Preventive Veterinary Medicine 215 (2023) 105912

Contents lists available at ScienceDirect

Preventive Veterinary Medicine

journal homepage: www.elsevier.com/locate/prevetmed

The ripple effect of animal disease outbreaks on food systems: The case of African Swine Fever on the Chinese pork market

Alejandro Acosta [a,*], Tim Lloyd [b], Steve McCorriston [c], Hao Lan [d]

[a] Food and Agriculture Organization of the United Nations (FAO), Rome, Italy
[b] Bournemouth University, Bournemouth, United Kingdom
[c] University of Exeter, Exeter, United Kingdom
[d] Xi'an Jiaotong-Liverpool University, Suzhou, China

ARTICLE INFO

Keywords:
Ripple effects
Food systems disruptions
Animal disease outbreaks
Price transmission
Local projections

ABSTRACT

Research on animal health economics has emphasised the importance of accounting for the indirect economic effects of animal disease outbreaks. Although recent studies have advanced in this direction by assessing consumer and producer welfare losses due to asymmetric price adjustments, potential over-shifting effects along the supply chain and spill-overs to substitute markets have been under-examined. This study contributes to this field of research by assessing the direct and indirect effects of the African swine fever (ASF) outbreak on the pork market in China. We employ impulse response functions estimated by local projection to calculate the price adjustments for consumers and producers, as well as the cross-effect in other meat markets. The results show that the ASF outbreak led to increases in both farmgate and retail prices but the rise in retail prices exceeded the corresponding change in farmgate prices. Furthermore, beef and chicken prices also rose, demonstrating the spill-over impacts of the outbreak to other markets. Overall, the evidence illustrates that a disruption in one part of a food system can have significant ripple effects across other parts of the system.

1. Introduction

Animal disease outbreaks are a significant and growing threat to global food systems (Rushton et al., 2018). Such shocks to a food system can cause disruption in the stability of food production along the food supply chain as well as impacting food import and export, food access, incomes and diets (Acosta et al., 2021; Savary et al., 2020). The African swine fever (ASF) outbreak in China was one such event. In China, the 2018 ASF outbreak resulted in the death from disease or culling of about 143 million pigs, a reduction of 40.5% and 39.3% in the stock of hogs and sows, respectively (USDA, 2019a; USDA, 2019b). As pork is the most important meat in the Chinese diet, and a main component of China's consumer price index, the ASF could have led to significant welfare losses (Ma et al., 2021).

Previous research on animal health economics has emphasised the importance of accounting for the indirect economic effects of animal disease outbreaks. Although recent studies have advanced in this direction by assessing potential welfare losses due to incomplete or asymmetric price adjustments (Dai et al., 2015; Seok et al., 2018; Acosta et al., 2020), the importance of demand and supply shifters (i.e. exogenous shocks linked to the outbreak) and spill-over effects across related markets remains to be examined. Price transmission analysis using time series data has been a widely used method for examining the pass-through or pass-back effects of economic shocks in marketing chains (Gardner, 1975; Serra and Zilberman, 2013; Ubilava, 2018, Lloyd, 2017). We will next summarise the key relevant contributions.

Lloyd et al. (2001) is one of the first studies to examine the price dynamics related to an animal disease outbreak of bovine spongiform encephalopathy (BSE) in UK beef production. Specifically, the publicity surrounding the announcement of a link between BSE and Creutzfeldt–Jakob disease (CJD) presented the largest 'food scare' in the UK, causing the wholesaler–producer and retailer–wholesaler marketing margins to expand. Sanjuán and Dawson (2003) extended the analysis of the BSE crisis by including structural breaks in the co-integration (i.e. long run) relationship,[1] illustrating that BSE caused a structural break in the beef price relationship between farmers and retailers. Furthermore,

* Corresponding author.
E-mail address: alejandro.acosta@fao.org (A. Acosta).

[1] Two or more non-stationary time series variables have a cointegrating relationship if their linear combination is stationary, meaning that they share a long-run equilibrium such as that between producer and consumer prices for the same product.

https://doi.org/10.1016/j.prevetmed.2023.105912
Received 7 October 2022; Received in revised form 11 March 2023; Accepted 5 April 2023
Available online 7 April 2023
0167-5877/

Lloyd et al. (2006) revealed the differential impacts of the BSE crisis on producers and retailers due to differences in market power.

Using a vector autoregression (VAR) model, Seok et al. (2018) showed that the effect of the highly pathogenic avian influenza (HPAI) shock on Korea's egg market prices was distributed unevenly, allowing processors to increase their margins. Employing a regime-dependent vector error-correction model, Acosta et al. (2020) showed that the HPAI outbreak in Mexico caused structural breaks in egg market price dynamics between producers and consumers, which was reflected in an increase in the absolute component of the market's margin.

Since animal disease outbreaks constitute both a shock to supply (via costs) and demand (via preferences), it is essential to assess the extent to which demand- and/or supply-side shifters affect price adjustment. Research has employed media proxies[2] to estimate impulse responses that originate from demand-side shock (Livanis and Moss, 2005; Hassouneh et al., 2010; Hassouneh et al., 2012; Saghaian et al., 2008). To investigate price effects related to supply-side shocks, studies have used variables such as the number of animals culled or trade restrictions as proxies (Kim et al., 2019; Park et al., 2008). Using impulse response functions, Dai et al. (2015) estimated the impact of diseases affecting pigs on retail pork prices and price spreads.

As noted, a growing body of literature has used VAR models in stationary or error-correction form to measure the price effects of food shocks via impulse response functions. These studies have primarily focused on sector-specific prices, within or across countries; however, animal disease outbreaks can have broader spill-over impacts on other parts of food systems. Employing impulse response functions using local projections (Jordà, 2005, 2009), this study aims to fill this gap by assessing the pass-back and pass-through[3] effects of price adjustments for consumers and producers in addition to cross-impacts in associated markets, while accounting for the supply- and demand-side effects of the shock.

