Information, Ministry of Agriculture and Rural Affairs of China. The analysis is applied to both vertical markets and spatial markets, covering price information at two stages along the supply chain and in seven main regions in China. First, in each region, we investigate prices at two levels of the vertical supply chain: producer price ($PP$) and retail price ($PR$). The former refers to live hog price paid to producers in rural markets; the latter refers to the average pork price paid by consumers. Note that Chinese consumers have a preference for locally slaughtered pork (instead of frozen pork possibly slaughtered in different locations), implying active transportation of live hog between production regions and consumption regions. This may be important as the nature of the supply chain can affect the vertical and spatial pricing patterns observed in the Chinese pork markets. Second, our analysis examines the dynamics of producer and retail prices in seven major regions in China: North, Northeast, East, Center, South, Southwest and Northwest.[4] Among those regions, Northeast, North and Center are the main pork producing areas while South, Southwest and East are mostly pork consuming areas, implying the presence of significant amount of trade among Chinese regions. This raises the question on how the ASF disease outbreak affected pork pricing across space.

Figure 1 reports the trajectories of producer and retail prices in seven regions over the period of January 2008 to June 2019. Several important features can be observed from the data plots showing regional producer prices, regional retail prices and regional price margins (defined using the maximum price minus the minimum price among the seven regions). First, Figure 1 shows that prices exhibit a succession of boom-bust periods, indicating the presence of pork cycles in the Chinese hog market (Gale et al., 2012; Zhao and Wu, 2015). This raises the question: How does the ASF disease outbreak affect the pork cycle? Our empirical analysis will answer this question. Second, the plots present similar price patterns of producer price and retail price, especially before the ASF disease outbreak (in August 2018). This suggests that Chinese pork markets are vertically integrated. But is that true across all regions? This is one of the hypotheses we investigate below. Third, the data plots in Figure 1 indicate some changes in spatial pricing patterns between pre-disease period and post-disease period. Moreover, the lower plot in Figure 1 (reporting spatial price margins) indicates that the ASF outbreak was followed by a short-term increase in the regional price margin. This raises questions about the dynamic nature of spatial price transmission in response to a major disease shock. Did the ASF outbreak affect the cointegration relationships between spatial prices? Did such linkages vary across regions? Our empirical model will address these issues, providing useful information on how a disease outbreak can affect the functioning and dynamics of vertical and spatial markets exhibiting significant cycles.

Table 1 reports the summary statistics of the data used in this study. The national average producer price and retail price during the sample period are 14.54 CNY and 23.69 CNY, respectively. The corresponding marketing margin is 9.15 CNY on average. Among all seven regions, the main production regions (e.g., Northeast, North and Center) show the lower average prices, while the regions with higher average prices are the main consumption ones (e.g., South, Southwest and East). Next, we develop an econometric analysis of these data to investigate the dynamic price effects of the ASF disease outbreak in the Chinese hog industry.

## 5. Econometric Analysis

We start our investigation with the estimation of equation (2), with a focus on the evolution of conditional mean prices across markets. As discussed above, our analysis relies on a final form specification conducted “two prices at a time”. We used the Bayesian Information Criterion (BIC) to guide us in choosing a model specification. The ASF disease outbreak is measured by a dummy variable $Di$. The variable $Di$ equals one after the ASF outbreak on August 3, 2018; $Di$ equals zero otherwise. Our choice of model specification involved the lag structure (including both own lag and cross lag effects), seasonal dummies, disease dummy and interactions of disease dummy with lagged prices.[5] Alternative model specifications were estimated and evaluated. They are reported in Table A1 in the Appendix. Short-term dynamics were captured by lagged prices up to 4 weeks, while longer-term dynamics were captured by own price lagged one-year (i.e., price lagged 53 weeks). The disease dummy $Di$ was introduced as an intercept shifter along with interaction effects with lagged prices. These interaction effects will allow us to investigate how the disease outbreak affects market dynamics. As suggested by the BIC criterion, lagged prices 1 and 2 weeks for both own and cross price effects provided a good representation of short-term dynamics, while the one-year own lagged price (i.e., price lagged 53 weeks) captured long-term dynamics for both producer price and retail price. Note that we did explore the presence of nonlinearities in price trasnmissions across markets, but the BIC criterion did not support such specifications.[6]

Table 2a and Table 2b report estimation results for vertical market at national level as well as regional levels. As shown in the first column of Table 2a, in the producer price (PP) equation at national level, all own lagged prices are statistically significant at the one percent level, indicating the existence of both short-term and long-term price dynamics. Also, the two cross-lagged prices are statistically significant at the ten and five percent level, respectively, implying prices respond to each other in vertical markets. Consistent with existing literature (e.g., Gale et al., 2012; Zhao and Wu, 2015), there is seasonality in Chinese hog price suggested by the seasonal dummies being significant at the one percent level. Our estimates show that the disease variable $Di$ has statistically significant price effects at the one percent level, both as an intercept shifter and as a slope shifter (as it interacts with lagged prices). These interaction effects indicate that the disease outbreak affects market dynamics. The exact nature of these dynamic effects is further explored below. In the second column in Table 2a, similar results are obtained for the retail price ($PR$) equation. Again, there are important price dynamics at the retail level. And the disease variable $Di$ and its interactions with lagged prices are statistically significant at the one percent level.

The other columns in Table 2a and Table 2b report the estimation results at regional level. The findings of price dynamics and seasonality obtained at the national level also apply to regional markets. And the disease variable $Di$ and its interaction terms are statistically significant in almost all regions. This suggests the ASF outbreak has important impacts on producer and retail pricing at both national and regional levels. The impacts on price cycles and market integration are analyzed in detail below.

Next, the estimates on spatial markets are shown in Table 3a and Table 3b. We focus our attention on selected results relating main production regions and main consumption regions. The production regions considered include Northeast and North, and the consumption regions considered include South and Southwest. Thus, we report four pairs (represented by NE-SW, N-SW, NE-S, N-S) for both producer and retail prices.

Table 3a shows the results for producer prices. In the first two columns, we find that the disease variable $Di$ alone is statistically significant in NE equation, but not in SW equation. Recalling that NE represents a main production region and SW represents a main consumption region, this result indicates that the disease outbreak has a larger impact on production than consumption, at least within the first year after the outbreak. This result is found to be valid in all four scenarios considered. This is our first important finding. It is consistent with the fact that ASF is a non-zoonotic disease (only infects hogs but not humans), thus affecting production but not demand, within the first year after the outbreak. Although the disease variable $Di$ alone is not significant in the main consumer regions, most of its interactions with lagged prices are significant in both production and consumption regions. This suggests that the disease outbreak affects market adjustments.

The findings discussed above also apply to the spatial analysis of retail prices. The disease variable $Di$ alone is only significant in main production regions (and not the main consumption regions). However, the interaction terms with lagged prices are significant in both production and consuming regions. The difference highlights the heterogeneous impacts of disease outbreak in affecting markets in production versus consumption regions. It reflects that an outbreak of non-zoonotic animal disease has its largest effect on the supply of the market. But dynamic adjustments imply that a supply shock eventually affects prices in all markets. The case of the Chinese pork market provides a nice illustration of market responses.

## 6. Economic implications

Our econometric analysis provides useful information on the nature of dynamic adjustments in response to a major disease shock. Our discussion proceeds in two steps:

first, the analysis of price dynamics in a vertical sector; and second, an investigation of spatial adjustments across regional markets.

### 6.1 Implications for vertical markets

We start using our econometric estimates to study the nature of price dynamics. As discussed in section 3, the longer-term market dynamics is captured by the dominant root $\lambda_1$ of the $DG$ matrix, while the other roots $(\lambda_2, \lambda_3, \ldots)$ capture shorter-term dynamics, with $|\lambda_1| \geq |\lambda_2| \geq |\lambda_3| \geq \cdots$. We calculated the characteristic roots associated with our vertical model.[7] Given that lagged prices interact with the disease dummy $Di$, the roots take different values in the pre-disease period ($\lambda_{pre}$ when $Di$ = 0) versus the post disease period ($\lambda_{post}$ when $Di$ = 1). The modulus of the first two roots $(\lambda_1, \lambda_2)$ are reported in Table 4. Except in the South and Southwest regions in the post-disease period, the dominant roots are always complex. For the South and Southwest regions, it is found that the dominant root $\lambda_{1,post}$ is real but the second root $\lambda_{2,post}$ is complex. These results indicate that the presence of market cycles is pervasive. They also document the presence of multiple cycles (which is common as we find multiple complex roots).

