https://doi.org/10.17221/350/2024-AGRICECON

The effect and dynamic transmission mechanism of African swine fever on pork prices in China: A study based on the staggered DID model and SVAR model

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Citation: Li Y., Wang Y., Zhu L., Yan B. (2026): The Impact and Dynamic Transmission Mechanism of African Swine Fever on Pork Prices in China: A Study Based on the Multi-Period DID Model and SVAR Model. Agric. Econ. – Czech, 72: 314–339.

Abstract: African swine fever (ASF) has spread rapidly, substantially disrupting the pork market. In this study, we treat the 2018 ASF outbreak in China as a quasi-natural experiment, using staggered difference-in-differences (DID) and spatial DID methods to assess its effect on pork prices. We use a structural vector autoregression model to identify the sources of price fluctuations. In the study, we also explore the mechanisms and heterogeneity in the effects of ASF on pork prices. The results show that (*i*) ASF significantly raises pork prices across various provinces; (*ii*) live pig prices are positively correlated with finishing pig feed prices, piglet prices and pork prices in the long term but negatively correlated with the ASF index; (*iii*) the key drivers of live pig price fluctuations include price inertia (59%), finishing pig feed prices (13%), piglet prices (11.5%), pork prices (10.8%) and the ASF index (5.6%); (*iv*) for pork prices, the largest driver is live pig prices (53.4%), followed by finishing pig feed prices (14%), piglet prices (13.6%), price inertia (13.4%) and the ASF index (5.6%); (*v*) mechanism analysis reveals that ASF affects pork price fluctuations through farming costs and wholesale-retail profits. The heterogeneity analysis results reveal that provinces with higher internet information levels, weaker agricultural development and those in the eastern region are more vulnerable to the effects of ASF. On the basis of these findings, we offer targeted policy recommendations.

Keywords: African swine fever; causal mediation effects; pork prices; staggered difference-in-differences; SVAR

Pork consumption plays a critical role in food security, public health and economic stability in many pork-consuming regions around the world. According to the U.S. Center for Disease Control and Prevention, pork consumption is responsible for approximately 525 000 illnesses, 2 900 hospitalisations and 82 deaths annually (Kashyap et al. 2024). As globalisation and urbanisation accelerate, the stability of pork prices has become a critical and urgent issue for many regions across the globe. With pork accounting for nearly one-third of global meat production, as reported by the Food and Agriculture Organization, fluctuations in pork prices can trigger severe disruptions, threatening agricultural economies and undermining food security for many regions across the globe (Rushton et al. 2018; Acosta et al. 2021). In recent years, the pork industry in many parts of the world has been severely affected by the rapid spread of African swine fever (ASF), a devastating and highly contagious disease with nearly 100% mortality among infected pigs (Savary et al. 2020). ASF threatens both pork production and the broader agricultural economy, endangering millions of livelihoods worldwide.

Fuelled by global trade and livestock mobility, the spread of ASF has disrupted supply chains and caused

Supported by the Ministry of Education Humanities and Social Sciences Research Planning Fund Project, Project No. 20YJA790041 and the Hunan Province Social Science Achievement Evaluation Project, Project No. XSP17YBZZ055.

https://doi.org/10.17221/350/2024-AGRICECON

dramatic price fluctuations across regions (Han et al. 2022). For example, between 2014 and 2017, the ASF outbreak in Eastern Europe led to the culling of nearly 800 000 pigs, causing severe supply shortages, soaring pork prices and a decline of USD 961 million in pork exports (Zhao et al. 2019). From June 2017 to April 2018, 71.7% of wild boar samples in the Zlín district of the Czech Republic tested positive for ASF, with a 92.5% mortality rate (Sauter-Louis et al. 2021). In China, ASF eliminated 150 to 225 million pigs, or approximately 25% of the global pig population, between 2018 and 2019 (Mason-D'Croz et al. 2020; You et al. 2021). This widespread devastation highlights that ASF is no longer a localised issue but rather a transboundary crisis that demands urgent international attention and cooperation (Sanchez-Cordon et al. 2018). Consequently, analysing the effect of ASF on the pork market and preventing its future disruptions is essential.

China provides a compelling setting to examine the effect of ASF on pork prices. First, with a population of 1.4 billion, China is nearly 18% of the global population. As the largest producer and consumer of pork, it dominates the global market and shapes its structure and dynamics (Yu et al. 2023). In recent years, China's consumption of pork products has reached 25 810.54 thousand tonnes, accounting for 45% of global pork consumption. Moreover, pork is more affordable and widely consumed in China than other meats are, making it a staple in both the agricultural market and the Chinese diet. Second, China has become one of the countries most severely affected by ASF (You et al. 2021). In August 2018, ASF severely affected China, resulting in 195 outbreaks and severe damage to the pig industry, as shown in Figure 1. The outbreak of African swine fever caused a marked decline in China's pork production in 2019 and exerted substantial pressure on the pork market. Pork prices increased from USD 2.79/kg at the end of 2018 to USD 8.42/kg in February 2020, reaching a historic high. The severe fluctuations in pork prices caused by the ASF outbreak significantly affected the normal development of the pig industry and had a notable effect on the consumer price index. Consequently, most consumers chose to reduce their pork consumption. The fluctuation in hog prices not only affects the earnings of farmers directly but also increases living costs for consumers and poses challenges to government macroeconomic regulation. Therefore, studying the effect of ASF on pork prices and its transmission mechanism has significant practical and policy value.

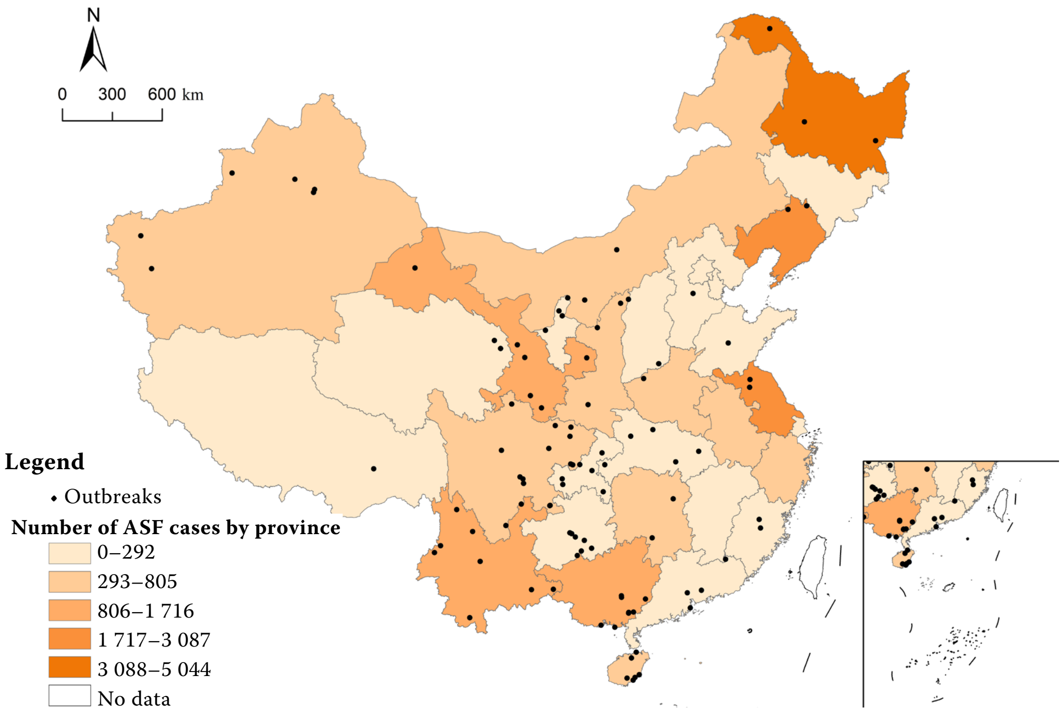

Figure 1. Spatial distribution of African swine fever (ASF) cases in various provinces in China

Source: Authors' own processing

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Despite the growing body of research on pork prices and ASF, several important gaps remain (Yao et al. 2022). First, although some progress has been made, particularly in assessing the effects of ASF, comprehensive studies in which the investigators evaluate its full effect across all affected regions remain scarce. Research often focusses on spatial distribution statistics but fails to establish clear causal relationships between ASF outbreaks and pork price fluctuations (Ma et al. 2020; Mason-D'Croz et al. 2020). Second, the sources of pork price fluctuations and transmission mechanisms in the context of ASF remain poorly understood, which creates a significant challenge for the pork industry and agricultural markets, as stakeholders often lack clear guidance on how to stabilise prices. Few study investigators have examined the interactive relationships and volatility patterns among price variables across different stages of the pork supply chain. Third, research on the mechanisms behind ASF remains incomplete. No framework clearly defines the roles of upstream production and the downstream wholesale and retail sectors in influencing price changes. Investigators in existing studies often overlook their distinct contributions. Understanding these mechanisms is vital for clarifying how disruptions at different stages affect the market and for improving policy interventions. Fourth, empirical research comparing the heterogeneous effects of ASF across regions is limited. Given these gaps, there is an urgent need for empirical research on how ASF affects pork prices and identifying effective policy responses. A systematic analysis of price fluctuations, including temporal and regional variations, is crucial for developing global strategies and enhancing policy effectiveness.

In this study, we use the staggered difference-in-differences (DID) method to analyse data from 30 provinces in China and investigate the monthly effect of ASF on pork prices from August 2018 to December 2019. The structural vector autoregression (SVAR) model supplements the results of the DID model to assess the patterns and interactive effects of price fluctuations within the pork supply chain. The analysis focusses on three key questions:

i) To what extent has ASF affected pork prices, and how long do these effects last?

ii) How does ASF affect pork prices, and do its effects differ?

iii) What are the sources of pork price fluctuations?

This article makes four key contributions to the literature. First, we applied a staggered DID model and a spatial DID model using data from 30 provinces and municipalities (excluding Tibet) to analyse the dynamic effects of ASF on pork prices. Few study investigators have used quasi-natural experiments to examine the disruptive effect of ASF. The inclusion of the spatial DID model allowed us to control for price transmission effects across provinces, ensuring accurate estimation of intervention effects. Second, we used the SVAR model to quantify the sources of pork price fluctuations in the ASF context and explore the dynamic relationships among various price variables within the pork supply chain. Third, we used a causal mediation effect model to further investigate the channels through which ASF affects pork prices, constructing a comprehensive price effect mechanism from the perspective of the industry production chain. Finally, we compared the heterogeneous effects of ASF on the basis of geographical location, information technology level and agricultural development. On the basis of these findings, we proposed rational suggestions.

Literature review

Influencing factors of pork price fluctuations. Pork price fluctuations are driven by a range of factors, including supply-side, demand-side and external shocks (Esposti and Listorti 2013; Assefa et al. 2017). First, supply-side factors such as feed prices, production costs and disease outbreaks have a major effect on pork prices. Results from studies in the United States (Carriquiry et al. 2020), Europe (Niemi 2020) and Latin America (Acosta et al. 2021) have shown that changes in feed prices and culling policies are significant drivers of price fluctuations. ASF, in particular, has caused sharp reductions in pig populations, disrupting both the immediate supply and long-term market stability (Mason-D'Croz et al. 2020). Second, demand-side factors such as consumer income, preferences and substitute goods also play a role. Research results from the United States and Europe (Tłuczak 2022; Lee et al. 2023; Kashyap et al. 2024) have shown that shifts in consumer demand, driven by income or health concerns, can amplify price fluctuations, especially during disease outbreaks.

Third, research on the effect of sudden external shocks, such as ASF, on pork prices has focussed primarily on supply disruptions and market responses in various regions. In Europe, ASF has disrupted domestic production and altered trade patterns, leading to restrictions on both imports and exports (Niemi 2020). However, gaps remain in understanding how ASF-induced price shocks spread throughout the international pork production chain, especially in terms

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of price transmission across upstream, midstream and downstream stages. Investigators in the literature often fail to compare the sources of price fluctuations, the heterogeneous effects of ASF shocks and the mechanisms behind price fluctuations within the pork industry production chain. In this study, we aim to address these gaps via advanced econometric models, such as the staggered DID and SVAR models, to analyse the effect of ASF on pork prices and its transmission mechanisms across the production chain. This study provides a framework for understanding the effect of ASF on pork prices, offering insights applicable to other markets, including Europe and major pork producers globally. These findings increase the understanding of how ASF and similar shocks disrupt pork production and pricing worldwide.