This study contributes to the existing literature in several ways. First, we construct a general framework that considers the demand- and supply-side effects of an animal disease outbreak on producers and consumers. Second, we estimate the spill-over effects into related markets to document the broader food system impacts of an animal disease outbreak. Third, we employ a recently developed technique called local projection (Jordà, 2009) to estimate the impulse response functions, which allows us to disentangle the effects of demand- and supply-side factors on price adjustment. Finally, we add to the research by assessing the effects of the ASF outbreak in China, an important and global animal disease shock that has not yet been examined from the perspective of price transmission analysis.

2. Methodological framework

To estimate the dynamic effects of disease events on prices at different stages of the value chain, impulse response functions are estimated using the local projection technique pioneered by Jordà (2005). This approach involves sequentially estimating (or projecting) a set of regressions comprising the information set available at time t, H periods into the future. Assuming that $y_t \equiv (y_{1t}, y_{2t}, ..., y_{Kt})'$ and the information set contains p lags of y_t, yields the following:

$$y_{t+h} = \alpha^s + B_1^h y_{t-1} + B_2^h y_{t-2} + \cdots B_p^h y_{t-p} + \mu_{t+h}, \qquad h = 0, 1, 2, \ldots, H, \tag{1}$$

where the same set of lagged variables is used to predict the value of y_t, $h = 1, 2, \ldots, H$ periods ahead, producing H separate models, each containing K equations; thus, superscripts denote the horizon being considered rather than powers. Attention is focused on the $(K \times K)$ matrix of autoregressive coefficients B_1^h, $h = 1,2,...,H$. As is evident from Eq. (1), B_1^h contains coefficients that measure the effect of changes in y_t on y_{t+h}, conditional on the information set available. As Jordà (2005) formally demonstrated, this matrix contains coefficients that comprise the impulse response functions.

Direct estimation of the coefficients quantifying the response of prices to specific shocks via Eq. (1) has a number of attractive properties, giving rise to the increasing popularity of local projection in macro-econometrics literature (see, inter alia, Ronayne, 2011 and Brugnolini, 2018). Most notably, the need to estimate and invert a VAR using the Wold decomposition in the usual two-step process is circumvented, since the coefficients of interest are estimated directly in Eq. (1). For cases in which the VAR does not exist or it offers a poor approximation of the data-generating process, misspecification errors are compounded when obtaining the vector moving average (VMA), giving rise to bias in the impulse response function that amplifies as the horizon grows. Local projection also offers a straightforward approach since the impulse response for the j^{th} variable in y_t can be estimated by univariate regression of y_{jt+h} on lags of itself and other variables in the information set.

A few other considerations are also noteworthy. First, as Jordà (2005) demonstrated, the regression errors μ_{t+h} from the projection in Eq. (1) are a VMA of order h, implying that the use of a robust estimator of covariance, such as the heteroscedasticity and autocorrelation consistent estimator of Newey and West (1987) and Andrews (1991), is preferable to least squares. This practice is adopted to calculate the confidence intervals displayed in the result figures.

The econometric approach proceeds in a practical way, identifying the variables of interest that are subject to the disease shock, given other factors that may also influence prices. We derive two sets of impulse responses. First, we focus on demand-side shocks on retail pork and upstream hog prices, controlling for the supply-side shock, the price of substitute meats and other costs. Specifically, this exploration of demand-side shock captures the intended response of consumers to the disease outbreak. The analysis can reflect specific concerns over potential health impacts and/or consumers' preferences in reducing consumption of products associated with a disease outbreak, even if the human health impacts are negligible. The second set of impulse responses focuses on the effect of the supply shock on retail pork and upstream hog prices, also controlling for demand-side shock, the prices of substitute meats and other costs. These specifications allow us to isolate the impacts of the demand- and supply-side aspects of disease events on pass-through and pass-back price transmission.

In summary, the regressions used in the local projection impulse response approach are as follows:

$$Pork_{t+h} = \alpha_h + \beta_{(h)} shock_t^D + \boldsymbol{\gamma X} + \mu_{(h)t+h} \quad h = 0, 1, 2, \cdots, H \tag{2}$$

where $Pork_{t+h}$ represents retail pork prices at time $t+h$, which is a function of the effect of demand shock, $shock_t^D$, conditional on the effects of other control variables ($\boldsymbol{X}$). These controls include lags of the dependent variable, the supply shock, prices of substitutes (*Chicken* and *Beef*), upstream hog prices, and other costs. $\beta_{(h)}$ is the coefficients of interest, which are the dynamic effects on retail pork prices, $Pork_{t+h}$, due to a demand shock, keeping all else constant.

Similarly, the effect on upstream hog prices, (Hog_{t+h})is expressed in Eq. (3) as a linear function of the demand shock, ($shock_t^D$) controlling for $\boldsymbol{X}$**,** which contains lags of the dependent variable, the supply shock, prices of substitutes, retail prices, and other costs.

$$Hog_{t+h} = \alpha_h + \beta_{(h)} shock_t^D + \boldsymbol{\gamma X} + \mu_{(h)t+h} \quad h = 0, 1, 2, \cdots, H \tag{3}$$

The effects of supply shocks on retail and upstream prices can also be

[2] Media proxies, such as the Baidu index in China, can be used to capture the level of public attention to a specific topic online.