Table 4 shows that, at national level, the modulus of the dominant root in the pre-disease period is $|\lambda_{1,pre}| =$ 0.994, while it is $\lambda_{1,post} =$ 0.987 in the post-disease period. We conducted two statistical tests about these roots: 1/ a "unit root" test: is each $|\lambda_1|$ statistically different from 1?; and 2/ are $|\lambda_{1,pre}|$ and $|\lambda_{1,post}|$ statistically different from each other? Under non-stationarity, these tests do not have a standard asymptotic distribution (Hamilton, 1994; Enders, 2014). We proceed conducting these tests using bootstrapping, resampling 500 times from the data. For the first test, we failed to reject the null hypothesis at the 5 percent significance level, concluding that price dynamics is non-stationary and exhibits a unit root. This same test result was also obtained in the regional models. Thus, we find that price dynamics are globally unstable in both national and regional markets. Our second test involved testing the null hypothesis that the modulus of the dominant root is the same in the pre-disease period versus the post-disease period: $|\lambda_{1,pre}| = |\lambda_{1,post}|$. Using bootstrapping, the test results are presented in Table 4, which reports strong evidence against the null hypothesis especially in the regional markets. It shows that $|\lambda_1|$ declined with the disease outbreak in the production regions (North and Northeast) but it increased in the other regions.[8]

Recall that a complex root ($\lambda = a + b\sqrt{-1}$) implies cyclical price patterns with a cycle of period $Per = [2\,\pi/\arctan\,(\frac{b}{a})]$. The common presence of complex roots implies that Chinese pork markets exhibit cycles. The lower panel in Table 4 reports the estimated periods of the cycle along with statistical test results (using bootstrapping). At the national level, the cycle period before disease outbreak is $Per_{pre} =$ 173 weeks (3 years and 4 months); it is statistically different from zero at the one percent significance level. These results are consistent with estimates from previous findings (Gale et al., 2012). In contrast, after the disease outbreak, the cycle reduces to $Per_{post} =$ 110 weeks (2 years and 1 month); it is statistically different from zero at the 10 percent significance level. Thus, we find that the disease outbreak has not eliminated the pork cycle in China. We also tested the null hypothesis that $Per_{pre} = Per_{post}$. At the national level, the results reported in

Table 4 show that the period of the cycle has declined with the ASF outbreak and that the decline is statistically significant at one percent level. This provides strong evidence that the ASF disease outbreak had major impacts on price dynamics and on the hog cycles.

Table 4 also reports the pork cycle results at the regional level. Across regions and before the disease outbreak the cycle period $Per_{pre}$ ranges from 168 weeks (3 years and 3 months) to 193 weeks (3 years and 9 months). These cycle periods are all statistically different from zero at the one percent significance level. These results indicate that similar market cycles existed in all regions. Table 4 also shows that the cycle period declined after the ASF outbreak in all regions. Testing the null hypothesis that $Per_{pre} = Per_{post}$ (using bootstrapping), we find that the decline in the cycle period $Per$ is statistically significant at the 1 percent level. This is another important result: our analysis uncovers strong evidence that the disease outbreak contributed to a reduction in the cycle period. To the extent that the pork cycle is associated with a poorly-informed response of producers to price signals,[9] we interpret this result as indirect evidence that pork producers adjusted their decision making in response to a large supply shock. This is a scenario where a disease outbreak may induce farmers to pay more attention to market conditions, inducing speedier supply adjustments which could explain the observed reduction in the cycle period. This scenario may also reflect resilient behavior of farmers: a large shock could improve the efficiency of production decisions, making farmers more resilient to market shocks. In turn, having supply adjusting faster to market conditions can increase the dynamic efficiency of markets. While we realize that this interpretation is tentative, we want to present it as an interesting topic worth further investigation.

Next, to investigate the nature of price dynamics, we conducted forward simulations of our estimated models. Figure 2 illustrates the simulated forward path of producer price and retail price under two scenarios: with versus without ASF outbreak. For producer price, the upper plot shows an obvious cyclical pattern under both scenarios, reflecting the existence of underlying market cycles. The forward price paths differ with and without disease outbreak. The ASF outbreak exerts complex impacts on hog cycle patterns, including a strong short-term price response to the ASF outbreak that shortens the cycle lengths and trigger cycle shifts. The retail price simulations present qualitatively similar results with a larger amplitude.

Based on the disease outbreak effects on the producer and retail prices, what are the implications for the vertical price margins? We analyze this issue by reporting simulated national and regional price margins in Figure 3. The vertical price margin is defined as the price difference between retail price and producer price in region *i* at time *t* ($PR_{i,t} - PP_{i,t}$). As shown, the vertical price margins also present cyclical patterns. Interestingly, the trajectories with and without disease outbreak are not very different (compared with changes in spatial price margins presented below), indicating that the ASF outbreak had only mild effects on vertical price transmission.

Table 5 reports cointegration results regarding the vertical market at both national and regional levels. As discussed in section 3, the analysis relies on the roots $(E_1, E_2)$ of the $\Pi$ matrix in equation (7b). Using bootstrapping for hypothesis testing, Table 5 shows that, at national level, both $E_1$ and $E_2$ are statistically different from zero at the one percent significance level, indicating that there exist two cointegration relationships among vertically-connected prices along the supply chain. We interpret this finding as indirect evidence of product differentiation and long-run linkages with the shadow pricing of the underlying product characteristics. Table 5 also reports that both eigenvalues remain significant at five percent level after disease outbreak, indicating that the impact of the ASF disease on vertical market integration was limited. But a very different picture emerges at the regional level. While $E_1$ and $E_2$ are still both statistically significant before the disease in all regions, their significance declines in several regions (e.g., N, NE, SW). In these cases, the $rank(\Pi)$ is reduced after the disease outbreak. We interpret this result as evidence that the ASF outbreak had adverse effects on the functioning of implicit markets for differentiated product characteristics in the Chinese pork market.

### 6.2 Implications for spatial markets

We now turn our attention to the functioning of spatial markets. Table 6 reports results on characteristic roots and price cycles applied to prices across regions. In a way similar to vertical markets, the dominant roots are found to be not different from a "unit root" in both pre-disease and post-disease regimes, indicating that the spatial systems are globally unstable at both national and regional levels. Consistent with vertical results, the cycle periods were significantly lower after the disease outbreak in all markets considered. Again, this is an important result that the disease outbreak triggered significant price changes captured by a shortened hog cycle.

The simulated forward paths of spatial price margins are reported in Figure 4. The spatial price margin is defined as the price difference between two regions $(i, j)$ at time $t$ ($PP_{i,t} - PP_{j,t}$ and $PR_{i,t} - PR_{j,t}$). In a way different from the vertical analysis, there are significant changes in spatial price differences between the two regimes, indicating that the ASF outbreak had large impacts on spatial price transmission. In response to the ASF disease, the Chinese government imposed transportation bans on hog trade among provinces. This had large effects on regional hog markets, creating a surplus in production areas and shortage in consumption areas. The reduction in interregional trade flows had negative effects on spatial market integration and increased spatial price differences (in contrast with the vertical results obtained in Figure 3).

Table 7 reports cointegration test results applied to the spatial markets. In a way similar to the vertical results, we find evidence of two cointegration relationships before disease, as both $E_1$ and $E_2$ are statistically different from zero at the one percent level. But the KP test results after disease outbreak look very different. The cointegration relationship totally disappears in some cases: NE-SW and NE-S for producer price, N-SW for retail price. Table 7 also shows that the ASF outbreak reduces the number of cointegration relationships among spatial markets (e.g., in N-SW and N-S for producer price, and NE-SW and NE-S for retail price). By comparing the vertical results from Table 5, we find that the disease outbreak had stronger adverse effects on long-run cointegration relationship in spatial markets than in vertical markets. We attribute these results as policy effects of interregional trade restrictions imposed following the ASF outbreak.