Transmission mechanisms of pork price fluctuations. Transmission mechanisms of pork price fluctuations have been widely studied, with a focus on long-term cointegration, short-term adjustments and nonlinear price transmission. First, results from research on long-term cointegration in pork markets have highlighted stable relationships across different stages of the production chain. For instance, results from a study of the Hungarian pork market (Bareith et al. 2025) revealed asymmetry in price transmission, with increases in producer prices having a greater effect on consumer prices than decreases did. Similarly, results from research on China's pork market via the SVAR model have shown that supply factors, such as pig herds and pig epidemic shocks, significantly influenced pork price fluctuations (Pang et al. 2023). Results from these studies suggest that long-term price dynamics are shaped by both market structure and external shocks, such as disease outbreaks. Second, short-term price adjustments in the pork market, particularly in response to external shocks such as ASF, are a critical area of focus. Retail prices are more sensitive to changes in producer prices, creating distortions in price transmission. This pattern is observed globally, including in the United States and Europe, where market power and structural changes impede efficient price transmission (Jong-Yeol and Brown 2018; Panagiotou 2021).

Third, recent research has focussed on the nonlinear nature of price transmission in response to external shocks such as ASF. Study results show that pork price transmission is often asymmetric. For example, Zhao and Wu (2015) identified two distinct regimes in China's pork price changes, mild and expansion, with larger shifts leading to larger adjustments. Similarly, ASF and COVID-19 in China showed a nonlinear relationship with price fluctuations, with ASF increasing the role of imported pork, although this effect decreased after the COVID-19 outbreak (Wang et al. 2022). In Europe, studies of the Czech market revealed asymmetric price transmission, especially between processors and retailers, with greater adjustments when prices increased (Rudinskaya 2019). These findings underscore the prevalence of nonlinear price dynamics across pork markets, driven by disease outbreaks and regulatory changes.

In summary, in this study, we identify several key gaps in the literature. First, few study investigators have investigated the causal relationship between ASF outbreaks and pork price fluctuations. Although some progress has been made, studies in which the investigators used robust methods, such as the DID model, to evaluate the effect of ASF precisely are lacking. Furthermore, few study investigators have accounted for the spatial effects of ASF across different regions. Second, limited attention has been given to examining the sources of pork price fluctuations from a vertical industry production chain perspective. There is a lack of research using the SVAR model to compare the contributions of different factors affecting price dynamics at each stage of the pork production chain. Third, there is no widely accepted framework for understanding the mechanisms through which ASF affects pork prices. Although investigators in several studies focussed on various factors, no consensus has emerged regarding the specific roles of upstream production costs and downstream sales margins in overall price fluctuations. Fourth, there is a noticeable gap in studies in which the investigators analyse the heterogeneous effects of ASF across regions. Given the potential for ASF outbreaks to reoccur, more in-depth and comprehensive research is needed to understand how such shocks affect different regions differently.

In this study, we present four key innovations. First, we develop a comprehensive analytical framework by using the DID model to assess the effect of ASF on pork prices, supplemented by a series of robustness checks, including parallel trend tests, sensitivity tests, propensity score matching (PSM)-DID tests and spatial DID tests. This methodology ensures the reliability and accuracy of the estimated intervention effects. Second, building on the DID model, we use the SVAR model to examine the sources of pork price fluctuations further. By analysing the dynamics within the pork production chain in this research, we compare the contributions of various factors to price fluctuations. Third, in the study, we construct a mechanism framework from the production perspective, focussing

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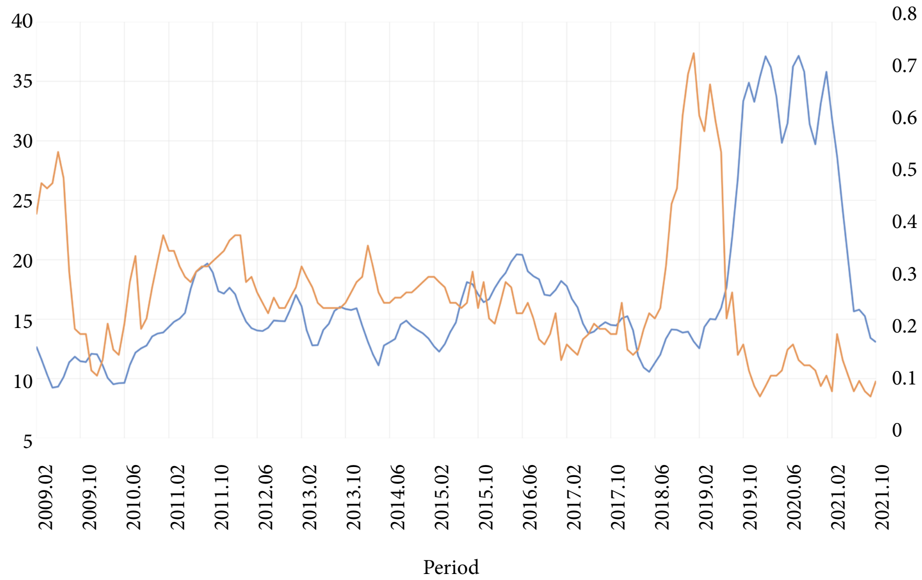

Figure 2. Trends in pig prices and the epidemic index in China

ASF – African swine fever
Source: Authors' own processing

on production costs and sales margins, to explain how disruptions in both the production and retail stages affect pork price fluctuations. Fourth, in this study, we explore the heterogeneous effects of ASF by considering geographic location, information technology levels and agricultural development, offering a more nuanced understanding of the regional variations in ASF. In this research, we evaluate the effect of ASF and provide insights that can be applied to other agricultural products. We contribute empirical evidence and theoretical perspectives to the global literature on agricultural price dynamics.

Theoretical analysis

According to information economics theory, because of information asymmetry and risk aversion, the initial outbreak of ASF may cause consumers to worry about pork safety, affecting consumer confidence and leading to a short-term decrease in pork demand (Kashyap et al. 2024). However, in the long term, as consumers' awareness of the epidemic increases and considering the essential role of pork in meat consumption, the demand for pork will gradually recover (Han et al. 2022). From the perspective of the supply and demand theory, the reduction in pork supply is much more significant than the demand reduction is, leading to a supply shortage and an increase in pork prices. According to price transmission theory, the severe effect of ASF leads to higher epidemic prevention expenses, increased losses in pig inventory and greater unit farming costs (You et al. 2021). These increased costs are passed on to pig prices, subsequently driving up pork prices along the supply chain. The trend of hog prices in China in the ASF context is shown in Figure 2.

The pig industry production chain consists of four main stages: breeding, farming, slaughtering and processing, and sales (Zira et al. 2021). The prices at each stage accumulate to form the final pork price. As shown in Figure 3, each stage is influenced by various factors owing to different work involved, which

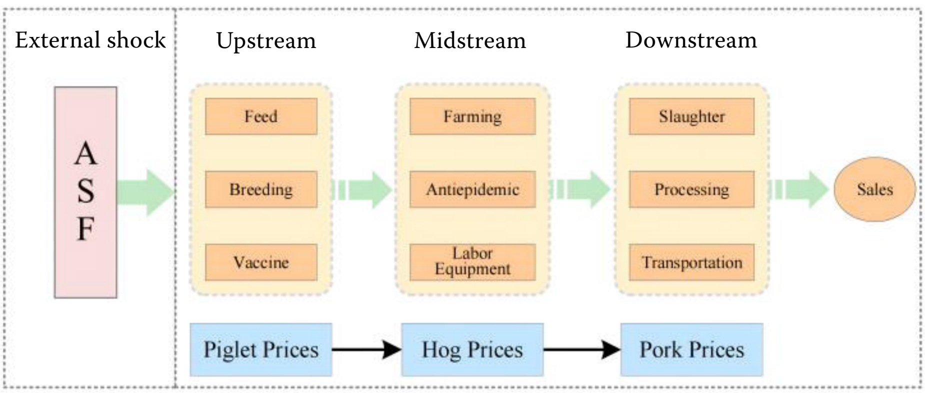

Figure 3. Composition of the pig industry chain

ASF – African swine fever
Source: Authors' own processing

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means that factors affecting each stage can also affect pork price fluctuations.

In the farming stage, the main factors influencing pork prices are farming costs, including piglet costs, feed costs, disease prevention costs and equipment and labour costs. Feed costs are the most significant component of pig farming costs, accounting for approximately 50%, and are composed mainly of corn, soybean meal, fish meal and mixed feed. Piglet costs subsequently fluctuate by approximately 30%. Because of the effect of ASF, the price of piglets in China has fluctuated dramatically, with the proportion of overall farming costs increasing from 25% in 2018 to 49% in 2020. Equipment and labour costs are relatively low and stable. However, with the spread of ASF, expenditures on epidemic prevention have significantly increased, further increasing overall farming costs. Slaughtering and processing, as the intermediary link between production and sales, affect pork prices primarily through processing profits, as this is the stage of pigs being purchased from farmers and the finished products being sold to wholesalers and retailers, resulting in limited profit margins. Rapid changes in pork prices can lead to losses when the sale price cannot cover acquisition and processing costs because of the time required for processing. The retail stage, the final link in the industry production chain, connects wholesalers and consumers. Like in the slaughtering and processing stage, pork prices are influenced by profit margins. However, retailers have more control over their profits, ensuring that the minimum selling price does not decrease below the cost, thus maintaining relatively stable profits. The maximum selling price is determined by the market, often allowing retailers to earn excess profits when market prices increase rapidly. Pork, as a staple food on the dining table, has stable end-consumer demand. When the current supply is low, high prices prevail, leading to unrestricted price increases. During the ASF period, pork prices increased rapidly, and end retailers profited significantly.

MATERIAL AND METHODS

Methods

Staggered DID model. To assess the effect of ASF on pork prices, in this study, we treated ASF as a quasi-natural experiment. Following related studies (Card and Krueger 1994; Gruber and Poterba 1994; Tut 2022; Hu et al. 2024), we considered external shocks such as policies and natural disasters. Therefore, we used a staggered DID approach with two-way fixed effects (TWFE) to analyse the effect of ASF, as outlined here. The TWFE specification includes province fixed effects and monthly fixed effects to control for time-invariant regional characteristics and common temporal shocks.

$$Y_{it} = \beta_0 + \beta_1 ASF_{it} + \lambda X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

where: Y_{it} – the explained variable, representing the pork price in province i at time t; ASF_{it} – the core explanatory variable, which indicates whether ASF affects province i at time t; X_{it} – includes control variables, such as the prices of live hogs, piglets, and finishing pig feed, all transformed into natural logarithms; μ_i and ν_t – province and time fixed effects, respectively; ε_{it} – the random error term; β_0 – denotes the constant term β_1 – the coefficient of the ASF treatment variable; λ – represents the coefficient vector of the control variables.

The variables are defined as follows:

The explanatory variable is ASF shock. The explained variable is pork prices. Building on the study by Yu et al. (2023), in this study, we used the average pork prices from provincial agricultural wholesale markets, represented by the monthly averages published by the Ministry of Agriculture and Rural Affairs, as the explained variable. Unlike live pig prices, which are often delayed owing to contracts or price bindings, pork prices, as the final product, are more elastic and respond more quickly to shocks. The control variables are the log prices of live pigs, piglets and finishing pig feed. Finishing pig feed is included to capture the effect of cost changes on pork prices, whereas live pig and piglet prices account for interdependencies within the pig production chain.