[3] Pass-back measures how responsive producers' prices are to changes in consumers' prices, and pass-through measures how responsive consumers' prices are to changes in producers' prices.

expressed using similar notation Eqs. (4) and (5), the only difference being that now we are estimating the effect of supply shock ($shock_t^S$), so that the effects of demand shock is now one of the controls. Specifically,

$$Pork_{t+h} = \alpha_h + \beta_{(h)} shock_t^S + \boldsymbol{\gamma X} + \mu_{(h)t+h} \quad h = 0, 1, 2, \cdots, H \tag{4}$$

where $Pork_{t+h}$ represent retail pork prices at time $t + h$, which is a function of the supply shock, ($shock_t^S$), controlling for the effects of control variables $\boldsymbol{X}$. These controls include lags of the dependent variable, the demand shock, prices of substitutes (*Chicken* and *Beef*), upstream hog prices and other costs. $\beta_{(h)}$ is the coefficients of interest, which represent the dynamic effects on retail pork prices, $Pork_{t+h}$, due to a supply shock, keeping all else constant.

As in Eq. (4), the effect of supply shock on hog prices can be estimated as follows:

$$Hog_{t+h} = \alpha_h + \beta_{(h)} shock_t^D + \boldsymbol{\gamma X} + \mu_{(h)t+h} \qquad h = 0, 1, 2, \cdots, H \tag{5}$$

In addition to the above equations, we also address the impact of the ASF disease event on spill-over markets. Most obviously, consumers can substitute the product related to the disease event with alternative products, which can occur even when an animal disease outbreak is not harmful to human health. This can be related to the demand shock, the supply shock, or both. The impacts of demand and supply shocks in substitute markets have different interpretations. With a demand shock, the potential decrease of demand in the specific market causes consumers to increase demand in related substitute markets, even if the inward shift in the demand function leads to lower prices in the "diseased" market. However, with a supply shock, the increase in prices due to the upward shift in the supply function causes consumers to increase consumption in alternative markets. The relevant specification for the local projection estimates for the spill-over effects are obtained as follows:

$$P_{t+h}^S = \alpha_h + \beta_{(h)} shock_t^D + \boldsymbol{\gamma X} + \mu_{(h)t+h} \qquad h = 0, 1, 2, \cdots, H \tag{6}$$

where P_{t+h}^S represent retail substitute (*Chicken* and *Beef*) prices at time $t + h$, which is a function of the demand shock, ($shock_t^D$), controlling for the effects of control variables ($\boldsymbol{X}$). These controls include lags of the dependent variable, the supply shock, retail pork prices, upstream hog prices, and other costs. As previously, $\beta_{(h)}$ are the coefficients of interest, which represent the dynamic effects on prices of substitutes due to a demand shock, keeping all else constant.

As with Eq. (6), the effect of a supply shock on substitute prices can be estimated as follows:

$$P_{t+h}^S = \alpha_h + \beta_{(h)} shock_t^s + \boldsymbol{\gamma X} + \mu_{(h)t+h} \qquad h = 0, 1, 2, \cdots, H \tag{7}$$

3. Data

We employ weekly prices at retail (*pork*) and producer (*hog*) levels as well as the retail prices of substitutes (*beef* and *chicken*) from 2017 to 2019. The average prices of *pork* and *hogs* in this period were 24.5 and 15 yuan/kg, respectively, while the average prices of *beef* and *chicken* were 65.8 and 14.7 yuan/kg, respectively. We also use the price of oil to proxy for other food chain costs, as energy and transportation costs are particularly significant and variable over the period. Other candidates for cost data (e.g. pork processing, wage rates and related considerations) were not available at the weekly frequency we require. Table 1 presents our data description and sources, and Table 2 details summary statistics.

The next step is to identify supply and demand shifters to isolate their effects on price transmission. Similar to the media indices employed in other research (Sanjuán and Dawson, 2003; Lloyd et al., 2006; Hassouneh et al., 2010; Dai et al., 2015), we constructed a demand-side shifter indicator using the number of internet searches with ASF as a keyword in Chinese provinces on the Baidu search index during the given period. The variable is measured as Index = search volume per person × number of individuals based on IP addresses. The number of searches is obtained at a daily frequency and aggregated across days and all regions to construct a weekly indicator (*dsearch*). In principle, this indicator may represent positive or negative shifts in demand (consumers looking for confirmation about the control of ASF or concerns regarding the spread of the disease); however, we assume that this search measure is more likely to represent negative attitudes about the safety of pork. The data for the ASF search index are presented in Fig. 1, reporting this measure in two formats. In Fig. 1(a), we present the weekly number of searches, and in Fig. 1(b), we report the cumulative total. The justification for the latter is that the 'memory' associated with the disease is likely to persist, even if the search number is relatively low in any particular week. Both measures are therefore used as demand shifters ($shock_t^D$) in the econometric analysis.

The most obvious variable to employ as a supply shifter is the number of animals culled because of ASF. These data are available from the United Nations Food and Agricultural Organization's (FAO) EMPRES-i website.[4] The data recorded include the number of case outbreaks, the provinces in which outbreaks were located and the number of animals culled as a consequence of the disease at weekly frequency. In Fig. 2, we present the number of slaughtered pigs

Table 1
Variable Definitions and Data Sources.