In summary, the ASF outbreak affected both vertical and spatial pricing (e.g., its effects on pork cycles). But our analysis shows its impacts on vertical and spatial markets were very different in at least two ways. The first difference relates to price margins: the disease triggered large rises on spatial price margins but with smaller impacts vertical price margins. The second difference concerns market integration: the disease outbreak had stronger adverse impacts on spatial cointegration than on vertical cointegration. We see these differences to be closely linked with the effects of interregional trade bans intended to restrict the disease spread. Though effective in controlling ASF spread, the trade restrictions present adverse effects on spatial market integration. To the extent that maintaining supply-demand balance is important, this identifies significant economic and policy tradeoff between reducing the spread of disease and creating market disruptions, especially across spatial markets.

A related issue is the location of production activities. Over the last few years, the Chinese hog markets have seen a move toward greater specialization toward pork in the northern regions. This means that pork self-sufficiency in southern China has deteriorated and the southern regions have exhibited an increased reliance on imports from northern areas. A consumption preference and habit for locally-slaughtered pork also contributed to large-scale transportation of live hogs across regions in China. In the presence of major contagious diseases such as ASF, the large interregional trade was problematic. While the bans on live animals helped control the disease spread, it also had significant negative effects on interregional market integration.

## 7. Conclusion

This paper has investigated the dynamic effects of animal disease on the functioning of vertical and spatial markets, with an application to the outbreak of African Swine Fever in the Chinese hog market. Base on a weekly dataset of producer and retail price in seven regions, this paper sheds new light on price dynamics, price cycles, market integration and their changes in response to a major disease outbreak.

Our empirical analysis generates several important findings. First, we evaluate how the ASF outbreak affects market cycles. While the presence of a hog cycle is well-established, much less is known about how a disease outbreak affects market cycles. Our forward-path simulations show that the ASF outbreak contributes to shortening the cycle period, indicating that a large production shock induced producers to improve their understanding of changing market conditions and adjust their production decisions in a timelier manner. We also document the nature and cyclical response of price margins to the disease outbreak. Our results show that the ASF outbreak triggered significant short-term rises in spatial price margins.

Second, we show how the ASF outbreak has significant impacts on both vertical and spatial markets. Our analysis evaluates short-term as well as longer-term price adjustments. We find larger long-term effects of the ASF outbreak on spatial prices than on vertical prices. This result is exemplified by a stronger decline in market integration across regions, likely reflecting inter-regional trade bans imposed by the Chinese government in an attempt to reduce the spread of ASF. We also document how the ASF outbreak had a more significant impact on pork prices in production regions (as opposed to consumption regions) during the first year after the outbreak.

Third, we provide indirect evidence that pork is a differentiated product, with the shadow pricing of its underlying product characteristics evolving with market conditions. Associating the pricing of differentiated products with multiple cointegration relationships, we show that the ASF outbreak has contributed to a reduction in cointegration relationships, especially among spatial markets. This result indicates that a major shock contributes to some deterioration in the functioning of implicit markets.

This study has developed a refined analysis of the dynamic impacts of a disease outbreak on vertical and spatial pricing. Our application focused on the recent outbreak of African Swine Fever in China. First, while ASF provides a great case study, we should keep in mind that our findings are conditional on the specific policy response to animal disease observed in China. It would be useful to expand our analysis to evaluate other diseases in other markets. Second, there is a need to investigate the effects of a disease outbreak on price volatility and on possible nonlinear price transmissions. Third, with the ASF outbreak occurring in 2018, there remains some uncertainty about its long-term impacts. Once information becomes available, there will be a need for further investigation of these long-term effects. These issues seem to be good topics for future research.

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Table 1. Summary statistics.

| Variables | Mean | St. Dev. | Min | Max | Variables (cont.) | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|---|---|---|---|
| PP | 14.54 | 2.60 | 9.19 | 20.80 | PR | 23.69 | 3.67 | 15.36 | 31.56 |
| PP_N | 14.44 | 2.53 | 9.48 | 20.91 | PR_N | 23.11 | 3.82 | 14.51 | 31.31 |
| PP_NE | 13.98 | 2.75 | 8.48 | 21.13 | PR_NE | 22.26 | 4.06 | 14.03 | 31.61 |
| PP_E | 14.59 | 2.58 | 9.34 | 20.96 | PR_E | 24.14 | 3.58 | 15.92 | 31.80 |
| PP_C | 14.42 | 2.62 | 9.15 | 20.72 | PR_C | 23.90 | 3.70 | 15.81 | 31.69 |
| PP_S | 14.56 | 2.57 | 9.56 | 21.21 | PR_S | 24.01 | 3.55 | 16.21 | 32.04 |
| PP_SW | 14.87 | 2.86 | 8.40 | 20.60 | PR_SW | 24.41 | 3.87 | 14.97 | 31.64 |
| PP_NW | 15.10 | 2.74 | 8.93 | 20.84 | PR_NW | 24.32 | 3.72 | 15.09 | 31.59 |
| Di | 0.09 | 0.28 | 0 | 1 | Q2 | 0.26 | 0.44 | 0 | 1 |
| Q1 | 0.26 | 0.44 | 0 | 1 | Q3 | 0.24 | 0.43 | 0 | 1 |

Table 2a. Vertical market regression results

| | National | | N | | NE | | E | |
|---|---|---|---|---|---|---|---|---|
| | PP | PR | PP | PR | PP | PR | PP | PR |
| PP1 | 1.904*** | 0.596*** | 1.662*** | 0.744*** | 1.807*** | 0.811*** | 1.652*** | 0.422*** |
| | (0.075) | (0.065) | (0.068) | (0.074) | (0.079) | (0.073) | (0.070) | (0.055) |
| PP2 | -0.919*** | -0.563*** | -0.672*** | -0.683*** | -0.788*** | -0.660*** | -0.684*** | -0.393*** |
| | (0.071) | (0.061) | (0.067) | (0.073) | (0.076) | (0.069) | (0.066) | (0.051) |
| PP53 | -0.009*** | | -0.012*** | | -0.010** | | -0.016*** | |
| | (0.003) | | (0.004) | | (0.005) | | (0.005) | |
| PR1 | -0.131* | 1.331*** | -0.028 | 1.151*** | -0.161** | 1.037*** | 0.013 | 1.318*** |
| | (0.070) | (0.062) | (0.054) | (0.061) | (0.071) | (0.068) | (0.076) | (0.063) |
| PR2 | 0.139** | -0.356*** | 0.03 | -0.191*** | 0.144** | -0.136** | 0.005 | -0.339*** |
| | (0.065) | (0.058) | (0.051) | (0.058) | (0.063) | (0.060) | (0.073) | (0.060) |
| PR53 | | -0.002 | | -0.002 | | -0.002 | | -0.003 |
| | | (0.002) | | (0.003) | | (0.003) | | (0.003) |
| Di | 3.694*** | 4.260*** | 2.875*** | 3.149** | 2.002*** | 1.480* | 3.989*** | 3.735*** |
| | (0.688) | (0.942) | (0.785) | (1.596) | (0.689) | (0.859) | (0.879) | (1.175) |
| Q1 | -0.051*** | -0.024 | -0.067*** | -0.017 | -0.057* | -0.026 | -0.060** | -0.007 |
| | (0.019) | (0.017) | (0.025) | (0.028) | (0.031) | (0.030) | (0.028) | (0.023) |
| Q2 | -0.014 | -0.01 | 0.01 | 0.017 | 0.04 | 0.023 | -0.011 | 0.003 |
| | (0.019) | (0.018) | (0.026) | (0.029) | (0.032) | (0.031) | (0.029) | (0.024) |
| Q3 | 0.018 | 0.027 | 0.021 | 0.071** | 0.029 | 0.048 | 0.033 | 0.046* |
| | (0.020) | (0.018) | (0.026) | (0.030) | (0.032) | (0.030) | (0.029) | (0.024) |
| PP1*Di | -0.538*** | | -0.284** | | -0.197** | | -0.438*** | |
| | (0.086) | | (0.110) | | (0.096) | | (0.091) | |
| PP2*Di | 0.358*** | | 0.169 | | 0.134 | | 0.249*** | |
| | (0.080) | | (0.104) | | (0.094) | | (0.086) | |
| PP53*Di | -0.085*** | | -0.100*** | | -0.092*** | | -0.087*** | |
| | (0.018) | | (0.028) | | (0.031) | | (0.025) | |
| PR1*Di | | -0.752*** | | -0.463*** | | -0.286*** | | -0.554*** |
| | | (0.098) | | (0.119) | | (0.091) | | (0.097) |
| PR2*Di | | 0.629*** | | 0.387*** | | 0.260*** | | 0.448*** |
| | | (0.086) | | (0.110) | | (0.089) | | (0.088) |
| PR53*Di | | -0.054*** | | -0.057** | | -0.038* | | -0.038** |
| | | (0.014) | | (0.028) | | (0.021) | | (0.019) |
| Constant | 0.180*** | 0.133** | 0.277*** | 0.074 | 0.255*** | 0.139 | 0.283*** | 0.136* |
| | (0.056) | (0.053) | (0.075) | (0.088) | (0.086) | (0.085) | (0.082) | (0.073) |
| Adj. $R^2$ | 0.997 | 0.999 | 0.994 | 0.996 | 0.992 | 0.997 | 0.992 | 0.997 |