The outbreak of ASF poses two main challenges for the pork market: first, consumers struggle to determine whether the pork they purchase comes from healthy or infected pigs, which may reduce demand; second, the outbreak has caused significant pig mortality, reducing the market supply. These factors combined could drive up pork prices. Building on the work of You et al. (2021), which suggests that the severity of an ASF outbreak affects pork supply, in this study, we investigated the threshold at which the number of infected pigs significantly affects pork prices.

To explore this effect, we collected monthly data on ASF-related pig infections across provinces since 2018, with a focus on the number of infected pigs each month. We further examined the relationship between ASF intensity and pork prices. To illustrate this relationship, we grouped the number of infected pigs into 10-pig intervals (Figure 4). Owing to missing data

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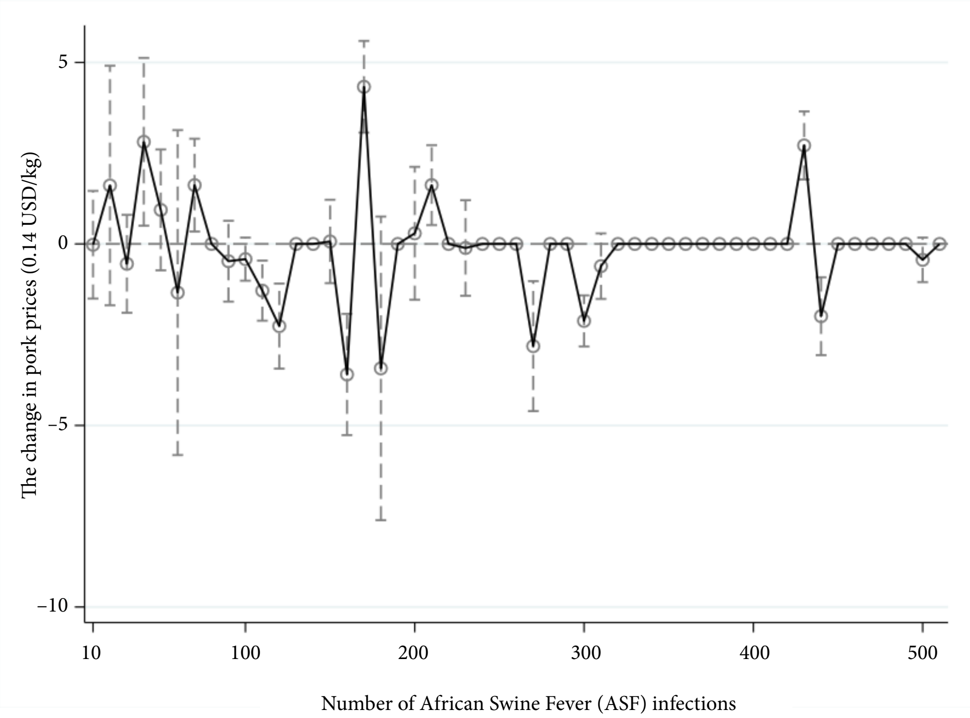

Figure 4. The relationship between African swine fever (ASF) and pork prices

Source: Authors' own processing

in some regions, coefficients and confidence intervals are not shown. The results show that when infections ranged from 30 to 40 pigs, pork prices began to fluctuate significantly; when infections reached 60 to 70 pigs, the fluctuations became more pronounced; and when infections were within the 100 to 200 range, the effect on pork prices was generally significant. Building on these findings and drawing from the relevant literature (Barr and Gibbs 2022), we defined ASF outbreaks involving more than 40 infected pigs as 'shock events' and examined their effect on pork prices. We used provinces with fewer than 40 infected pigs as the control group to compare the effects of varying ASF intensities on pork prices.

On the basis of these findings, we designated provinces with more than 40 infected pigs the treatment group ($D_i = 1$), whereas those with fewer than 40 infected pigs constituted the control group ($D_i = 0$). We set a time dummy variable to 1 ($T_t = 1$) after the shock and 0 ($T_t = 0$) for before. Because we used monthly data, we attributed ASF shocks occurring after the 15th to the following month. The core explanatory variable was the interaction term between the grouping and time dummy variables, with the coefficient β_1 indicating the effect of ASF on pork prices.

Robustness tests of the DID model. In this study, we conducted a series of robustness checks on the DID model, including pre-trend and no anticipation effect tests (Nagengast and Yotov 2025), followed by an examination of spatial effects. Specifically, the pre-trend test involved parallel trend and parallel sensitivity tests, whereas we tested the no anticipation effect through a placebo test. We assessed spatial effects via a spatial DID model [spatial Durbin model (SDM)].

SVAR model. In this study, we built on previous research to construct an SVAR model (Liu et al. 2012), further investigating transmission in China's hog industry production chain from the prices of finishing pig feed (*feed*), piglets (*piglet*), live hogs (*hog*), pork (*pork*), the epidemic width index (*EWI*) and and the ASF impact variable for hog prices (*ASF*). In this study, we focussed on vertical price transmission along the variable chain. The SVAR model helps reveal causal relationships between variables and estimates their interlinking effects. In this study, we used impulse response functions and variance decomposition in the SVAR model to evaluate the dynamic transmission effects and effect paths of pork prices to understand the linkage mechanisms in the pork price system further.

The general form of the SVAR model is presented as follows:

$$Ay_t = \delta + \Gamma_1 y_{t-1} + ... + \Gamma_p y_{t-p} + u_t \quad (2)$$

where: A – the contemporaneous parameter matrix, reflecting the contemporaneous interactions among the variables; y_t – the vector of endogenous variables, including feed, piglet, hog, pork, *EWI*, and *ASF*;

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δ – the intercept vector; Γ_1, ..., Γ_p – the coefficient matrices of the lagged endogenous variables; p – the lag order; and u_t – the vector of structural disturbance terms. Var (u_t) is a diagonal matrix $E(u_t u_t') = \Omega_u$. Generally, the contemporaneous parameter matrix A is a non-singular matrix. Therefore, multiplying both sides of Equation (2) by A^{-1} yields the corresponding reduced vector autoregression (VAR) form:

$$y_t = A^{-1}\delta + A^{-1}\Gamma_1 y_{t-1} + \ldots + A^{-1}\Gamma_p y_{t-p} + A^{-1}u_t \qquad (3)$$

The general VAR formula is as follows:

$$y_t = C + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \varepsilon_t (5-5) \qquad (4)$$

where: C – the vector of constant terms; y_t – the vector of endogenous variables; Γ_1, ..., Γ_p – the coefficient matrices of the lagged endogenous variables; p – the lag order; and ε_t – the vector of reduced-form error terms.

Comparing Equations (3 and 4), we observed the following relationships:

$$\begin{aligned} \phi_k &= A^{-1}\Gamma_k \\ C &= A^{-1}\delta \\ \varepsilon_t &= A^{-1}u_t \\ \Omega_\varepsilon &= E(\varepsilon_t \varepsilon_t') = A^{-1}\Omega_u (A^{-1})' \end{aligned} \qquad (5)$$

where: ϕ_k – the reduced-form coefficient matrix for the k-th lag; Γ_k – the structural coefficient matrix for the k-th lag; A – the contemporaneous parameter matrix; C – the vector of constant terms; δ – the intercept vector; ε_t – the vector of reduced-form error terms; u_t – the vector of structural disturbance terms; Ω_ε – the covariance matrix of the reduced-form error terms; Ω_u – the covariance matrix of the structural disturbance terms; E – denotes the expectation operator; and the prime symbol (′) – denotes matrix transposition.

By solving the VAR equations, we obtained ϕ_k, Ω_ε, C, and then we estimated the SVAR parameters via the relationships shown in Equation (5). The long-term constraint matrix of SVAR transforms it into the vector moving average form:

$$y_t = (A - \sum_{i=1}^{p}\Gamma_i)^{-1}\delta + (A - \sum_{i=1}^{p}\Gamma_i L^i)^{-1}u_t \qquad (6)$$

The long-term constraint condition is $\psi = (A - \sum_{i=1}^{p}\Gamma_i)^{-1}$, in the following form:

$$\psi = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ NA & 1 & 0 & 0 & 0 \\ NA & NA & 1 & 0 & 0 \\ NA & NA & NA & 1 & 0 \\ NA & NA & NA & NA & 1 \end{pmatrix} \qquad (7)$$

Here, 0 indicates no long-term effect between variables, whereas NA suggests the presence of a long-term effect. In this study, we made the following five assumptions regarding the long-term parameter matrix from the perspective of vertical transmission in the hog industry production chain (Liu et al. 2012):

i) Upstream and midstream finishing pig feed prices, piglet prices and hog price changes have long-term effects on pork price changes.

ii) Upstream finishing pig feed prices and piglet price changes have long-term effects on hog price changes, but pork price changes do not have long-term effects on hog price changes.

iii) Finishing pig feed price changes have long-term effects on piglet price changes, but hog and pork price changes do not have long-term effects on piglet price changes.

iv) Feed price changes are not subject to long-term effects from other variable changes.

v) The epidemic width index (*EWI*) has long-term effects on price changes at all stages of the hog industry production chain.

Using these configurations in this study, we introduced *EWI*. The final parameter matrix is as follows:

$$\psi = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ NA & 1 & 0 & 0 & 0 \\ NA & NA & 1 & 0 & 0 \\ NA & NA & NA & 1 & 0 \\ NA & NA & NA & NA & 1 \end{pmatrix} \qquad (8)$$

The corresponding vector order is $\begin{pmatrix} d\ln asf \\ d\ln feed \\ d\ln piglet \\ d\ln hog \\ d\ln pork \end{pmatrix}$.

A five-variable VAR system is established concerning finishing pig feed prices (feed), piglet prices (piglet), hog prices (hog), pork prices (pork) and the EWI.

The specific work is as follows:

i) Stationarity test: Avoiding spurious regression in the analysis requires checking for stationarity. Thus, we used the augmented Dickey–Fuller test.

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ii) Cointegration test: We used the Johansen cointegration test to examine the existence of long-term equilibrium relationships between the variables and to determine the number and vectors of cointegrating relationships.

iii) Impulse response function: We used this function to explore the dynamic interactions and trends among the variables over time.

iv) Variance decomposition: We used this analysis to evaluate the contribution of various external shocks to each variable in the model, providing insight into the relative importance of these shocks.

Table 1. Dates of the first ASF outbreaks in various provinces in China

Province	Date
Liaoning	2018.8.3
Henan	2018.8.16
Jiangsu	2018.8.19
Zhejiang	2018.8.23
Anhui	2018.8.30
Heilongjiang	2018.9.5
Inner Mongolia	2018.9.14
Jilin	2018.9.20
Shanxi	2018.10.17
Yunnan	2018.10.20
Hunan	2018.10.22
Guizhou	2018.10.25
Chongqing	2018.11.4
Hubei	2018.11.7
Jiangxi	2018.11.8
Fujian	2018.11.8
Sichuan	2018.11.15
Shanghai	2018.11.17
Beijing	2018.11.23
Tianjin	2018.11.29
Shaanxi	2018.12.2
Qinghai	2018.12.12
Guangdong	2018.12.19
Gansu	2019.1.13
Ningxia	2019.1.19
Guangxi	2019.2.18
Shandong	2019.2.20
Hebei	2019.2.24
Xinjiang	2019.4.3
Tibet	2019.4.7
Hainan	2019.4.19

Source: Authors' own processing

Material

Because the ASF epidemic in China lasted from August 2018 to July 2019, we selected monthly data from 2018 and 2019 for the entire country and 30 provinces to assess the effect of ASF on various variables. The specific outbreak times in each province are detailed in Table 1. We selected the price variables for the hog industry production chain from the national average monthly market prices of livestock products from February 2009 to October 2021. The average price data represent the average values from fixed monitoring points in each province. We excluded the Tibet region because of substantial amounts of missing data. We primarily compiled the timing of ASF outbreaks in each province from the website of the Ministry of Agriculture and Rural Affairs. We sourced the monthly data for each variable from the China Animal Husbandry and Veterinary Yearbook and the BRIC Agricultural Database. We used interpolation to fill in the gaps for missing data. We log-transformed all price data to eliminate potential heteroscedasticity and improve model accuracy and robustness.