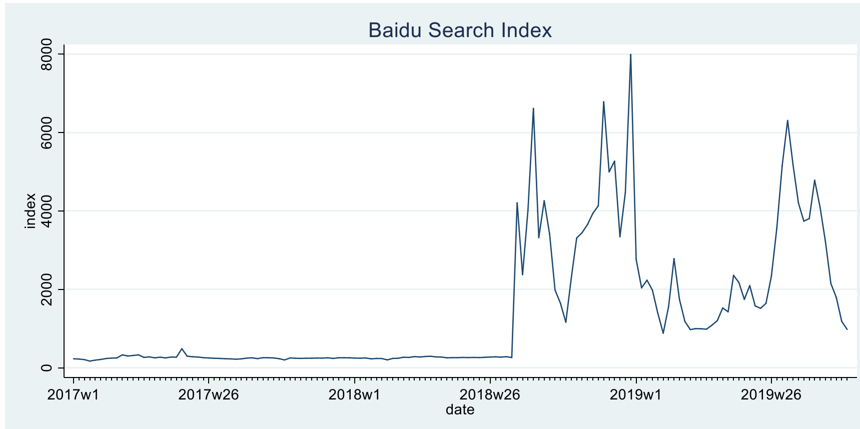
Variable	Definition	Unit	Data source
Pork	Price of pork	yuan/kg	CAIY,
Hogs	Price of live hogs	yuan/kg	CAHVY,
Beef	Price of beef	yuan/kg	CYAPS
Chicken	Price of chicken	yuan/kg	
Oil	Crude oil price at Daqing oil field	USD/ barrel	WIND database
Baidu Search	Cumulative Baidu search index	Index	Baidu.com
Culled	Number of animals culled due to ASF	Head	FAO EMPRESS
Total Culled	Cumulative number of animals culled due to ASF	Head	FAO EMPRESS
Import Price	Pork import unit value	USD/kg	WIND database

Notes: CAIY is the China Animal Industry Yearbook, CAHVY is the China Animal Husbandry and Veterinary Yearbook, and CYAPS is the China Yearbook of Agricultural Price Survey.

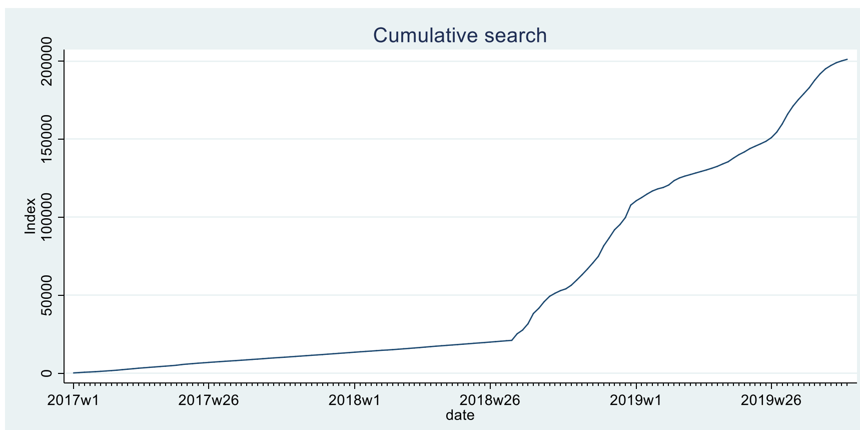
Table 2
Summary Statistics.

Variable	N	Mean	Median	Standard deviation	Minimum	Maximum
Pork (yuan/ kg)	144	25.1	24.5	4.31	19.2	43.4
Hogs (yuan/ kg)	144	15	14.4	3.2	10.4	27.8
Beef (yuan/ kg)	144	65.8	64.4	3.65	61.7	78.7
Chicken (yuan/ kg)	144	24.7	24.3	3.38	17.1	33.6
Oil (USD/ barrel)	144	271	269	49.6	132	379
Baidu search (index)	144	1397	282	1707	171	7994
Import price (USD/kg)	144	1.84	1.81	0.185	1.53	2.27

[4] https://empres-i.apps.fao.org/



(a): Baidu Search Index for ASF (weekly total)



(b): Baidu Search Index for ASF (cumulative total)

Fig. 1. (a) Baidu Search Index for ASF (weekly total). Fig. 1(b)**:** Baidu Search Index for ASF (cumulative total). Fig. 1**:** Internet Search Index for 'ASF': Number of Searches Across China Aggregated Across All Provinces.

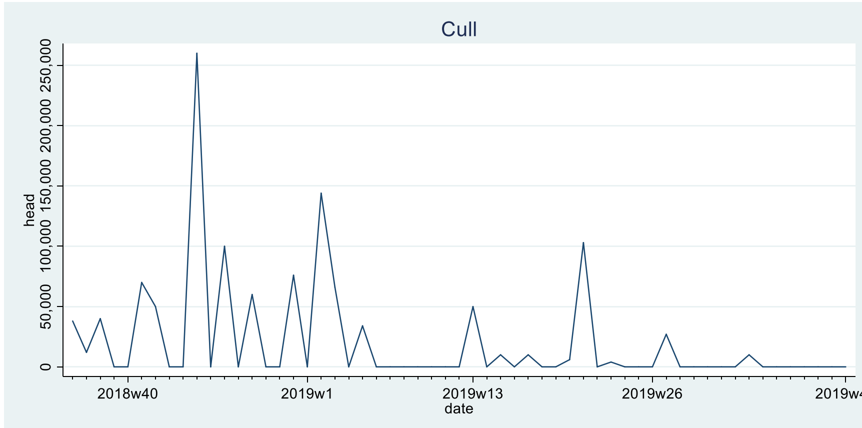
following confirmation of ASF in Chinese pig herds in two formats. In Fig. 2(a), the data represent the number of animals culled due to ASF per week from early 2018 to late 2019. As no animals were reported as being culled due to the disease outbreak in some weeks, we also report the total number of animals culled over the disease period in Fig. 2(b), which is recorded as the cumulative weekly number of animals culled since early 2018.