Note: Standard errors are reported in parenthesis. *p<0.1; **p<0.05; ***p<0.01. N represents North; NE represents North-East; E represents East; C represents Center; S represents South; SW represents South-West; NW represents North-West.

Table 2b. Vertical market regression results (cont.)

| | C | | S | | SW | | NW | |
|---|---|---|---|---|---|---|---|---|
| | PP | PR | PP | PR | PP | PR | PP | PR |
| PP1 | $1.792^{***}$ | $0.635^{***}$ | $1.627^{***}$ | $0.580^{***}$ | $1.750^{***}$ | $0.690^{***}$ | $1.469^{***}$ | $0.609^{***}$ |
| | (0.068) | (0.056) | (0.051) | (0.060) | (0.058) | (0.078) | (0.062) | (0.074) |
| PP2 | $-0.817^{***}$ | $-0.574^{***}$ | $-0.643^{***}$ | $-0.517^{***}$ | $-0.765^{***}$ | $-0.650^{***}$ | $-0.475^{***}$ | $-0.552^{***}$ |
| | (0.064) | (0.052) | (0.051) | (0.060) | (0.058) | (0.078) | (0.063) | (0.074) |
| PP53 | $-0.014^{***}$ | | $-0.013^{***}$ | | $-0.006^{***}$ | | $-0.007^{***}$ | |
| | (0.004) | | (0.005) | | (0.002) | | (0.003) | |
| PR1 | -0.115 | $1.166^{***}$ | 0.01 | $1.020^{***}$ | 0.054 | $1.257^{***}$ | $0.200^{***}$ | $1.295^{***}$ |
| | (0.071) | (0.060) | (0.039) | (0.052) | (0.044) | (0.061) | (0.048) | (0.059) |
| PR2 | $0.128^{*}$ | $-0.208^{***}$ | -0.003 | -0.064 | -0.046 | $-0.289^{***}$ | $-0.198^{***}$ | $-0.340^{***}$ |
| | (0.065) | (0.055) | (0.038) | (0.050) | (0.043) | (0.060) | (0.047) | (0.057) |
| PR53 | | -0.002 | | 0.003 | | -0.001 | | -0.002 |
| | | (0.003) | | (0.005) | | (0.002) | | (0.002) |
| Di | $4.430^{***}$ | $5.286^{***}$ | $1.303^{***}$ | $3.808^{**}$ | $0.591^{***}$ | 0.316 | $2.489^{***}$ | $3.747^{***}$ |
| | (0.762) | (1.183) | (0.436) | (1.566) | (0.221) | (0.417) | (0.585) | (0.921) |
| Q1 | $-0.075^{***}$ | -0.019 | $-0.068^{***}$ | 0.003 | $-0.047^{***}$ | $-0.046^{**}$ | $-0.054^{***}$ | $-0.049^{**}$ |
| | (0.025) | (0.021) | (0.026) | (0.034) | (0.014) | (0.019) | (0.018) | (0.022) |
| Q2 | -0.038 | -0.025 | -0.017 | -0.01 | $-0.029^{*}$ | -0.03 | 0.009 | -0.006 |
| | (0.026) | (0.022) | (0.028) | (0.036) | (0.015) | (0.021) | (0.019) | (0.023) |
| Q3 | 0.037 | $0.042^{*}$ | 0.033 | 0.009 | 0.014 | 0.031 | 0.008 | 0.029 |
| | (0.026) | (0.022) | (0.027) | (0.035) | (0.015) | (0.021) | (0.019) | (0.023) |
| PP1*Di | $-0.514^{***}$ | | $-0.407^{***}$ | | $-0.326^{***}$ | | $-0.248^{***}$ | |
| | (0.087) | | (0.086) | | (0.072) | | (0.095) | |
| PP2*Di | $0.297^{***}$ | | $0.286^{***}$ | | $0.266^{***}$ | | 0.119 | |
| | (0.083) | | (0.085) | | (0.066) | | (0.090) | |
| PP53*Di | $-0.111^{***}$ | | 0.026 | | $0.025^{**}$ | | $-0.043^{***}$ | |
| | (0.023) | | (0.021) | | (0.011) | | (0.017) | |
| PR1*Di | | $-0.721^{***}$ | | $-0.552^{***}$ | | $-0.336^{***}$ | | $-0.512^{***}$ |
| | | (0.103) | | (0.132) | | (0.087) | | (0.101) |
| PR2*Di | | $0.565^{***}$ | | $0.403^{***}$ | | $0.304^{***}$ | | $0.408^{***}$ |
| | | (0.091) | | (0.121) | | (0.081) | | (0.092) |
| PR53*Di | | $-0.068^{***}$ | | -0.011 | | 0.022 | | $-0.046^{***}$ |
| | | (0.018) | | (0.021) | | (0.014) | | (0.015) |
| Constant | $0.267^{***}$ | $0.170^{**}$ | $0.274^{***}$ | 0.059 | $0.121^{**}$ | $0.213^{***}$ | $0.169^{**}$ | $0.268^{***}$ |
| | (0.075) | (0.067) | (0.076) | (0.111) | (0.047) | (0.066) | (0.066) | (0.081) |
| Adj. $R^2$ | 0.994 | 0.998 | 0.994 | 0.994 | 0.998 | 0.998 | 0.997 | 0.998 |

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 3a. Spatial market regression results for producer prices ($PP$)