RESULTS

Regression results of the staggered DID

In this research, we used the staggered DID model to determine how ASF affected pork prices, as shown in Table 2.

Model (1), which excluded control variables and fixed effects, revealed a significantly positive effect at the 1% significance level. This finding indicates that the ASF shock had a driving effect on the increase in pork prices. Model (2), which included control variables, showed a negative coefficient at the 1% level, and the result suggested a decrease in pork prices. Given the differences among the 30 provinces in terms of geography, economy and culture, there may be inherent characteristics that do not change over time, potentially causing confounding effects. Therefore, we included individual fixed effects in Model (3). The results showed a negative correlation at the 1% significance level for ASF, whereas live pig prices, piglet prices and finishing pig feed prices all showed positive correlations at the 1% level. To account for cumulative time effects, model 4 included both individual and time fixed effects. The results showed that, after accounting for control variables, individual fixed

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Table 2. Regression results of the staggered difference-in-differences (DID)

Variables	OLS	OLS	FE	TWFE
	(1)	(2)	(3)	(4)
ASF	8.210***	–0.455**	–0.956***	0.354*
	(0.740)	(0.217)	(0.228)	(0.188)
ln*piglet*	–	0.373	2.623***	1.840***
		(0.438)	(0.651)	(0.588)
ln*hog*	–	27.592***	25.516***	16.257***
		(0.560)	(0.755)	(1.237)
ln*feed*	–	–1.752	15.436***	–3.863
		(1.136)	(4.422)	(2.992)
Month *FE*	no	no	no	yes
Pro *FE*	no	no	yes	yes
Constant	24.396***	–47.198***	–67.988***	–19.004***
	(0.333)	(1.686)	(4.905)	(2.864)
R^2	0.154	0.926	0.944	0.986
Observations	720	718	718	718

***, ** and *significance levels at 0.01, 0.05 and 0.1, respectively; the price is measured in USD per kilogram (USD 0.14/kg
ASF – African swine fever; FE – fixed effects; TWFE – two-way fixed effects; OLS – ordinary least squares.
Source: Authors' own processing

effects and time fixed effects, the ASF shock significantly increased pork prices at the 10% significance level. This finding suggests that the ASF shock significantly drove up pork prices nationwide.

Robustness test results of the DID model

Parallel trend test results. The parallel trend assumption is crucial for the validity of the DID model, which assumes that, before the policy implementation,

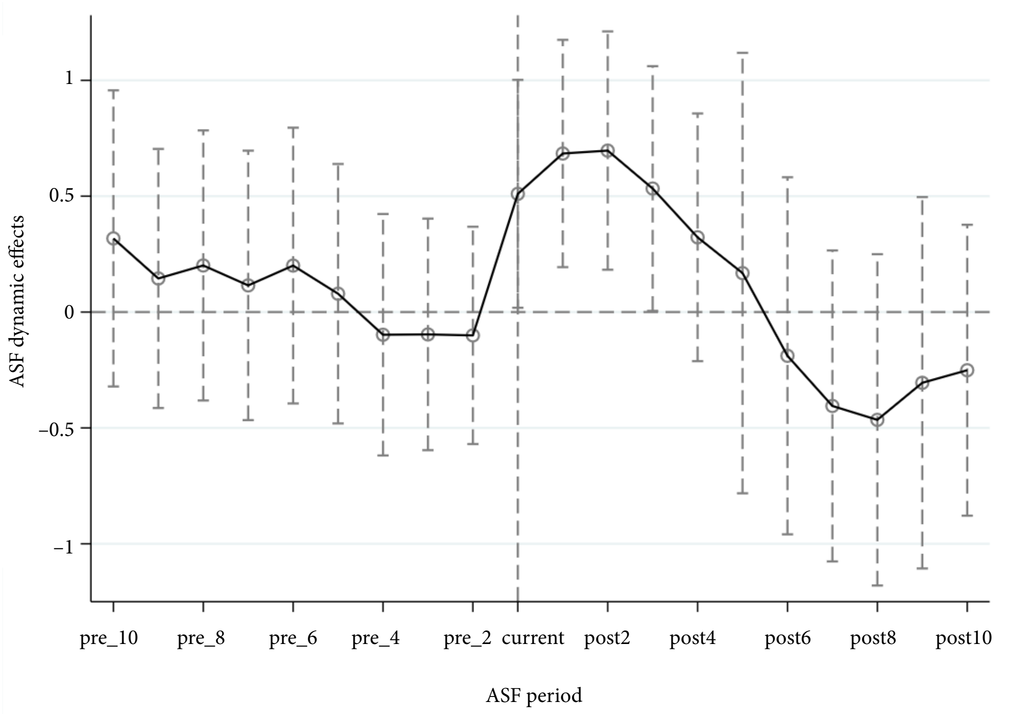

Figure 5. African swine fever (ASF) of the parallel trend test results

Source: Authors' own processing

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the treatment and control groups followed similar trends. To test the parallel trend effect of ASF on pork prices, we developed the following model to analyse the dynamic effect of ASF on pork prices.

$$Y_{it} = \beta_0 + \sum_{\substack{k=-10 \\ k\neq -1}}^{10} \beta_k (D_i \times T_t)^k + \lambda X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{9}$$

where: D_i and T_t – the province and time dummy variables for the ASF shock, respectively; $\beta_k (D_i \times T_t)^k$ – the effect of the ASF shock in each period before and after the shock. We used the month before the shock as the baseline period, and the other variables and Equation (1) remained unchanged.

We aggregated the ASF shock into dynamic effects over the previous and subsequent 10 periods, as shown in Figure 5. Before the ASF outbreak, pork prices fluctuated at approximately zero, indicating stability, with the treatment and control groups following similar trends. After the ASF shock, pork prices quickly responded. As a staple food, pork prices immediately increased owing to the reduced pig supply. Figure 5 shows a significant increase in pork prices in the month of the ASF shock and the following three months, demonstrating the substantial effect of ASF on pig supply and its role in driving the rapid increase in pork prices.

Pork prices peaked two months after the ASF shock and then decreased, a change driven by government control measures, trade-imported pork and increased pig supply. The government enforced stricter transportation controls, enhanced quarantine protocols and suspended the 'green channel' policy for livestock while also introducing culling compensation subsidies. In addition to ASF control, extensive imports and 19 key support policies facilitated the pig industry's recovery, including regulatory relaxations, increased domestic investment and the entry of large-scale producers, which quickly restored pig numbers. After three months, the rapid recovery of domestic pig farming significantly increased the pork supply, causing prices to gradually decrease, eventually below production costs, leading to widespread economic losses across the industry. This swift recovery exposed the vulnerability of China's pig farming sector, particularly its high production costs (Han et al. 2022). Although some producers may withstand short-term financial losses, others may be forced out of the market. Small-scale businesses face greater challenges, whereas large-scale producers can better absorb the risks associated with market price fluctuations.

Overall, the results showed that before the ASF shock, the coefficient was not significant and passed the parallel trend test (Roth et al. 2023). After the shock, the coefficient significantly increased, confirming ASF's significant effect on pork prices, with the price decrease aligning with actual conditions.

Parallel trend sensitivity test results. Investigators in previous studies have highlighted the inefficiency of pre-treatment parallel trend tests, with analyses based on pre-treatment trends potentially leading to bias in post-treatment trend tests and treatment effect estimates. In this study, we adopted the honest DID

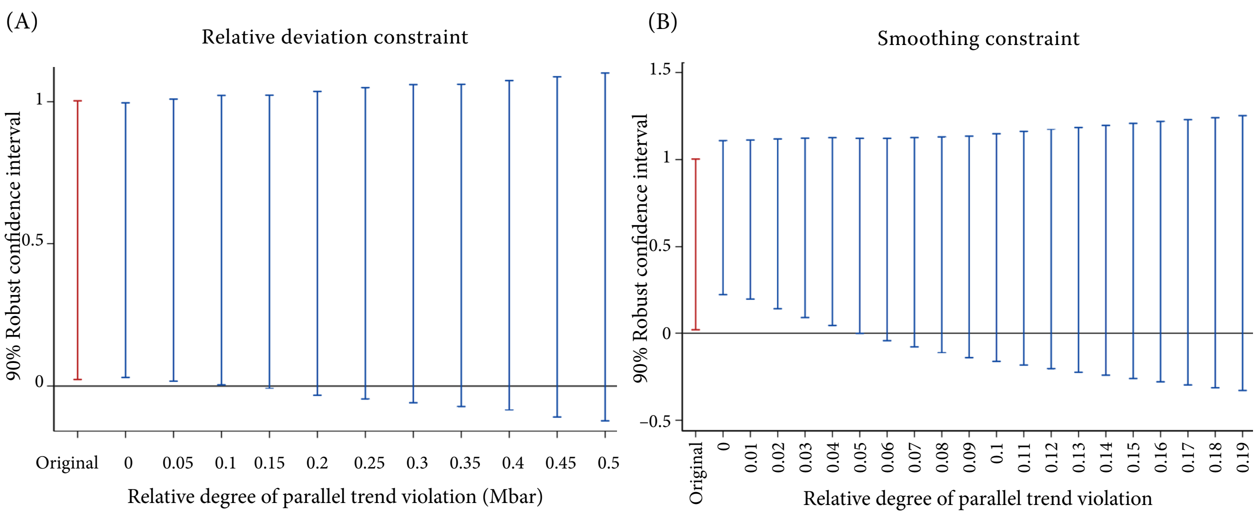

Figure 6. Relative deviation constraint (A) and smoothing constraint (B) of the parallel trend sensitivity test (month of African swine fever)

Source: Authors' own processing

https://doi.org/10.17221/350/2024-AGRICECON

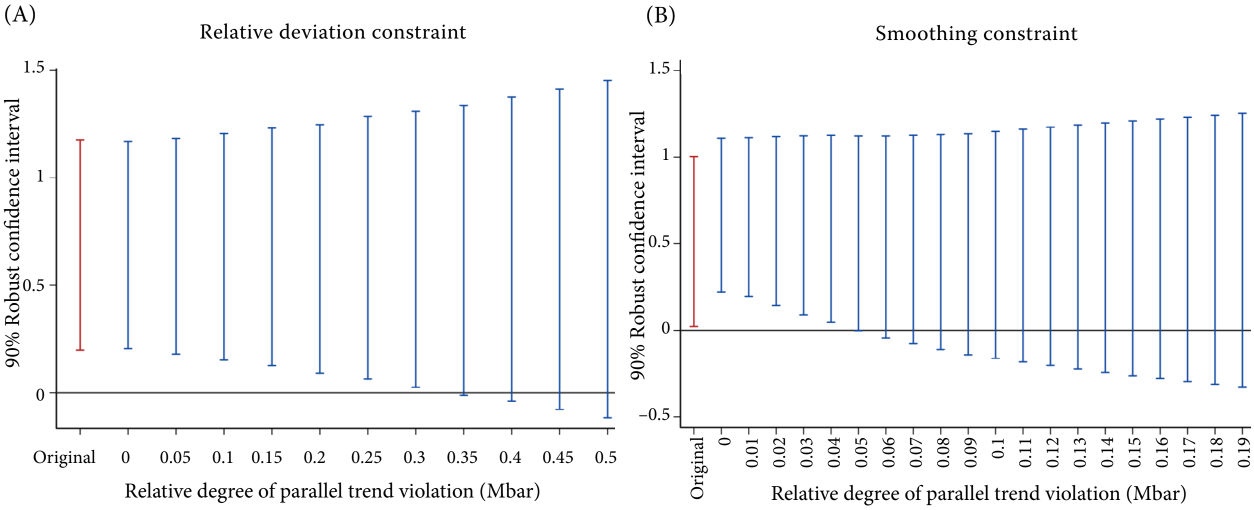

Figure 7. Relative deviation constraint (A) and smoothing constraint (B) of the parallel trend sensitivity test (the first month after African swine fever)