In principle, the data reported in Fig. 2 (the number of animals culled each week and the cumulative total) should serve as a useful measure of the supply-side shock associated with ASF; however, in the econometric analysis, the cull data did not reveal any significant impacts on prices due to ASF. This contradicts media reports on the extent of the crisis and the data on prices in the post-2018 period, which indicated considerably raised prices in both the retail and upstream markets, consistent with marked changes in availability. The data on animals culled due to ASF are also inconsistent with data on the reduction in herd numbers reported by the United States Department of Agriculture (USDA, 2019a). According to USDA data, herd numbers were expected to decrease by 36% between 2017 and October 2020, which is inconsistent with the culled data reported in FAO EMPRES-i. The most obvious potential reason for this inconsistency is that the cull data do not fully represent the ASF crisis in China.

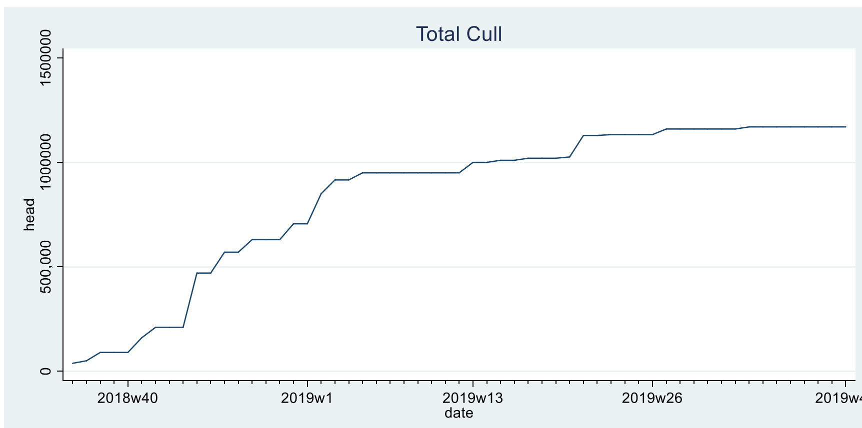
This has an important implication for the econometric analysis; in essence, requiring an alternative proxy for the supply shifter ($shock_t^S$) that is correlated with the disease event. The choice of alternatives is constrained by data availability and the need for weekly frequency. After considerable effort to identify a suitable alternative, the variable that most suitable in this context was determined to be prices of imported pork (*dimport*). Given China's role as the most significant pork consuming nation in world markets, the disease outbreak (which coincided with a relaxation of Chinese trade tensions with the US and Canada) led to a rise in pork imports. Given the 'large country' effect of China in the world pork market, import prices rose considerably in the disease period. Thus, the price of imported pork is used as a proxy for the supply shifter.

4. Results and discussion

Our main results are reported in Figs. 3 and 4. Each figure presents the impulse response functions of shocks to demand (Fig. 3) and supply (Fig. 4) on retail pork prices, upstream hog prices and the prices of beef and chicken (all expressed in yuan/kg). Each impulse response function traces the effect of a one-unit shock for a period of 18 weeks following the shock. For the demand shock, we simulate the effect of a one-unit change in the Baidu search Index, and for supply shock we simulate a one-dollar increase in the import price. One advantage of the linear projection framework we adopt (Jordà, 2005, 2009) is that the impulse responses are reported with 95% confidence intervals, which aid our



(a): Animals Culled Due to ASF (Weekly)



(b): Animals Culled Due to ASF (Cumulative Weekly Total)

Fig. 2. (a) Animals Culled Due to ASF (Weekly). Fig. 2(b)**:** Animals Culled Due to ASF (Cumulative Weekly Total). Fig. 2**:** Number of Pigs Culled Due to Confirmed ASF Outbreaks in China.

interpretation of the statistical significance of the projected effects. As the results in Fig. 3 show, the demand-side impacts of ASF are not statistically significant (the confidence interval encompasses zero). This suggests that consumers did not associate ASF with negative health impacts, which most likely due to the fact that ASF is not a zoonotic disease.[5] This result is robust to alternative definitions of the demand-side shifter; specifically, whether we use the number of searches or the cumulative number of searches. Conversely, Fig. 4 shows that the local projection impulse responses for the supply-side shifter are significant, with three important policy implications.

First, the effect of ASF on prices in the supply chain originated from the supply-side and not via demand. This suggests that in any future ASF outbreak in China, the government must focus on increasing the national supply of pork to reduce the social welfare losses that could arise from higher prices. Indeed, in response to the 2018 ASF outbreak, the Chinese government introduced a special subsidy programme for pork production to ramp up the supply of pork (Ma et al., 2021). The government also reduced import tariffs and attempted to directly increase imports, although the effectiveness of these policy measures was limited due to the global nature of the shock to pork supply (Mason-D′Croz et al., 2020). However, small and uninsured herd owners, who constituted about 60% of pig production in China and primarily relied on their livestock for income and household nutrition, were disproportionately affected during the outbreak, in part, due to low biosecurity levels (Wang et al., 2018).

Second, the impact of the ASF outbreak on retail prices was greater than its impact on upstream hog prices. In response to the ASF outbreak, while price increases at the farmgate and retail levels are both statistically significant (at a 5% significance level), our analysis shows that retail pork prices increased at around twice the size of hog price increases. This implies that the impact of ASF was 'over-shifted' to consumers. This result remains robust to alternative specifications. From a policy perspective, the ASF outbreak's effect on consumers and producers is important in terms of 'who paid' for the animal disease outbreak. Clearly, consumers' social welfare was diminished as they paid more for pork and the relative change in prices emphasises an impact of ASF on consumers. This is particularly important since pork constitutes about 63% of the total meat consumed in China (Ortega et al., 2009; He et al., 2016). Despite criticisms regarding food reserves as costly, inflexible and prone to generating corruption (Gilbert and Morgan, 2010), increasing state frozen pork reserves could be a strategic approach for buffering extreme price spikes in retail pork markets (Torero and von Braun, 2010; Von Braun and Tadesse, 2012).