| | NE-SW | | N-SW | | NE-S | | N-S | |
|---|---|---|---|---|---|---|---|---|
| | NE (PA) | SW (PB) | N (PA) | SW (PB) | NE (PA) | S (PB) | N (PA) | S (PB) |
| PA1 | 1.668*** | 0.092*** | 1.600*** | 0.127*** | 1.612*** | 0.173*** | 1.537*** | 0.205*** |
| | (0.046) | (0.018) | (0.045) | (0.024) | (0.050) | (0.037) | (0.046) | (0.047) |
| PA2 | -0.682*** | -0.071*** | -0.611*** | -0.106*** | -0.614*** | -0.120*** | -0.544*** | -0.158*** |
| | (0.048) | (0.018) | (0.046) | (0.023) | (0.052) | (0.038) | (0.048) | (0.048) |
| PA53 | -0.012*** | | -0.011*** | | -0.010** | | -0.011*** | |
| | (0.005) | | (0.004) | | (0.004) | | (0.004) | |
| PB1 | -0.035 | 1.675*** | 0.069 | 1.664*** | 0.06 | 1.441*** | 0.140*** | 1.460*** |
| | (0.075) | (0.037) | (0.064) | (0.038) | (0.054) | (0.050) | (0.046) | (0.051) |
| PB2 | 0.041 | -0.697*** | -0.066 | -0.685*** | -0.067 | -0.499*** | -0.141*** | -0.511*** |
| | (0.070) | (0.035) | (0.060) | (0.036) | (0.053) | (0.048) | (0.045) | (0.050) |
| PB53 | | -0.003* | | -0.003* | | -0.012*** | | -0.012*** |
| | | (0.002) | | (0.002) | | (0.004) | | (0.004) |
| Di | 1.735** | -0.081 | 3.096*** | 0.037 | 2.159*** | -0.195 | 3.351*** | 0.418 |
| | (0.751) | (0.280) | (0.840) | (0.262) | (0.704) | (0.493) | (0.781) | (0.459) |
| Q1 | -0.062** | -0.031** | -0.067*** | -0.042*** | -0.063** | -0.034 | -0.069*** | -0.062** |
| | (0.031) | (0.014) | (0.025) | (0.014) | (0.031) | (0.025) | (0.025) | (0.025) |
| Q2 | 0.037 | -0.038*** | 0.016 | -0.040*** | 0.044 | -0.005 | 0.009 | -0.009 |
| | (0.032) | (0.015) | (0.026) | (0.015) | (0.032) | (0.026) | (0.025) | (0.026) |
| Q3 | 0.033 | 0.011 | 0.011 | 0.009 | 0.011 | 0.025 | 0.005 | 0.022 |
| | (0.034) | (0.015) | (0.029) | (0.015) | (0.031) | (0.026) | (0.025) | (0.026) |
| PA1:Di | -0.175* | | -0.266** | | -0.161* | | -0.327*** | |
| | (0.098) | | (0.110) | | (0.095) | | (0.109) | |
| PA2:Di | 0.125 | | 0.143 | | 0.087 | | 0.193* | |
| | (0.096) | | (0.104) | | (0.093) | | (0.103) | |
| PA53:Di | -0.085*** | | -0.109*** | | -0.094*** | | -0.116*** | |
| | (0.032) | | (0.029) | | (0.033) | | (0.030) | |
| PB1:Di | | -0.178** | | -0.226*** | | -0.325*** | | -0.352*** |
| | | (0.075) | | (0.072) | | (0.083) | | (0.083) |
| PB2:Di | | 0.147** | | 0.190*** | | 0.267*** | | 0.258*** |
| | | (0.068) | | (0.066) | | (0.081) | | (0.082) |
| PB53:Di | | 0.045*** | | 0.041*** | | 0.078*** | | 0.066*** |
| | | (0.013) | | (0.012) | | (0.024) | | (0.023) |
| Constant | 0.271*** | 0.078** | 0.284*** | 0.069 | 0.283*** | 0.270*** | 0.276*** | 0.244*** |
| | (0.086) | (0.039) | (0.078) | (0.043) | (0.089) | (0.074) | (0.075) | (0.074) |
| Adj. $R^2$ | 0.992 | 0.999 | 0.994 | 0.999 | 0.992 | 0.994 | 0.994 | 0.994 |

Note: *p<0.1; **p<0.05; ***p<0.01. For simplicity, we use PA to represent producer prices in production regions (NE, N), and use PB to represent producer prices in consumption regions (SW, S).

Table 3b. Spatial market regression results for retail prices ($PR$)

| | NE-SW | | N-SW | | NE-S | | N-S | |
|---|---|---|---|---|---|---|---|---|
| | NE (PA) | SW (PB) | N (PA) | SW (PB) | NE (PA) | S (PB) | N (PA) | S (PB) |
| PA1 | 1.683*** | 0.116*** | 1.622*** | 0.190*** | 1.688*** | 0.287*** | 1.626*** | 0.393*** |
| | (0.040) | (0.023) | (0.044) | (0.028) | (0.038) | (0.038) | (0.040) | (0.043) |
| PA2 | -0.704*** | -0.088*** | -0.640*** | -0.155*** | -0.711*** | -0.250*** | -0.654*** | -0.351*** |
| | (0.041) | (0.024) | (0.044) | (0.028) | (0.039) | (0.039) | (0.041) | (0.044) |
| PA53 | -0.008** | | -0.007** | | -0.010*** | | -0.009*** | |
| | (0.003) | | (0.003) | | (0.003) | | (0.003) | |
| PB1 | 0.097* | 1.587*** | 0.115* | 1.522*** | 0.064 | 1.156*** | 0.093** | 1.108*** |
| | (0.059) | (0.039) | (0.060) | (0.042) | (0.042) | (0.047) | (0.041) | (0.048) |
| PB2 | -0.082 | -0.616*** | -0.101* | -0.558*** | -0.043 | -0.197*** | -0.067* | -0.154*** |
| | (0.056) | (0.037) | (0.057) | (0.039) | (0.041) | (0.046) | (0.040) | (0.047) |
| PB53 | | -0.002 | | -0.004* | | -0.002 | | -0.004 |
| | | (0.002) | | (0.002) | | (0.004) | | (0.004) |
| Di | 2.213** | -0.783 | 4.803*** | -0.713 | 2.496*** | 1.41 | 4.687*** | 2.289 |
| | (1.057) | (0.534) | (1.767) | (0.527) | (0.956) | (1.657) | (1.710) | (1.593) |
| Q1 | -0.076** | -0.035* | -0.054* | -0.064*** | -0.086** | 0.014 | -0.062** | -0.026 |
| | (0.033) | (0.021) | (0.031) | (0.020) | (0.034) | (0.035) | (0.030) | (0.033) |
| Q2 | 0.048 | -0.043* | 0.036 | -0.062*** | 0.02 | -0.003 | 0.003 | -0.004 |
| | (0.035) | (0.022) | (0.032) | (0.021) | (0.037) | (0.039) | (0.034) | (0.037) |
| Q3 | 0.038 | 0.016 | 0.051 | 0.005 | 0.037 | 0.02 | 0.052 | -0.004 |
| | (0.036) | (0.022) | (0.035) | (0.022) | (0.033) | (0.036) | (0.032) | (0.035) |
| PA1:Di | -0.056 | | -0.347*** | | -0.102 | | -0.368*** | |
| | (0.104) | | (0.132) | | (0.100) | | (0.129) | |
| PA2:Di | 0.011 | | 0.230* | | 0.051 | | 0.260** | |
| | (0.101) | | (0.120) | | (0.097) | | (0.118) | |
| PA53:Di | -0.063*** | | -0.093*** | | -0.070*** | | -0.095*** | |
| | (0.024) | | (0.031) | | (0.024) | | (0.031) | |
| PB1:Di | | -0.106 | | -0.136 | | -0.348** | | -0.361*** |
| | | (0.096) | | (0.091) | | (0.138) | | (0.134) |
| PB2:Di | | 0.095 | | 0.122 | | 0.248** | | 0.220* |
| | | (0.090) | | (0.085) | | (0.125) | | (0.123) |
| PB53:Di | | 0.049*** | | 0.048*** | | 0.039* | | 0.040* |
| | | (0.016) | | (0.015) | | (0.024) | | (0.023) |
| Constant | 0.257*** | 0.151** | 0.248*** | 0.182*** | 0.256*** | 0.177* | 0.239*** | 0.220** |
| | -0.094 | -0.061 | -0.09 | -0.06 | -0.094 | -0.107 | -0.09 | -0.104 |
| Adj. $R^2$ | 0.996 | 0.998 | 0.996 | 0.998 | 0.996 | 0.994 | 0.996 | 0.994 |

Note: *p<0.1; **p<0.05; ***p<0.01. For simplicity, we use PA to represent retail prices in production regions (NE, N), and use PB to represent retail prices in consumption regions (SW, S).