Source: Authors' own processing

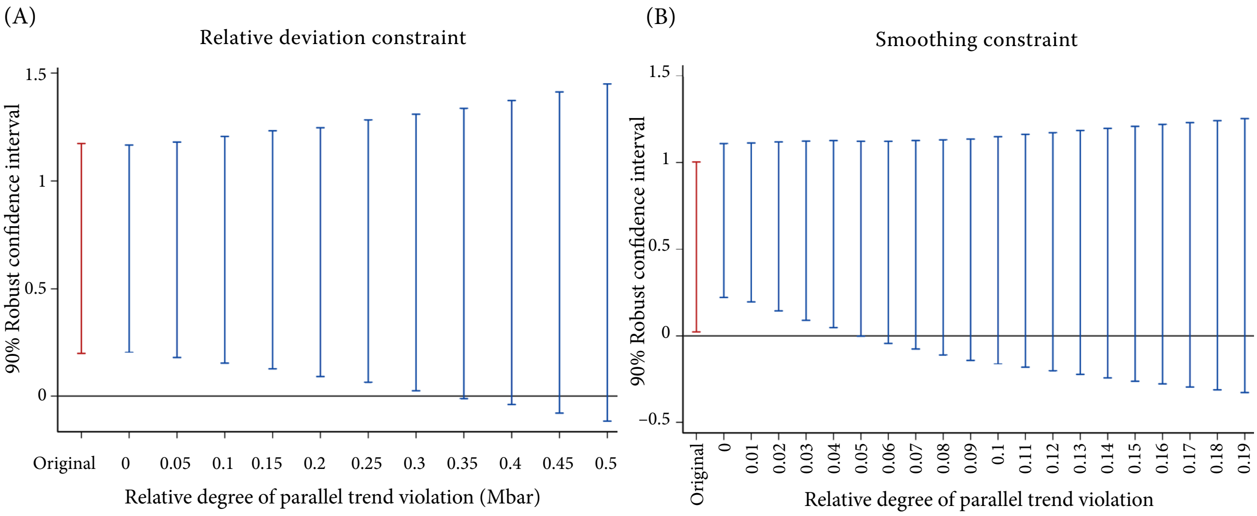

Figure 8. Relative deviation constraint (A) and smoothing constraint (B) of the parallel trend sensitivity test (second month after African swine fever)

Source: Authors' own processing

method proposed by Rambachan and Roth (2023) for sensitivity analysis of the parallel trend assumption, examining the effect of deviations from this assumption on estimates and confidence intervals. The test includes two steps: first, the maximum deviation of the parallel trend (Mbar) is calculated; second, the confidence interval for the post-treatment point estimate is constructed on the basis of the Mbar. If the confidence interval for the post-treatment point estimate, under the maximum deviation, does not include zero, it indicates that the treatment effect is robust to parallel trend deviations. In this study, we set Mbar at 0.5, with the results shown in Figures 6 through 9. Under the relative deviation constraint, the ASF shock led to a robust increase in pork prices during the shock month. Under the smoothing constraint, even with a 21% pre-treatment trend deviation, pork prices still increased significantly in the shock month.

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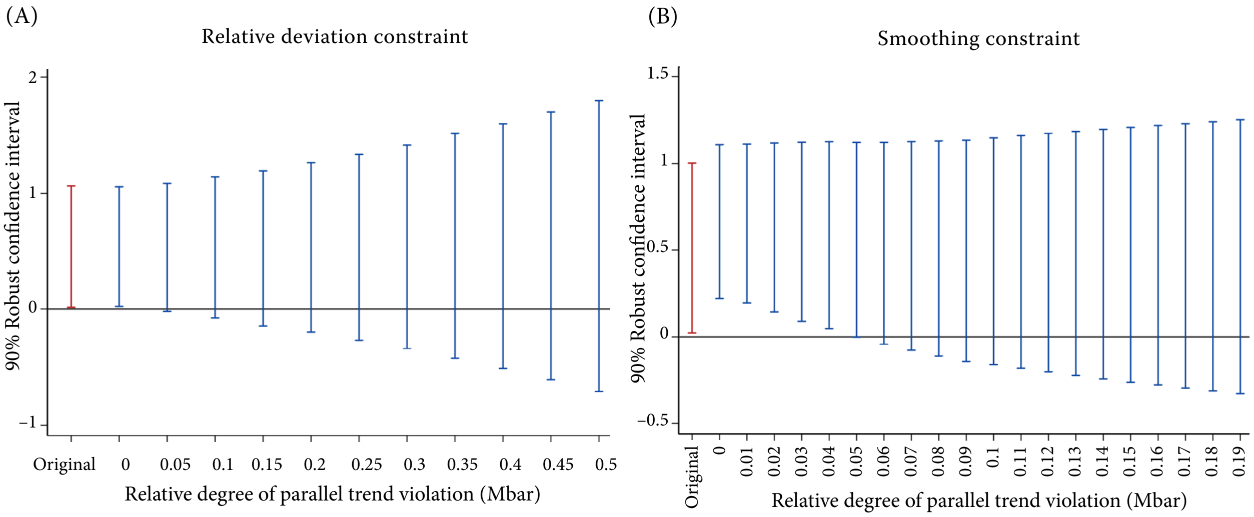

Figure 9. Relative deviation constraint (A) and smoothing constraint (B) of the parallel trend sensitivity test (three months after African swine fever)

Source: Authors' own processing

The sensitivity test confirmed robust results for the first, second and third months after the ASF shock. This finding suggests that even with some deviation from the parallel trend, the ASF shock had a significant driving effect on pork prices across regions.

Placebo test results. To test the validity of the estimates and check for potential anticipatory effects, we conducted a placebo test by randomly assigning provinces and shock timings for the ASF effect (Nagengast and Yotov 2025). A TWFE DID model, including control

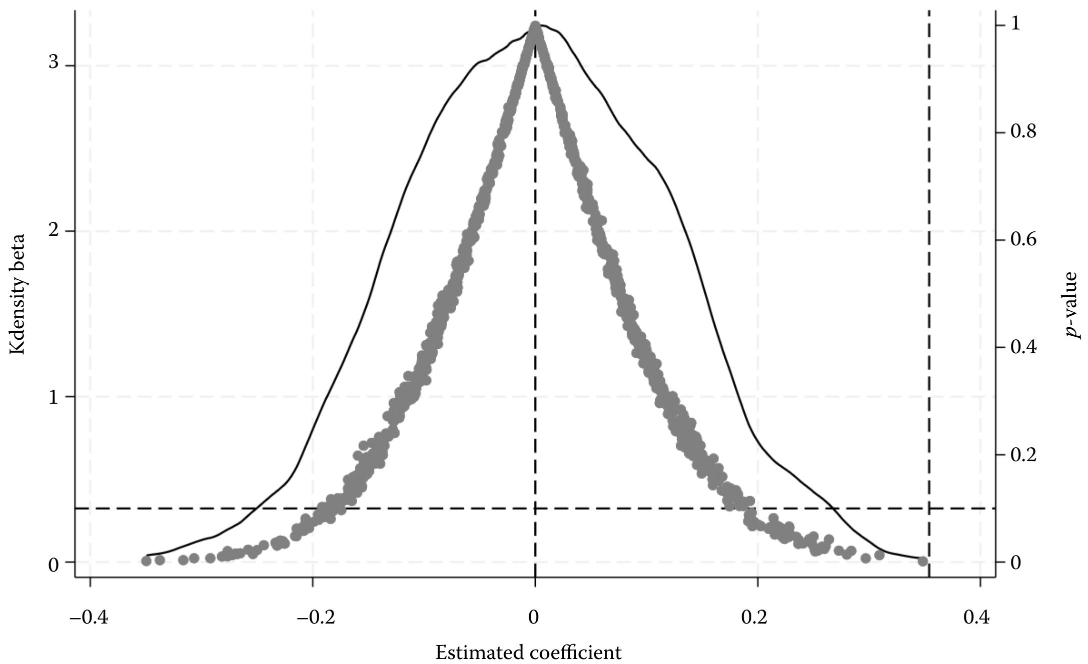

Figure 10. Placebo test results

Source: Authors' own processing

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Table 3. Propensity score matching difference-in-differences (PSM–DID) matched results

Matching method		Matched timing	ln*piglet*	ln*hog*	ln*feed*
Bias (%)	Kernel matching (0.05)	pre	79.0	92.7	–8.6
		post	–1.4	2.4	6.5
	Radius matching (0.05)	pre	79.0	92.7	–8.6
		post	–1.0	2.3	6.0
	Nearest neighbour matching (1 : 3)	pre	79.0	92.7	–8.6
		post	–3.3	2.4	10.1

Source: Authors' own processing

variables, time fixed effects and province fixed effects, was estimated 1 000 times to assess the effect of unobservable factors. If the coefficient was close to zero, it indicated no anticipatory effect. Figure 10 shows that the placebo test coefficients followed a normal distribution at approximately zero, significantly differing from the actual estimates. In addition, most *P*-values exceeded 0.1, suggesting that the results were not significant under randomly generated shocks, which confirms the robustness of the baseline model's estimates.

Mitigating endogenous issues. To reduce sample selection bias and examine potential endogeneity, we used the PSM-DID method. The matching bias remained less than 10%, confirming the reliability of the matching process (Zhou et al. 2023). Table 3 presents the matching results from three PSM-DID specifications. Column 1 reports the results of kernel matching with a calliper of 0.05. Column 2 uses radius matching, also with a calliper set to 0.05. Column 3 uses 1 : 3 nearest neighbour matching as an additional robustness check. The matching bias remained within 10.1%. These results indicate acceptable matching quality across all specifications.

On the basis of these matched samples, Table 4 shows that the ASF shock had a consistently positive and statistically significant effect on pork prices. The coefficients in Columns 1 through 3 remained significant at the 10% and 5% levels, supporting the robustness of the findings.

Table 4. Propensity score matching difference-in-differences (PSM-DID) test results

Variables	Kernel matching (1)	Radius matching (2)	Nearest neighbour matching (3)
		Pork price	
ASF	0.318*	0.318*	0.471**
	(0.188)	(0.188)	(0.220)
ln*piglet*	1.842***	1.842***	1.863***
	(0.392)	(0.392)	(0.466)
ln*hog*	16.191***	16.191***	16.111***
	(0.660)	(0.660)	(0.792)
ln*feed*	–4.733**	–4.733**	–5.286*
	(2.319)	(2.319)	(2.751)
Month *FE*	yes	yes	yes
Pro *FE*	yes	yes	yes
Constant	–19.487***	–19.487***	–18.982***
	(3.037)	(3.037)	(3.572)
R^2	0.984	0.984	0.982
Observations	697	697	508

***, ** and *significance levels at 0.01, 0.05 and 0.1, respectively; the price is measured in USD per kilogram (USD 0.14/kg)
ASF – African swine fever; *FE* – fixed effects
Source: Authors' own processing

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Table 5. Moran's I results for *ASF* (African swine fever) and *pork*

Time	I	Z	*P*-value
2018.1	0.069	2.082	0.037
2018.2	0.150	3.753	0.000
2018.3	0.166	4.004	0.000
2018.4	0.179	4.233	0.000
2018.5	0.131	3.260	0.001
2018.6	0.037	1.408	0.159
2018.7	0.007	0.814	0.416
2018.8	0.034	1.366	0.172
2018.9	0.054	1.879	0.060
2018.10	0.086	2.567	0.010
2018.11	0.148	3.661	0.000
2018.12	0.200	4.641	0.000
2019.1	0.213	4.924	0.000
2019.2	0.162	3.905	0.000
2019.3	0.113	2.938	0.003
2019.4	0.021	1.123	0.261
2019.5	–0.012	0.463	0.643
2019.6	0.022	1.187	0.235
2019.7	0.092	2.510	0.012
2019.8	0.044	1.705	0.088
2019.9	0.097	2.639	0.008
2019.10	0.119	3.064	0.002
2019.11	0.126	3.164	0.002
2019.12	0.240	5.398	0.000

Source: Authors' own processing

These results suggest that ASF led to a noticeable increase in pork prices, reducing concerns over endogeneity and strengthening the accuracy and credibility of our empirical conclusions.