Third, in the context of the econometric framework, this 'over-

[5] We would like to thank a referee for pointing this out.

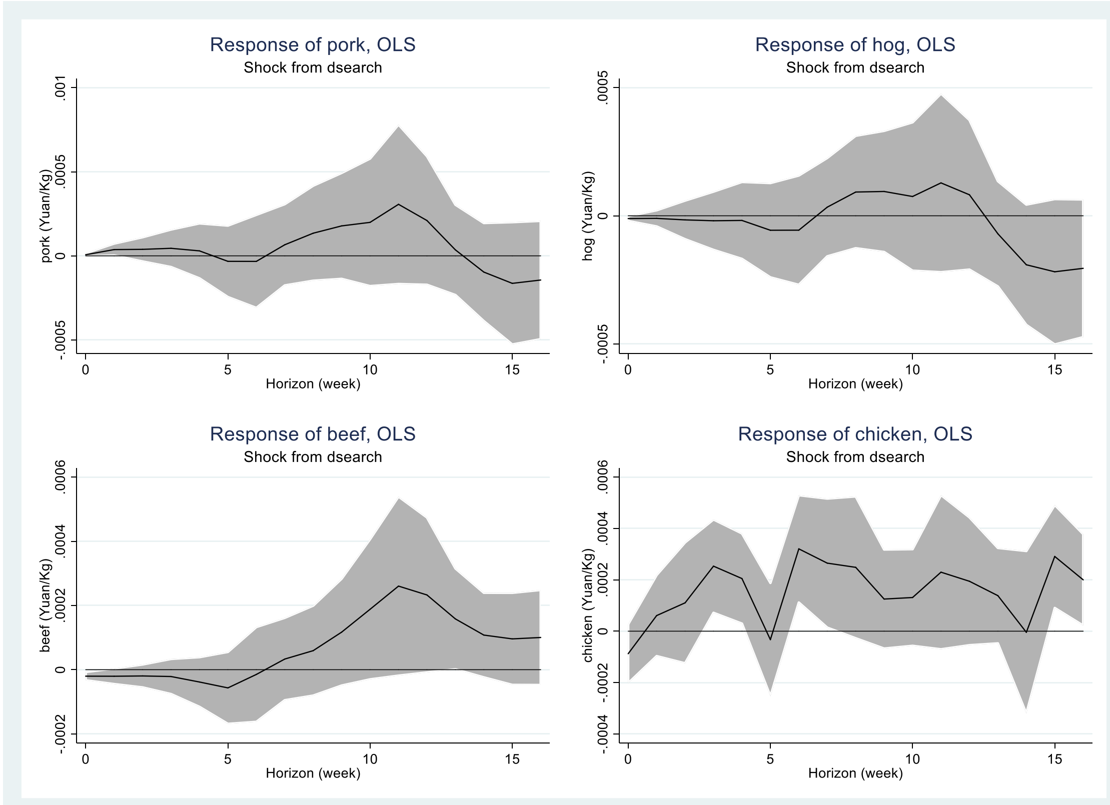


Fig. 3. Local Projection Impulse Responses: Demand Shifter Effects.

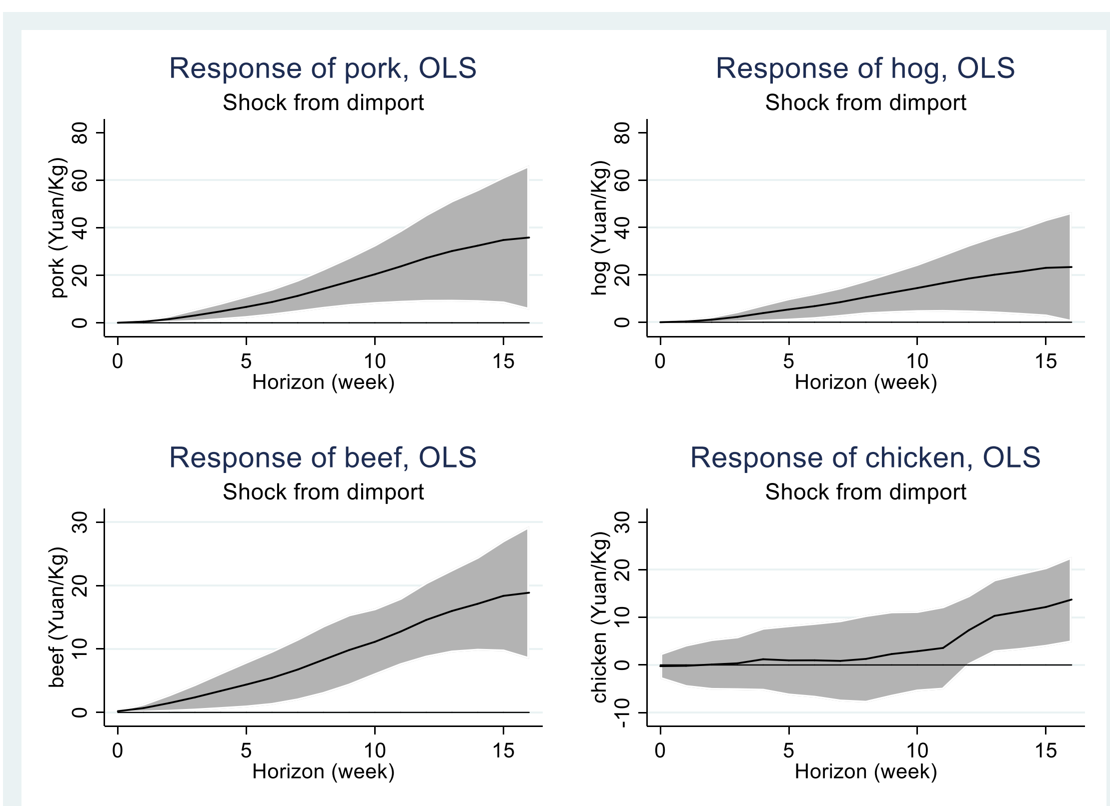


Fig. 4. Local Projection Impulse Responses: Supply Shifter Effects.