Table 4. Characteristic roots and hog cycles in vertical models

| Statistics | | National | N | NE | E | C | S | SW | NW |
|---|---|---|---|---|---|---|---|---|---|
| Dominant roots | $\lvert\lambda_{1,pre}\rvert$ | 0.994 (0.136) | 0.996 (0.228) | 0.996 (0.236) | 0.992 (0.104) | 0.994 (0.998) | 0.994 (0.122) | 0.994 (0.118) | 0.996 (0.232) |
| | $\lvert\lambda_{1,post}\rvert$ | 0.987 (0.319) | 0.998 (0.406) | 1.006 (0.292) | 0.987 (0.152) | 0.989 (0.755) | 0.978* (0.094) | 0.987 (0.213) | 0.984* (0.087) |
| | $\lvert\lambda_{1,pre}\rvert - \lvert\lambda_{1,post}\rvert$ | 0.007* (0.095) | -0.002*** (0.001) | -0.010*** (0.001) | 0.005*** (0.001) | 0.005*** (0.001) | 0.016*** (0.001) | 0.007*** (0.001) | 0.012*** (0.001) |
| Second roots | $\lvert\lambda_{2,pre}\rvert$ | 0.966*** (0.001) | 0.963*** (0.001) | 0.963*** (0.001) | 0.968*** (0.001) | 0.967 (0.001) | 0.964 (0.126) | 0.962 (0.133) | 0.956*** (0.001) |
| | $\lvert\lambda_{2,post}\rvert$ | 0.972** (0.044) | 0.982 (0.264) | 0.990 (0.496) | 0.972* (0.073) | 0.973* (0.064) | 0.953 (0.030) | 0.971* (0.054) | 0.982*** (0.002) |
| Cycle period (weeks) | $Per_{pre}$ | 173*** (0.001) | 173*** (0.001) | 170*** (0.001) | 168*** (0.001) | 174*** (0.001) | 171*** (0.001) | 176*** (0.001) | 193*** (0.001) |
| | $Per_{post}$ | 110* (0.085) | 113* (0.067) | 116 (0.119) | 110 (0.151) | 109 (0.290) | 57 (0.382) | 60 (0.473) | 110** (0.034) |
| | $Per_{pre} - Per_{post}$ | 63*** (0.001) | 60*** (0.001) | 54*** (0.001) | 58*** (0.001) | 65*** (0.001) | 124*** (0.001) | 116*** (0.001) | 83*** (0.001) |

Note: The numbers in parentheses are the P-values corresponding to testing the null hypothesis $\lvert\lambda_i\rvert = 1$ ("unit root") in the first, second, fourth and fifth row, testing $\lvert\lambda_{1,pre}\rvert = \lvert\lambda_{1,post}\rvert$ in the third row, testing $Per = 0$ in the sixth and seventh row, and testing $Per_{pre} = Per_{post}$ in the last row. All tests were conducted using bootstrapping. The periods were calculated using the estimated dominant root $\lambda_1$, except for $Per_{post}$ in the South and Southwest where $\lambda_2$ was used (as $\lambda_1$ was real).

Table 5. Cointegration test in vertical models

| Statistics | Di | Eigenvalues | National | N | NE | E | C | S | SW | NW |
|---|---|---|---|---|---|---|---|---|---|---|
| Eigenvalue | Di=0 | $E1_{pre}$ | 0.049*** (17.136) | 0.076*** (17.135) | 0.182*** (32.369) | 0.063*** (25.478) | 0.085*** (50.820) | 0.081*** (26.463) | 0.056*** (14.126) | 0.075*** (14.088) |
| | | $E2_{pre}$ | 0.007*** (9.470) | 0.010*** (13.409) | 0.009*** (12.743) | 0.010*** (7.624) | 0.011*** (13.360) | 0.009*** (10.593) | 0.006*** (12.604) | 0.007*** (9.463) |
| | Di=1 | $E1_{post}$ | 0.294** (6.339) | 0.251** (5.689) | 0.245*** (8.625) | 0.328** (6.139) | 0.380*** (12.416) | 0.217*** (9.984) | 0.076*** (13.286) | 0.224*** (17.115) |
| | | $E2_{post}$ | 0.199** (4.902) | 0.164 (2.115) | 0.109 (1.799) | 0.164** (4.352) | 0.256*** (9.469) | 0.113* (3.667) | 0.026 (2.453) | 0.163*** (7.690) |

Note: the Kleibergen-Kaap rank test values are included in the parenthesis. E1 is the larger eigenvalue; E2 is the smaller eigenvalue. All tests were conducted using bootstrapping. The cointegration vectors are available from the authors upon request.

Table 6. Characteristic roots and hog cycles in spatial models (selected regions)

| Statistics | | PP | | | | PR | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | NE-S | N-S | NE-SW | N-SW | NE-S | N-S | NE-SW | N-SW |
| Dominant roots | $\lvert\lambda_{1,pre}\rvert$ | 0.996 (0.216) | 0.997 (0.301) | 0.995 (0.202) | 0.996 (0.267) | 0.992* (0.075) | 0.993 (0.108) | 0.993 (0.133) | 0.994 (0.158) |
| | $\lvert\lambda_{1,post}\rvert$ | 1.005 (0.239) | 0.998 (1.025) | 1.007 (0.134) | 0.998 (0.374) | 1.003 (0.317) | 0.996 (0.238) | 1.004 (0.278) | 0.999 (0.338) |
| | $\lvert\lambda_{1,pre}\rvert - \lvert\lambda_{1,post}\rvert$ | -0.009*** (0.001) | -0.001*** (0.001) | -0.012*** (0.001) | -0.002*** (0.001) | -0.011*** (0.001) | -0.003*** (0.001) | -0.011*** (0.001) | -0.005*** (0.001) |
| Second roots | $\lvert\lambda_{2,pre}\rvert$ | 0.974*** (0.001) | 0.974*** (0.001) | 0.962*** (0.001) | 0.962*** (0.001) | 0.963*** (0.001) | 0.960*** (0.001) | 0.992 (0.122) | 0.993 (0.142) |
| | $\lvert\lambda_{2,post}\rvert$ | 0.989 (0.367) | 0.982 (0.202) | 0.989 (0.370) | 0.983 (0.331) | 0.988 (0.472) | 0.980 (0.114) | 1.001 (0.305) | 0.993 (0.413) |
| Cycles (weeks) | $Per_{pre}$ | 156*** (0.001) | 164*** (0.001) | 175*** (0.001) | 169*** (0.001) | 187*** (0.001) | 202*** (0.001) | 184*** (0.001) | 193*** (0.001) |
| | $Per_{post}$ | 115 (0.109) | 113** (0.013) | 118 (0.132) | 112* (0.075) | 114 (0.208) | 113** (0.016) | 114 (0.344) | 113 (0.431) |
| | $Per_{pre} - Per_{post}$ | 41*** (0.001) | 51*** (0.001) | 57*** (0.001) | 57*** (0.001) | 73*** (0.001) | 89*** (0.001) | 70*** (0.001) | 80*** (0.001) |

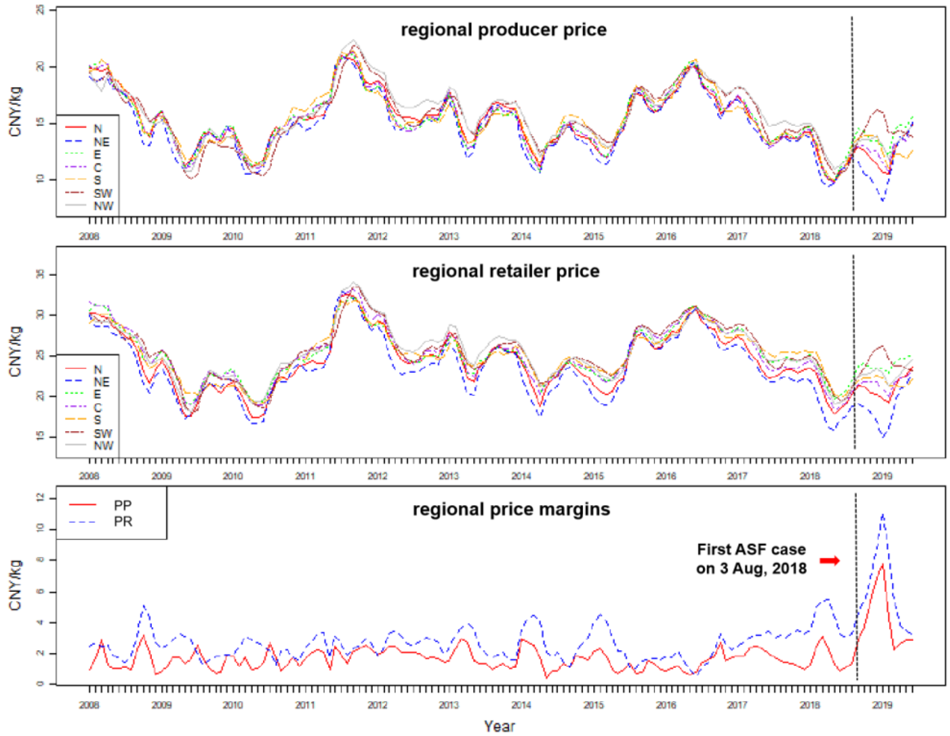
Note: The numbers in parentheses are the P-values corresponding to testing the null hypothesis $\lvert\lambda_i\rvert = 1$ ("unit root") in the first, second, fourth and fifth row, and testing $\lvert\lambda_{1,pre}\rvert = \lvert\lambda_{1,post}\rvert$ in the third row, testing $Per = 0$ in the sixth and seventh row, and testing $Per_{pre} = Per_{post}$ in the last row. All tests were conducted using bootstrapping. The periods were calculated using the estimated dominant root $\lambda_1$, except for $Per_{post}$ in NE-SW and N-SW where $\lambda_2$ was used (as $\lambda_1$ was real).