Spatial effect test results. ASF may reduce hog production in a province, prompting resource adjustments from neighbouring regions and inducing interprovincial pork price linkages. Despite China's well-developed e-commerce, pork is a staple food with high consumption and strong timeliness, making sole reliance on online purchases unrealistic. Thus, the spatial interdependence of pork prices is practically grounded. To test whether such price transmission existed across provinces, we used Moran's I index to examine the spatial correlation of monthly pork prices (Table 5).

To construct the spatial weight matrix, we adopted a distance-based contiguity approach to capture interprovincial linkages. Because long-distance pork transportation entails substantial costs, actual flows were more dependent on neighbouring regions, and the effect of ASF was therefore more likely to be transmitted through adjacent provinces (Herrera et al. 2024). Specifically, we used provincial capitals' geographic coordinates as reference points, and we considered two provinces contiguous if the straight-line distance between them was less than 8° of latitude and longitude, approximately 700 to 900 kilometres (Xin et al. 2022). The formulation is as follows:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} < 8 \tag{10}$$

where: d_{ij} – the straight-line distance between the centroids of provinces i and j; $(x_i, y_i),(x_j, y_j)$ – the latitude and longitude coordinates of the respective provincial centroids.

The Moran's I results indicated that, under the ASF shock, pork prices across provinces exhibited a pronounced high–high clustering pattern. From the perspective of supply and demand, on the one hand, ASF led to a sharp decrease in the local pork supply, driving up prices within the affected province. On the other hand, the province could source pork from neighbouring regions, thereby increasing demand in adjacent markets. Given the stickiness of the pork supply in production, this heightened demand could not be fully met in the short term, resulting in price increases in neighbouring provinces.

In the study, we followed Gao et al. (2024) and used a DID SDM to test whether ASF generated spatial spillover effects on pork prices in neighbouring provinces. We constructed the spatial weight matrix on the basis of adjacency, and we used the model to analyse the interprovincial transmission of pork prices systematically. The model is specified as follows:

$$\begin{aligned} Y_{it} &= \eta_0 + \rho WY_{it} + \eta_1 WASF_{it} + \eta_2 ASF_{it} + \\ &+ \eta_3 WX_{it} + \eta_4 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{11}$$

where: Y_{it} – the pork price; X_{it} – a set of control variables; WY_{it}, $WASF_{it}$, and WX_{it} – the spatially lagged terms of Y_{it}, ASF_{it} and X_{it}, respectively.

The results showed that, on the basis of the adjacency matrix, the ASF coefficient was 0.385 and significantly positive at the 5% level, indicating a notable upward effect of ASF on regional pork prices. In contrast, the coefficient for neighbouring provinces was positive but not statistically significant, implying only a weak effect on their pork prices. Overall, ASF did not produce

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Table 6. Spatial spillover effect analysis

Variables	The adjacency matrix		
	SDM	SAR	SEM
	(1)	(2)	(3)
	Pork price		
ASF	0.385**	0.361**	0.304*
	(0.186)	(0.185)	(0.182)
W × *ASF*	0.467	–	–
	(0.590)		
CV	yes	yes	yes
W × *CV*	yes	yes	yes
ρ	0.300***	0.300***	–
	(0.087)	(0.072)	
λ	–	–	0.286***
			(0.094)
sigma2_e	1.459***	1.480***	1.447***
	(0.075)	(0.076)	(0.077)
Direct effects	0.405**	0.371*	–
	(0.193)	(0.191)	
Indirect effects	0.787	0.158	–
	(0.751)	(0.108)	
Total effects	1.192	0.529*	–
	(0.795)	(0.289)	
R^2	0.370	0.938	0.937
Observations	720	720	720

***, ** and *significance levels at 0.01, 0.05 and 0.1, respectively; the price is measured in USD per kilogram (USD 0.14/kg *ASF* – African swine fever; *CV* – control variables; SAR – spatial autoregressive model; SDM – spatial Durbin model; SEM – spatial error model; W – spatial weight matrix
Source: Authors' own processing

a significant interprovincial spillover effect. To assess robustness, Columns 2 and 3 of Table 6 report the estimates from the spatiotemporal TWFE spatial autoregressive model and spatial error model. The results were largely consistent with those of the SDM, confirming the robustness of the findings.

Heterogeneity analysis

Geographical differences. The eastern, central and western regions of China differ significantly in geographic features, climate conditions and agricultural models, which directly affect the transmission of ASF (Ito et al. 2022). The eastern region, which is economically developed, has frequent pig transportation, dense livestock farming and high levels of modernisation to meet market demand. The central region relies on decentralised, small-scale family farming with low pig transportation frequency. The western region also depends on traditional, small-scale family operations, with limited modern facilities and low transportation frequency. The results are shown in columns 1 to 3 of Table 7.

Results of regression analysis revealed that ASF significantly increased pork prices in the eastern region, with a coefficient of 0.485, which is significant at the 10% level. This effect was likely due to frequent pig transportation and intensive farming. In the central region, the coefficient was 0.881, which is high but not statistically significant, possibly because of lower transportation frequency and a more decentralised farming model. The coefficient for the western region was 0.343, which is not significant, suggesting that ASF had a weaker effect on pork prices, likely because of smaller farming scales, fewer modern facilities and low transportation frequency.

Level of informatisation. Media tools are crucial in spreading food safety knowledge and influencing

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Table 7. Heterogeneity analysis results

Variables	Geographical differences			Level of informatisation		Scale of agricultural production	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	eastern	central	western	stronger	low	large	smaller
ASF	0.485*	0.881	0.343	0.508**	0.279	0.225	0.391**
	(0.266)	(0.549)	(0.298)	(0.208)	(0.361)	(0.282)	(0.196)
ln*piglet*	3.069***	–1.401	–0.381	2.687***	–0.854	–0.186	2.545***
	(0.484)	(1.766)	(1.828)	(0.462)	(1.604)	(1.592)	(0.474)
ln*hog*	12.538***	18.315***	20.135***	12.037***	23.119***	20.046***	13.405***
	(1.270)	(2.040)	(2.716)	(0.717)	(2.791)	(2.626)	(0.789)
ln*feed*	5.809*	–8.385	–8.066*	3.196	–9.912*	–9.065*	–0.151
	(3.292)	(5.819)	(4.169)	(2.186)	(5.329)	(5.128)	(2.093)
Year *FE*	yes	yes	yes	yes	yes	yes	yes
Pro *FE*	yes	yes	yes	yes	yes	yes	yes
Constant	–22.296***	–9.007	–17.375***	–17.702***	–21.814***	–16.585***	–17.546***
	(5.550)	(8.273)	(3.838)	(2.963)	(5.888)	(5.128)	(3.021)
R^2	0.993	0.994	0.982	0.992	0.984	0.980	0.993
Observations	238	144	336	382	336	335	383

***, ** and *significance levels at 0.01, 0.05 and 0.1, respectively; prices are measured in USD/kg (0.14 USD/kg)
ASF – African swine fever; *FE* – fixed effects
Source: Authors' own processing

consumer behaviour, with the speed and extent of information flow directly affecting consumer decisions and potentially altering market responses (Kashyap et al. 2024). In this study, we explored how differences in informatisation levels affected pork price fluctuations under ASF. On the basis of the average internet penetration rates for 2018 and 2019, we divided the sample into two groups: high informatisation (penetration rate above average) and low informatisation (penetration rate below average). The results are shown in columns 4 and 5 of Table 7. The results showed that, in high informatisation areas, ASF significantly increased pork prices, whereas in low informatisation areas, the increase in price, although present, was not statistically significant. This finding suggests that faster information flow in high informatisation areas led to a more sensitive market response, whereas slower information flow in low informatisation areas resulted in smaller price fluctuations.

Scale of agricultural production. In this study, we examined the effect of the agricultural production scale on pork price fluctuations under ASF (Mutegi et al. 2024). The results are presented in columns 6 and 7 of Table 7. We divided the sample into two groups on the basis of the 2018 average ratio of primary industry value added to gross domestic product: one with a larger agricultural production scale and one with a smaller scale. The regression results showed that in provinces with a larger agricultural production scale, ASF had a positive but statistically nonsignificant effect on pork prices. These findings indicate that these provinces, with a strong agricultural supply base and predominantly confined pig farming, were more resistant to the effect of ASF. Conversely, in provinces with a smaller agricultural production scale, ASF significantly increased pork prices at the 5% level, likely because these provinces, with a greater focus on secondary and tertiary industries, had a weaker primary industry supply, leading to supply shortages and increasing pork prices.

Causal mediation mechanism results

In the study, we identified hogs culled from ASF as the explanatory variable, pork prices as the explained variable and hog farming costs and wholesale-retail profits as mechanism variables to explore the mechanism of the ASF effect on pork prices. Currently, the mainstream methods for testing causal mediation effects include the stepwise regression coefficient test, Sobel test and bootstrap-based test. Results from simulation studies have shown that, compared with the other two methods, the bootstrap test has greater statistical

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Table 8. Bootstrap test results of the causal mediation mechanism for farming costs

	Observed coefficient	SE	Z	$P>\|Z\|$	[95% confidence interval]
Indirect effect	–0.070	0.014	–4.82	0.000	–0.096 –0.038
Direct effect	–0.039	0.017	–2.31	0.021	–0.076 –0.011

Source: Authors' own processing

Table 9. Bootstrap test results of the causal mediation mechanism for wholesale and retail profits

	Observed coefficient	SE	Z	$P>\|Z\|$	[95% confidence interval]
Indirect effect	–0.066	0.016	–4.19	0.000	–0.103 –0.039
Direct effect	–0.040	0.014	–2.94	0.003	–0.068 –0.012

Source: Authors' own processing

power. The bootstrap method is recognised as a direct test of coefficient products that can replace the Sobel method, so in this study we used the bootstrap method for causal mediation effect testing.

Farming cost mechanism test. Farming costs mainly include feed costs, labour costs and other costs, such as medical expenses and housing. In this study, we used the bootstrap test to examine the causal mediation mechanism of farming costs between the ASF epidemic and pork prices. According to the mediation test results (Table 8), the indirect effect of farming costs on pork price fluctuations caused by the epidemic was 0.07, the direct effect of farming costs on pork price fluctuations caused by the epidemic was 0.04, and a causal mediation effect was established. Overall, the total effect of farming costs on pork price fluctuations was 0.11, with direct effects accounting for 35.78% and indirect effects accounting for 64.22%. Comparatively, the effect of farming costs on pork price fluctuations was mainly indirect, and farming costs played a significant causal role in the pork price fluctuations caused by the ASF epidemic.

Test of the mechanism of wholesale and retail profits. Wholesale and retail profits mainly involve the profits generated by wholesalers and pork retailers from buying pork products from slaughterhouses and selling them at offline retail points. In this study, we used Stata 18.0 software (StataCorp LLC, College Station, TX, USA) to perform bootstrap tests to verify the causal mediating effect of wholesale and retail profits between the ASF epidemic and pork price fluctuations. According to the mediation test results (Table 9), at the 1% significance level, the indirect effect of wholesale and retail profits on pork price fluctuation was 0.066, establishing a causal mediation effect. At the 1% significance level, the direct effect of wholesale and retail profits on pork price fluctuations was 0.04. Overall, the total effect of wholesale and retail profits on pork price fluctuation was 0.106, with indirect effects accounting

Table 10. Stationarity test results

Variable	ADF statistic	5% critical value	*P*-value	Conclusion
ln*feed*	–2.019 429	–2.880 722	0.278 3	unstable
ln*piglet*	–2.620 186	–2.880 853	0.091 2	unstable
ln*hog*	–2.350 739	–2.880 722	0.157 7	unstable
ln*pork*	–2.161 718	–2.880 722	0.221 3	unstable
ln*EWI*	–2.570 707	–2.880 463	0.101 3	unstable
Dln*feed*	–7.296 776	–2.880 722	0.000 0	unstable
Dln*piglet*	–4.167 537	–2.880 853	0.001 0	unstable
Dln*hog*	–7.577 294	–2.880 722	0.000 0	unstable
Dln*pork*	–7.598 081	–2.880 722	0.000 0	unstable
Dln*EWI*	–13.019 40	–2.880 591	0.000 0	unstable

Source: Authors' own processing
ADF – augmented Dickey–Fuller test; *EWI* – epidemic width index

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Table 11. Cointegration test results

Null hypothesis	Eigenvalue	Trace statistic	*P*-value	Max-Eigen statistic	*P*-value
$R = 0$	0.587 623	241.168 8	0.000 0	134.644 3	0.000 0
$R = 1$	0.317 022	106.524 5	0.000 0	57.956 58	0.000 0
$R = 2$	0.158 864	48.567 90	0.012 3	26.296 23	0.043 3
$R = 3$	0.109 064	22.271 67	0.131 6	17.553 29	0.090 5

Source: Authors' own processing

for 62.26% and direct effects accounting for 37.73%. Therefore, the direct effect of wholesale and retail profits on pork price fluctuations was much lower than its causal mediation effect.