shifting' effect is also informative regarding the nature of the industrial organisation of Chinese meat supply chains as it provides evidence suggesting an imperfectly competitive meat supply chain in China.[6] While growing concerns have been raised regarding the concentration of firms in the Chinese food retail sector (Dai et al., 2015; Sexton and Xia, 2018), these results warrant a more detailed examination of the meat supply chain in China as the potential exercise of market power could have a significant influence on the effect of disease shocks on consumers and producers.

Finally, we find that the outbreak generates adverse spill-over effects on consumers in other associated markets, as the price of alternative meats also rise. Specifically, in response to the (one-dollar/kg) ASF shock, the retail price of beef and chicken rose by about 19 yuan/kg and 15 yuan/kg, respectively. Thus, if the prices of substitutes also rise as demand shifts towards these markets, then the welfare loss to consumer surplus originates in the shocked meat market as well as related markets. Such adverse spill-over effects can make substitution difficult for consumers, leading to harmful food security and nutritional repercussions such as reduced protein intake, particularly for the most vulnerable groups in Chinese society. Consequently, policymakers should maintain a food system-level view and consider applying interventions in substitute markets as well. Indeed Ma et al. (2021) found that reallocating some subsidies from the promotion of hog production to chicken production could lower a pork price spike following an animal disease outbreak.

5. Conclusions

Estimating the burden of disease on the food system can be a complex endeavour due to the market structure of supply chains; thus, it is crucial to assess the differential price impacts of animal disease shocks on producers and consumers to fully capture the broader welfare losses associated with these shocks. This study uses impulse response local projections to estimate the effects of demand- and supply-side shifters associated with ASF outbreak on price adjustments faced by different stakeholders in the Chinese pork value chain. This econometric framework can be applied to any animal disease outbreak, across a variety of settings.

The findings indicate that the ASF outbreak in China caused upstream hog prices and retail pork prices to increase, with the supply-side shock accounting for the dominant effect on price adjustments. In contrast to studies in other countries using similar media-based proxies for consumer preferences, we did not find statistically significant evidence supporting the assertion that the effects of the ASF outbreak originated in demand. Furthermore, the finding that retail pork prices rose more than upstream hog prices, indicates the potential exercise of market power in Chinese pork supply chains. These results provide evidence regarding how the industrial organisation of meat supply chains can redirect the burden of disease outbreaks onto different actors within meat supply chains. The results also suggest that the reduction in supply of pork due to ASF led to higher substitute meat prices, subsequently lowering consumers' ability to substitute consumption of other meats for pork consumption and illustrating the wider food system impacts of the ASF outbreak.

These findings do not come without limitations. The most relevant limitation is that the available culled hog data are considered not to be fully representative of the ASF crisis in China. Thus, in the econometric analysis, the cull data did not indicate any significant impacts on prices due to ASF. This has important implications for the econometric analysis requiring us to use a proxy for the supply shifter. The choice of alternatives was constrained by data availability and its frequency. After considerable effort to identify a suitable alternative, the variable that worked best in this context was found to be prices of imported pork. Nevertheless, the number of animals culled due to ASF would be a better proxy variable as supply shifter.

Policy interventions should focus on ameliorating the impact of disease outbreaks on consumers as well as producers. A range of policy options should address enhancing domestic supply by promoting sustainable production locally; increasing state reserves of frozen pork as a mechanism to buffer extreme spikes in retail pork prices; conducting a detailed examination of the level of market efficiency in the pork supply chain, as the presence of market power could be exacerbating the effect of disease shocks on consumers and producers; and subsidising the production of chicken as a close meat substitute that could help to smooth the effects of a pork price increase.

These results have important policy implications, indicating that animal disease outbreaks not only constitute welfare losses at the producer end, but the burden of disease can also significantly affect consumers and spill over into related markets. The findings highlight that these 'indirect' consequences vis-à-vis price adjustments must be considered and included in policy responses to effectively ameliorate societal losses from animal disease outbreaks. Indeed, a major portion of the burden of the impact of disease outbreaks can fall on consumers. Overall, the study illustrates that a disruption in one part of the food system can have major ripple effects on other parts of the system.

Acknowledgements

This research was conducted by the Livestock Policy Lab (LPL). The LPL is a science-policy platform hosted by the Livestock Information, Sector Analysis, and Policy Branch (NSAL) of the Animal Production and Health Division (NSA) at the FAO.