Table 7. Cointegration test in spatial models (selected regions)

| Statistics | Di | Eigenvalues | PP | | | | PR | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | NE-S | N-S | NE-SW | N-SW | NE-S | N-S | NE-SW | N-SW |
| Eigenvalue | Di=0 | $E1_{pre}$ | 0.040*** (18.530) | 0.036*** (15.829) | 0.087*** (28.903) | 0.079*** (20.289) | 0.052*** (15.286) | 0.060*** (15.523) | 0.067*** (26.784) | 0.078** (22.635) |
| | | $E2_{pre}$ | 0.012*** (7.999) | 0.013*** (7.081) | 0.014*** (12.606) | 0.014*** (14.437) | 0.009*** (14.597) | 0.009*** (14.660) | 0.009*** (11.323) | 0.009*** (13.580) |
| | Di=1 | $E1_{post}$ | 0.163 (1.795) | 0.255** (4.031) | 0.189 (2.608) | 0.272** (5.078) | 0.140* (3.519) | 0.239 (2.563) | 0.166** (6.413) | 0.252** (3.894) |
| | | $E2_{post}$ | 0.010 (0.459) | 0.019 (1.327) | 0.048 (0.908) | 0.090 (1.990) | 0.009 (0.355) | 0.004 (0.068) | 0.090 (2.921) | 0.139* (3.751) |

Note: the Kleibergen-Kaap rank test values are included in the parenthesis. All tests were conducted using bootstrapping. E1 is the larger eigenvalue; E2 is the smaller eigenvalue.

Figure 1. Regional producer prices $PP$, retail prices $PR$ and spatial price margins




Note: (1) the regional price margins in the third plot is defined using the maximum price minus the minimum price among seven regions. (2) the dashed vertical line shows the beginning of ASF disease outbreak.

Figure 2. Forward paths of producer price $PP$ and retail price $PR$ at national level

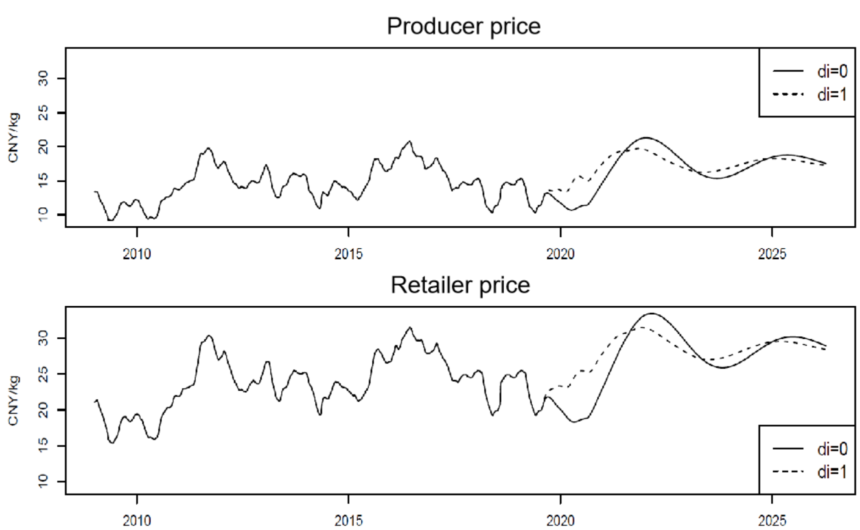


Figure 3. Forward paths of vertical price margins $(PR - PP)$ at national and regional level

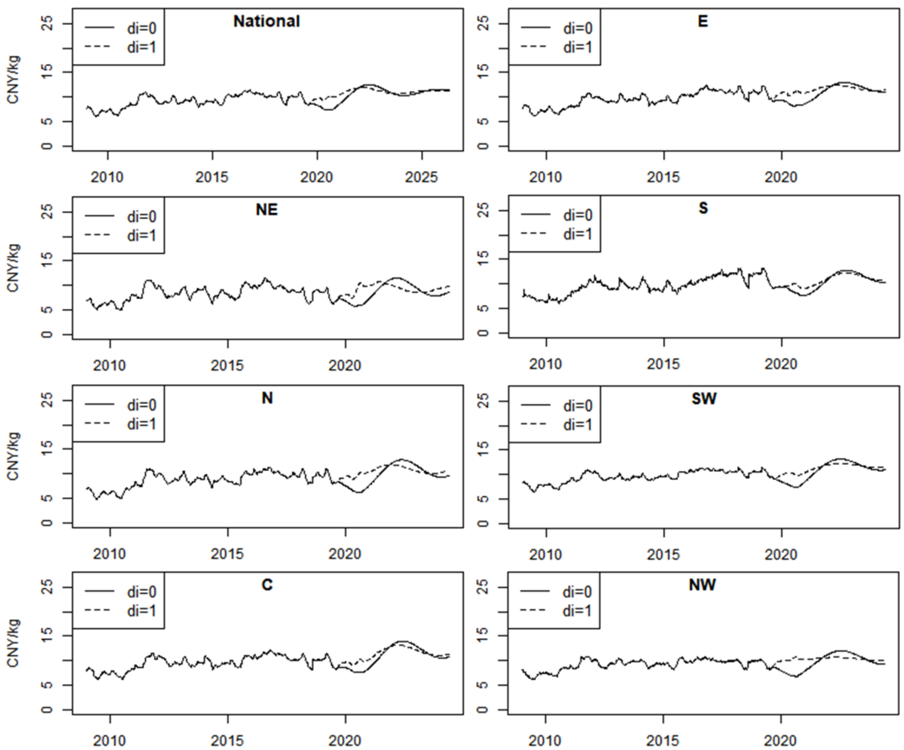
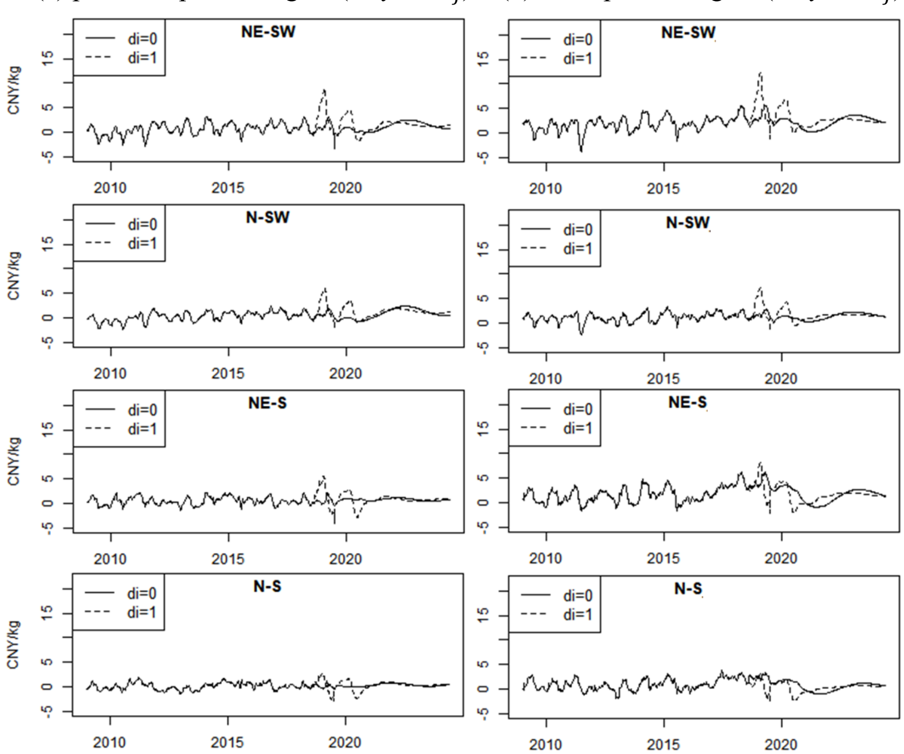