Factors of pork price fluctuations based on the SVAR model

On the basis of the relevant literature (Ahmed et al. 2011; Dybowski and Adämmer 2018; Pang et al. 2023; Aizenman et al. 2024; Liu et al. 2024), we sequentially present the results of the following tests: the stationarity test, cointegration test, vector error correction model (VECM) test, stability and Granger causality test, impulse response function test and variance decomposition test. The detailed results are as follows:

Stationarity test results. Before we analysed the price relationships in various stages of the hog industry production chain, we needed to test the stationarity of the variables. In this study, we used the augmented Dickey−Fuller test in EViews 13.0 software (S&P Global Inc., Seal Beach, CA, USA) to examine the stationarity of five price variables: finishing pig feed prices (*feed*), piglet prices (*piglet*), live hog prices (*hog*), pork prices (*pork*) and the EWI. As shown in Table 10, the logarithmic transformations of these five price variables were nonstationary. Nevertheless, after we performed first-order differencing, all price variables became stationary, with *P*-values less than 0.05. Therefore, the selected variables met the prerequisites for using the cointegration model to examine long-term equilibrium relationships among price variables.

Cointegration test results. After confirming the stationarity of the price variables, we tested for cointegration relationships. Because we used first-order differencing sequences, the lag order for the cointegration test was 0. We used EViews software to perform the Johansen cointegration test, choosing a model with intercept and trend terms in the cointegration relationships but without an intercept term in the VAR model. As shown in Table 11, there were three cointegration relationships (R = 3) among the price variables in the hog industry production chain at the 5% significance level.

Therefore, on the basis of the model results and the economic realities of the hog industry, we excluded two of the cointegration equations. The following cointegration equation represents the long-term equilibrium relationships in the hog industry price system:

$$\ln hog_t = -0.0071 \ln EWI + 0.1120 \ln feed_t + \\ + 0.1130 \ln piglet_t + 0.9670 \ln pork_t \tag{12}$$

Equation (12) revealed the existence of long-term equilibrium relationships within China's hog industry price system. Specifically, hog prices $\ln hog_t$ had a long-term positive relationship with piglet prices $\ln piglet_t$ and pork prices $\ln pork_t$ but a negative relationship with finishing pig feed prices $\ln feed$. In the long run, holding other explanatory variables constant, a 1% change in pork and piglet prices resulted in hog prices changing by 1.078% and 1.013% in the same direction, respectively; a 1% change in feed prices resulted in hog prices changing by 0.026% in the opposite direction. Compared with the effects of pork and piglet prices, the effect of finishing pig feed prices on hog price changes was smaller, and the relationship between feed prices and hog prices was anomalously negative. This anomaly corroborates the reason for long-term losses in the hog farming industry: increasing feed prices led to decreasing hog prices.

Vector error correction model (VECM) test results. On the basis of the cointegration test results, the pork price system exhibited long-term equilibrium relationships among key price variables in the hog industry production chain. In this study, we used the VECM to examine short-term dynamic relationships and long-term cointegration relationship changes in prices. The preliminary test settings for the VECM model were consistent with the cointegration test settings mentioned earlier. The short-term deviation error from long-term equilibrium

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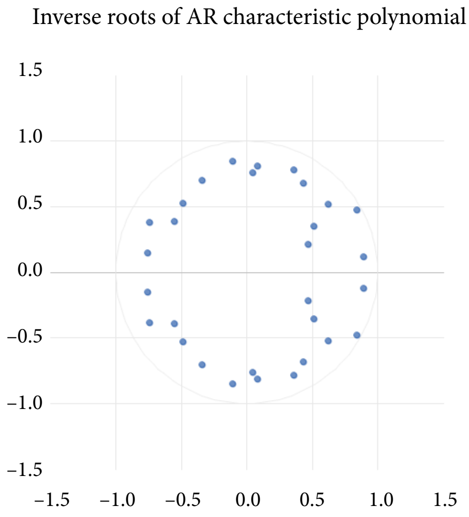

Figure 11. Stability test of the structural vector autoregression (SVAR) model

AR – autoregressive
Source: Authors' own processing

was set as the ECM. The VECM model estimation results were as follows:

$$ECM_t = \ln hog_t - 0.783 + \\ + 0.026 \ln feed_t - 0.013 \ln piglet_t - 1.078 \ln pork_t \quad (13)$$

The VECM results identified four error correction mechanisms, each corresponding to one of the endogenous price variables as the dependent variable. The estimated short-term adjustment coefficients were as follows: –0.676 4 for hog prices, –0.003 5 for feed prices, –0.570 6 for piglet prices and –0.267 5 for pork prices. These values indicate that, in the current period, deviations from long-term equilibrium were corrected by 67.64, 0.35, 57.06 and 26.75%, respectively. Among the four, hog prices adjusted the fastest toward equilibrium, followed closely by piglet prices – both exceeding 50% correction in one period. Pork prices showed a moderate speed of adjustment, whereas feed prices exhibited minimal short-term correction, suggesting near-static behaviour in the short run. These results imply asymmetry in the price adjustment process within the hog supply chain. In the long run, hog and piglet prices played a dominant role in driving the overall price system, whereas pork and feed prices acted more as followers. This finding is consistent with the market structure, where upstream price signals often lead to downstream price movements.

Stability and Granger test results. Before conducting impulse response and variance decomposition, we first used the lag length criterion command to test the VAR lag order. Among the five test results, we chose a lag order of 6 on the basis of the majority rule. On this basis, we conducted a stability test of the VAR model, as shown in Figure 11. All the eigenvalues lie within the unit circle, with none outside, indicating that the model passed the stability test.

We used the Granger test to investigate the causal relationships between variables, as presented in Table 12. TThe results show no evidence that the other variables Granger-caused changes in finishing pig feed prices. Similarly, the other price variables did not Granger-cause changes in the EWI. However, at the 5% significance level, piglet prices, hog prices, and pork prices significantly Granger-caused changes in the other variables.

Impulse response function test results. Given that both the stability of the model and the Granger causality test results were confirmed, we further conducted impulse response analysis and variance decomposition. The impulse response function can comprehensively reflect the dynamic transmission effects among variables in the hog industry production chain, revealing the effect of shocks on each endogenous variable and other endogenous price variables

Table 12. Granger causality test results

Explained variable	*F*-statistic (all)	d*f* (all)	Probability
Dln*feed*	33.476 91	24	0.094 4
Dln*piglet*	84.587 15	24	0.000 0
Dln*hog*	79.940 11	24	0.000 0
Dln*pork*	106.153 9	24	0.000 0
Dln*EWI*	34.886 95	24	0.070 1

EWI – epidemic width index
Source: Authors' own processing

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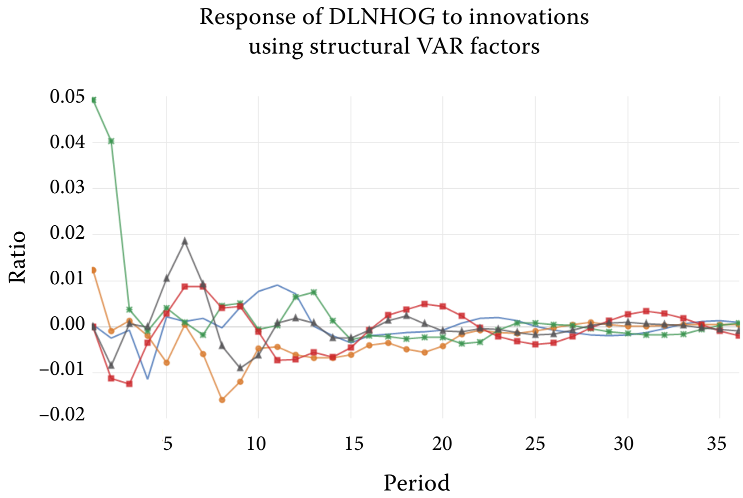

Figure 12. Impact of African swine fever (ASF) on hog prices and its transmission effects

VAR – vector autoregression
Source: Authors' own processing

in both the current and future periods. The impulse response results for hog and pork prices are shown in Figures 12 and 13.

The impulse response results with hog prices as the response variable are shown in Figure 12. Initially, the hog price change rate was influenced mainly by its price inertia and the change rate of finishing pig feed prices, both of which had significant positive effects. When the hog price change rate was affected by one standard deviation of inertia, it increased by 0.049 in the current period and decreased to 0 by the fourth period. The effect of finishing pig feed price changes increased in the current period by 0.012, became negative in the second period, reached a maximum negative effect of 0.016 in the eighth period and then decayed to 0.016. The effect of pork price changes was mainly positive, reaching a maximum value of 0.018 5 in the sixth period. The effect of piglet price changes showed a complex alternating pattern of inhibition and promotion. The initial effect of the EWI was 0, with a maximum negative effect of 0.011 3 in the fourth period and a maximum positive effect of 0.009 1 in the eleventh period, indicating a long-lasting effect.

The impulse response results with pork prices as the response variable are shown in Figure 13. Initially, the change in the pork price rate was significantly influenced by the shift in hog prices and price inertia. The effect of hog price changes increased the current period's pork price change rate by 0.031, reaching a maximum value of 0.036 in the second period, then gradually decayed to 0, with a slight negative effect after the 15th period. The initial positive effect of pork price inertia was 0.011, with negative effects in periods 2 through 4, reaching a maximum value of 0.015 in the sixth period and decaying to 0 by the 20th period, overall showing a predominantly positive