References

Acosta, A., Barrantes, C., Ihle, R., 2020. Animal disease outbreaks and food market price dynamics: Evidence from regime-dependent modelling and connected scatterplots. Aust. J. Agric. Resour. Econ. 64 (3), 960–976.
Acosta, A., McCorriston, S., Nicolli, F., Venturelli, E., Wickramasinghe, U., ArceDiaz, E., Scudiero, L., Sammartino, A., Schneider, F., Steinfeld, H., 2021. Immediate effects of COVID-19 on the global dairy sector. Agric. Syst. 192.
Andrews, D.W.K., 1991. Heteroskedasticity and autocorrelation consistent covariance matrix estimation. Econometrica 59, 817–858.
Brugnolini, L., 2018, About local projection impulse response function reliability. CEIS Working Paper No. 440.
Dai, J., Li, X., Wang, X., Yu, Q., & Mao, X., 2015, Food scares, market power and farm-retail price spread: The case of pork market in China. Paper selected for Presentation at the 2015 Agricultural and Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, California.
Gardner, B., 1975. The farm-retail price spread in competitive food industry. Am. J. Agric. Econ. 57, 399–409.
Gilbert, C.L., Morgan, C.W., 2010. Food price volatility. Philos. Trans. R. Soc. B: Biol. Sci. 365 (1554), 3023–3034.
Hassouneh, I., Serra, T., Gil, J.M., 2010. Price transmission in the Spanish bovine sector: the BSE effect. Agric. Econ. 41, 33–42.
Hassouneh, I., Radwan, A., Serra, T., Gil, J.M., 2012. Food scare crises and developing countries: The impact of avian influenza on vertical price transmission in the Egyptian poultry sector. Food Policy 37, 264–274.
He, Y., Yang, X., Xia, J., Zhao, L., Yang, Y., 2016. Consumption of meat and dairy products in China: A review. Proc. Nutr. Soc. 75 (3), 385–391.
Jordà, Ò., 2005. Estimation and inference of impulse responses by local projections. Am. Econ. Rev. 95 (1), 161–182.
Jordà, Ò., 2009. Simultaneous confidence regions for impulse responses. Rev. Econ. Stat. 91 (3), 629–647.
Kim, Y., Pendell, D.L., & Xia, T., 2019, Price transmission and supply shocks: The role of upstream and downstream market power. Agricultural and Applied Economics Association Meeting, Atlanta, Georgia.
Livanis, G., & Moss, C.B. 2005. Price transmission and food scares in the U.S. beef sector. American Agricultural Economics Association meeting, Providence, Rhode Island.
Lloyd, T., 2017. Presidential address: Forty years of price transmission research in the food industry: Insights, challenges and prospects. J. Agric. Econ. 68 (1), 3–21.
Lloyd, T., McCorriston, S., Morgan, C.W., Rayner, A.J., 2001. The impact of food scares on price adjustment in the UK beef market. Agric. Econ. 25, 347–357.
Lloyd, T.A., McCorriston, S., Morgan, C.W., Rayner, A.J., 2006. Food scares, market power and price transmission: The UK BSE crisis. Eur. Rev. Agric. Econ. 33 (2), 119–147.

[6] Specifically, contingent upon details regarding consumer demand, 'over-shifting' can only arise in supply chains in which market power can be freely exercised.

Ma, M., Wang, H.H., Hua, Y., Qin, F., Yang, J., 2021. African swine fever in China: Impacts, responses, and policy implications. Food Policy, 102065.
Mason-D′Croz, D., Bogard, J.R., Herrero, M., Robinson, S., Sulser, T.B., Wiebe, K., Willenbockel, D., Godfray, H.C.J., 2020. Modelling the global economic consequences of a major African swine fever outbreak in China. Nat. Food 1 (4), 221–228.
Newey, W.K., West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. Int. Econ. Rev. 777–787.
Ortega, D.L., Wang, H.H., Eales, J.S., 2009. Meat demand in China. China Agric. Econ. Rev. 1 (4), 410–419.
Park, M., Jin, Y.H., Bessler, D.A., 2008. The impacts of animal disease crises on the Korean meat market. Agric. Econ. 39 (2), 183–195.
Ronayne, D., 2011. Which impulse response function? AgEcon Search Work. Pap. No 2068–2018-2263.
Rushton, J., Mieghan, B., Bellet, C., Torgerson, P., Shaw, A., Marsh, T., Pigott, D., et al., 2018. Initiation of global burden of animal diseases programme. Lancet 392 (10147), 538–540.
Saghaian, S.H., Ozertan, G., Spaulding, A.D., 2008. Dynamics of price transmission in the presence of a major food safety shock: Impact of H5N1 Avian influenza on the Turkish poultry sector. J. Agric. Appl. Econ. 40, 1015–1031.
Sanjuán, A.I., Dawson, P.J., 2003. Price transmission, BSE and structural breaks in the UK meat sector. Eur. Rev. Agric. Econ. 30 (2), 155–172.
Savary, S., Akter, S., Almekinders, C., Harris, J., Korsten, L., Rötter, R., Waddington, S., Watson, D., 2020. Mapping disruption and resilience mechanisms in food systems. Food Secur. 12, 695–717.
Seok, J.H., Kim, G., Reed, M.R., Kim, S.E., 2018. The impact of avian influenza on the Korean egg market: who benefited? J. Policy Model. 40 (1), 151–165.
Serra, T., Zilberman, D., 2013. Biofuel-related price transmission literature: a review. Energy Econ. 37, 141–151.
Sexton, R.J., Xia, T., 2018. Increasing concentration in the agricultural supply chain: Implications for market power and sector performance. Annu. Rev. Resour. Econ. 10, 229–251.
Torero, M., & von Braun, J., 2010, Alternative mechanisms to reduce food price volatility and price spikes. International Food & Agricultural Trade Policy Council.
Ubilava, D., 2018. The role of El Niño southern oscillation in commodity price movement and predictability. Am. J. Agric. Econ. 100 (1), 239–263.
USDA, 2019b, Chinese hog farmers take risks to restock despite widespread African swine fever. GAIN Report: CH19035.
USDA, 2019a, Specter of African swine fever casts pall over year of the pig; beef imports benefit. GAIN Report: CH19006.
Von Braun, J., Tadesse, G., 2012. Global food price volatility and spikes: an overview of costs, causes, and solutions. ZEF-Discuss. Pap. Dev. Policy (161)).
Wang, T., Sun, Y., Qiu, H.J., 2018. African swine fever: an unprecedented disaster and challenge to China. Infect. Dis. Poverty 7 (1), 1–5.