Figure 4. Forward paths of spatial price margins in selected regions

(a) producer price margins $(PP_i - PP_j)$ (b) retail price margins $(PR_i - PR_j)$



**Appendix**

Table A1. Lag order selection for vertical models for national producer price $PP$ and retail price $PR$

| Variable | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | PP | | | | PR | | | |
| | AR (1) | AR (2) | AR (3) | AR (4) | AR (1) | AR (2) | AR (3) | AR (4) |
| PL1 | 1.120*** | 1.904*** | 1.841*** | 1.847*** | 0.241*** | 0.596*** | 0.570*** | 0.579*** |
| | (0.020) | (0.075) | (0.084) | (0.084) | (0.023) | (0.065) | (0.074) | (0.074) |
| PL2 | | -0.919*** | -0.810*** | -0.898*** | | -0.563*** | -0.536*** | -0.607*** |
| | | (0.071) | (0.141) | (0.143) | | (0.061) | (0.121) | (0.123) |
| PL3 | | | -0.036 | 0.306** | | | 0.006 | 0.299** |
| | | | (0.085) | (0.147) | | | (0.073) | (0.125) |
| PL4 | | | | -0.265*** | | | | -0.239*** |
| | | | | (0.085) | | | | (0.072) |
| PL53 | -0.016*** | -0.009*** | -0.009*** | -0.009*** | | | | |
| | (0.004) | (0.003) | (0.003) | (0.003) | | | | |
| PP1 | -0.087*** | -0.131* | 0.009 | 0.011 | 0.832*** | 1.331*** | 1.414*** | 1.419*** |
| | (0.015) | (0.070) | (0.088) | (0.087) | (0.016) | (0.062) | (0.081) | (0.080) |
| PP2 | | 0.139** | -0.16 | -0.217 | | -0.356*** | -0.519*** | -0.623*** |
| | | (0.065) | (0.140) | (0.146) | | (0.058) | (0.129) | (0.136) |
| PP3 | | | 0.154** | 0.118 | | | 0.076 | 0.142 |
| | | | (0.075) | (0.141) | | | (0.068) | (0.131) |
| PP4 | | | | 0.094 | | | | 0.039 |
| | | | | (0.075) | | | | (0.068) |
| PP53 | | | | | -0.003 | -0.002 | -0.002 | -0.002 |
| | | | | | (0.003) | (0.002) | (0.002) | (0.002) |
| Di | 4.994*** | 3.694*** | 3.613*** | 3.388*** | 3.862*** | 4.260*** | 4.262*** | 3.950*** |
| | (0.978) | (0.688) | (0.696) | (0.693) | (1.479) | (0.942) | (0.942) | (0.938) |
| PL1*Di | -0.250*** | -0.538*** | -0.545*** | -0.530*** | | | | |
| | (0.050) | (0.086) | (0.104) | (0.104) | | | | |
| PL2*Di | | 0.358*** | 0.370** | 0.431** | | | | |
| | | (0.080) | (0.171) | (0.183) | | | | |
| PL3*Di | | | -0.0002 | -0.156 | | | | |
| | | | (0.100) | (0.184) | | | | |
| PL4*Di | | | | 0.092 | | | | |
| | | | | (0.097) | | | | |
| PL53*Di | -0.102*** | -0.085*** | -0.084*** | -0.079*** | | | | |
| | (0.026) | (0.018) | (0.018) | (0.018) | | | | |
| PP1*Di | | | | | -0.120*** | -0.752*** | -0.790*** | -0.792*** |
| | | | | | (0.046) | (0.098) | (0.116) | (0.115) |
| PP2*Di | | | | | | 0.629*** | 0.711*** | 0.854*** |
| | | | | | | (0.086) | (0.190) | (0.202) |
| PP3*Di | | | | | | | -0.043 | -0.338* |
| | | | | | | | (0.107) | (0.204) |
| PP4*Di | | | | | | | | 0.163 |
| | | | | | | | | (0.107) |
| PP53*Di | | | | | -0.036 | -0.054*** | -0.054*** | -0.051*** |
| | | | | | (0.022) | (0.014) | (0.014) | (0.014) |
| Adj. $R^2$ | 0.993 | 0.997 | 0.997 | 0.997 | 0.996 | 0.999 | 0.999 | 0.999 |
| BIC | -82.094 | **-457.477** | -446.125 | -441.092 | -27.056 | **-557.342** | -541.454 | -540.644 |

Note: *p<0.1; **p<0.05; ***p<0.01. Only selected key variables are reported in this table.

## Footnotes

[1] Source: Author's calculation using information obtained from Ministry of Agriculture and Rural Affair of China.

[2] We also conducted the analysis based on a more general VAR specification applied to $n$ prices. The results are available from the authors upon request. When $n$ becomes large, the number of parameters to estimate grows fast, making the estimation and interpretation of the model more difficult. This applies to our case where $n = 2 \times 7 = 14$, 2 being the number of vertical markets and 7 being the number of regions. As discussed in Zellner an Palm (1974), our "final form" specification applied "two markets at a time" remains valid, making the estimation and interpretation of our econometric analysis much easier.

[3] We classify regions according to the relative importance of production and consumption: a region is called a "production region" when it produces more than it consumes; and it is called a "consumption region" when it consumes more than it produces. In this context, the Southwest region is classified as a consumption region: although it is large producer, its consumption exceeds its production.

[4] A map and overview of these seven regions in China can be found at https://www.chinacheckup.com/blogs/articles/regions-of-china.

[5] Our analysis focuses on the Chinese domestic market. We do not examine the role of trade as trade is only a small part of the Chinese pork market. Indeed, pork imports currently constitute less than 4 percent of Chinese pork consumption according to Department of Statistics of China.

[6] In our exploration of alternative specifications, we considered nonlinear effects and other interaction effects between the disease dummy and lagged prices. The BIC criterion indicated that these specifications were "not better" than the one reported in Tables 2 and 3. In particular, we did not find strong evidence of threshold effects in price dynamics. In other words, the specification reported in tables 2-3 was found to provide the "best fit" to the data at the national level as well as for most regions.

[7] Note that our vertical model includes two prices $(PP, PR)$ with prices lagged 1, 2 and 53 periods. From equation (3), this means that $m = 53$ and the $DG$ matrix is of dimension $(106 \times 106)$, implying that each estimated model has $106$ roots.

[8] Note that, while $|\lambda_{i,pre}|$ and $|\lambda_{i,post}|$ depend on the parameters of lagged prices $P_{t-j}$ and of the interaction variables $Di \times P_{t-j}$, the term $[|\lambda_{i,pre}| - |\lambda_{i,post}|]$ depends only on the parameters of $Di \times P_{t-j}$. It means that the statistical significance of $[|\lambda_{i,pre}| - |\lambda_{i,post}|]$ comes from the high statistical significance of the interaction variables $Di \times P_{t-j}$.

[9] For evidence of "naive" response of hog producers to price signals, see Chavas (1999).