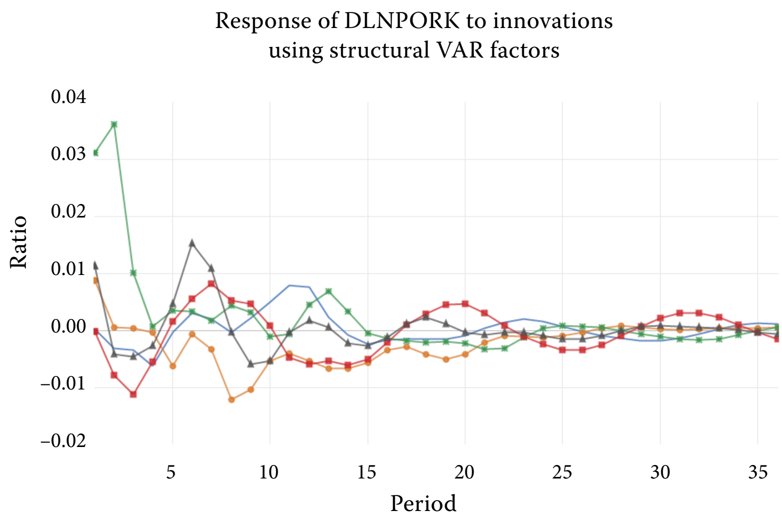

Figure 13. Impact of ASF on pork prices and its transmission effects

VAR – vector autoregression
Source: Authors' own processing

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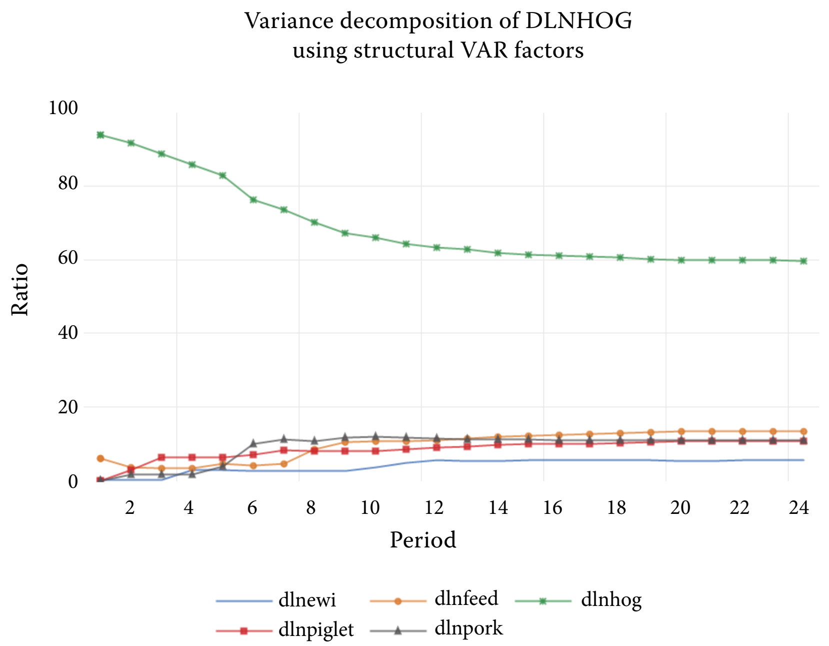

Figure 14. Variance decomposition of hog prices

VAR – vector autoregression
Source: Authors' own processing

effect. The effect of piglet price changes had no effect in the current period, with a maximum negative effect of 0.011 in the third period, then alternating between positive and negative effects. The effect of finishing pig feed price changes gradually decreased from 0.009 to –0.012 in the current period, decaying to 0 after the 27th period. The EWI had no significant effect in the current period, with a maximum negative effect of 0.006 in the fourth period, positive effects from the fifth to the 13th periods and slight negative effects afterward.

This analysis clearly reveals that multiple factors influenced fluctuations in hog and pork prices and that their dynamic transmission effects are of significant reference value to the hog industry production chain.

Variance decomposition test results. Variance decomposition is mainly used to analyse the degree of contribution of each price variable to shocks. We calculated

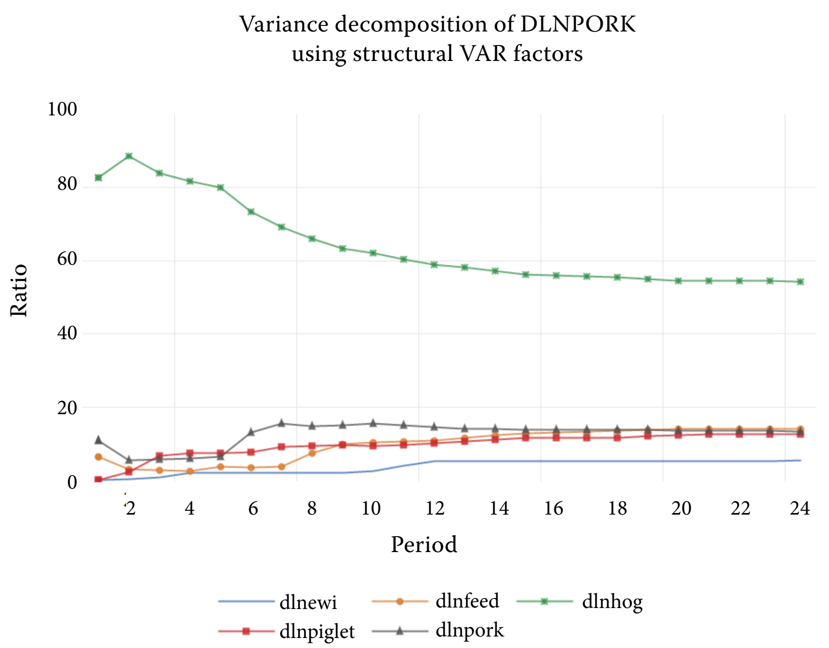

Figure 15. Variance decomposition of pork prices

VAR – vector autoregression
Source: Authors' own processing

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the contribution of disturbance terms to the forecast error variance in the vector autoregression (VAR) model to compare the dynamic effects of various factors on hog and pork prices.

Variance decomposition of the effect of external shocks on hog prices: As shown in Figure 14, we were able to obtain the degree of influence of each price variable on hog price changes. In the short term, the hog price change rate was influenced mainly by price inertia, with a contribution rate of 94%. In the long term, the primary sources of hog price fluctuations were price inertia, finishing pig feed prices, piglet prices and pork prices, with contribution rates of 59, 13, 11.5 and 10.8%, respectively. The contribution rate of the EWI to hog price fluctuations was relatively low, at only 5.6%. Therefore, the main sources of hog price fluctuations were their own supply and demand factors, followed by feed prices on the raw material side, piglet prices on the upstream side and pork prices on the downstream side, with the EWI having the smallest effect.

Variance decomposition of the effect of external shocks on pork prices: As shown in Figure 15, we were able to obtain the degree of influence of each price variable on pork price changes. In the short term, the main sources of pork price fluctuations were hog prices and price inertia, with contributions of 82.6% and 10.8% in the first period, respectively. In the long term, the main sources of pork price changes were hog prices, finishing pig feed prices, piglet prices and price inertia, with contribution rates of 53.4, 14, 13.6 and 13.4%, respectively. Hog prices contributed the most, accounting for approximately half, whereas the latter three factors were relatively close in terms of their contributions. The EWI initially had a minor effect on pork price fluctuations (i.e. less than 1%) but gradually increased and stabilised at approximately 5.6%, making the smallest contribution among all the variables.

DISCUSSION

Our research has three key similarities with existing research. First, ASF affected both the supply of pigs and the demand structure, increasing pork prices. Dynamic analysis results revealed that pork prices increased in the month of the ASF outbreak and in the subsequent three months. As the government and investors entered the pig farming sector, prices gradually decreased, even below demand levels, causing widespread economic losses (Han et al. 2022). Second, the effect of ASF on pork prices varied across regions (Ma et al. 2024). Third, like other scholars, we used the VAR model to analyse the factors influencing pork price fluctuations (Zakharova and Liskova 2025), finding that multiple factors contributed to price fluctuations. However, this study differs in several ways. First, we conducted a spatial analysis and found that ASF significantly affected pork prices within the affected province but had little effect on neighbouring provinces. Second, the effect of ASF on price fluctuations was more pronounced in regions with high internet penetration and weak agricultural foundations. Finally, in the SVAR model analysis, we examined price variables across different stages of the pork supply chain, revealing varying contributions of these factors to price fluctuations and providing a more comprehensive analysis.

Our research has significant relevance for regions such as Europe. China's pork market, production chain and sales system share many similarities with those of Europe, so the effect mechanisms of ASF in China are likely to produce similar effects in Europe. Pork consumption plays a vital role in food security, public health and economic stability in pork-consuming regions around the world. Although some European regions have already faced ASF outbreaks, the ongoing threat still poses substantial risks to the pig farming industry. China is the world's largest producer and consumer of pork, so fluctuations in China's market have a profound effect on the international supply chain. Supply disruptions and price fluctuations caused by ASF have already been evident in China. As the market has recovered and the pig farming industry has restructured, China's shift toward large-scale farming provides valuable lessons for Europe and other regions to address similar shocks better. Given China's international influence on pork markets, its instability affects not only the domestic economy but also international market structures. Therefore, studying the effect of ASF in China offers essential insights for preventing pork supply crises in other countries and provides policy recommendations for stabilising the international pork market. Moreover, similar shocks, such as other epidemics or natural disasters, could have comparable effects, highlighting the importance of further research on these mechanisms for prevention and response.

CONCLUSION

In this study, we used a staggered DID model to examine the effect of ASF on pork prices across different provinces in China. We used a cointegration model to identify long-term relationships between the EWI and prices at various stages of the

https://doi.org/10.17221/350/2024-AGRICECON

hog industry production chain. In addition, we used an SVAR model to investigate the sources of pork price fluctuations. We also conducted mechanism tests to explore how the epidemic affected pork prices and its heterogeneous effects. The main findings are as follows:

i) Results from the staggered DID model show that the ASF epidemic positively affected pork prices, increasing them by approximately 3.54%. Results from the spatial DID model further reveal that there were no spillover effects on neighbouring provinces. In addition, provinces with higher levels of internet information, weaker agricultural infrastructure and those in the eastern region were more susceptible to the effect of ASF, leading to an increase in pork prices.

ii) There was a long-term equilibrium relationship between the EWI and prices at different stages of the hog industry production chain. Hog prices had a long-term positive relationship with finishing pig feed prices, piglet prices and pork prices but a negative relationship with the EWI.

iii) ASF had a dynamic transmission effect on prices from upstream to downstream in the hog industry production chain. In the short term, the hog price change rate was most significantly influenced by price inertia, followed by the change rate of finishing pig feed, both of which had initial positive effects. The pork price change rate was initially influenced by the hog price change rate and its price inertia.

iv) In the long term, the main sources of hog price fluctuations were price inertia (59%), finishing pig feed prices (13%), piglet prices (11.5%) and pork prices (10.8%), with the EWI contributing only 5.6%. For pork prices, the main long-term sources of change were hog prices (53.4%), finishing pig feed prices (14%), piglet prices (13.6%) and price inertia (13.4%). The EWI initially had the smallest effect on pork prices (less than 1%), gradually increasing to stabilise at approximately 5.6%.

v) The ASF epidemic affected pork price fluctuations through two main channels: farming costs and wholesale retail profits. The total effects of these two mechanisms on pork price fluctuations were similar, approximately 0.1, with indirect effects accounting for more than 60%, indicating that indirect effects were predominant.

Studying the mechanisms through which ASF affects pork price fluctuations can help mitigate severe price fluctuations caused by the epidemic and promote stable and reasonable pork prices. On the basis of these conclusions, we recommend the following:

i) Enhance ASF surveillance and rapid response systems. SVAR and mediation analysis results confirmed that farming costs, especially feed prices, played a critical role in transmitting ASF shocks to downstream pork prices. The development of disease-resistant pig breeds, the promotion of efficient and affordable feed and improvements in production technologies can reduce cost-related price fluctuation and help mitigate disruptions across the supply chain.

ii) Low production costs alleviate upstream price pressures. SVAR and mediation analysis results confirmed that farming costs – especially feed prices – played a critical role in transmitting ASF shocks to downstream pork prices. The development of disease-resistant pig breeds, the promotion of efficient and affordable feed and improvements in production technologies can reduce cost-related price fluctuation and mitigate supply chain disruptions.

iii) Strengthen price regulation and market information disclosure. The impulse response results show that ASF shocks caused short-term fluctuation in pork prices. Transparent price information and regular market monitoring reports can guide expectations and reduce speculation. Establishing and activating regional pork reserves in a timely manner may also help smooth market fluctuations and protect both producers and consumers.

iv) Expand economic and technical support for affected farmers. Mechanism test results revealed that ASF significantly increased production costs while indirectly contributing to retail price gains. Protecting vulnerable farmers from disproportionate losses requires targeted support, such as direct subsidies, low-interest credit and technical assistance, which should be prioritised in severely affected regions. These measures can accelerate production recovery and improve system resilience.

v) Promote integration and coordination in the hog industry production chain. Variance decomposition analysis highlights that price inertia was a major long-term contributor to pork price fluctuations. Enhancing vertical coordination within the hog industry – particularly among feed suppliers, breeders, processors and retailers – can reduce delays in price adjustment and improve response efficiency. Standardising production processes and promoting insurance mechanisms across the supply chain are essential steps toward reducing systemic risk and stabilising prices.

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Received: September 20, 2024
Accepted: December 17, 2025