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Pork Market Shocks and Inflation Dynamics in China

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Abstract

Background and Objectives: Pork occupies a central position in China's consumption basket and plays a critical role in shaping inflation dynamics, particularly through its substantial weight in food prices and its salience in public inflation expectations. Fluctuations in pork prices have long been associated with the so-called "pig cycle," traditionally viewed as a supply-driven phenomenon rooted in biological production lags. However, with the increasing complexity of China's food system, market liberalization, and heightened uncertainty arising from disease outbreaks, policy interventions, and global shocks, pork prices are no longer determined solely by supply-side factors. Demand-side pressures and precautionary behavior have become increasingly important, potentially amplifying inflation volatility. Existing studies often rely on linear frameworks or event-based approaches, which may obscure the nonlinear and state-dependent nature of inflation responses to pork-market shocks. Against this backdrop, this study aims to examine how different types of pork-market structural shocks—supply, demand, and precautionary demand—affect inflation dynamics in China across distinct inflation volatility regimes. By explicitly incorporating regime dependence, the study seeks to provide a more nuanced understanding of pork-driven inflation transmission and its implications for macroeconomic stabilization.

Methodology: The analysis employs monthly data covering the period from January 2009 to November 2024. A two-stage empirical strategy is adopted. In the first stage, pork-market structural shocks are identified using a structural vector autoregression (SVAR) framework inspired by the commodity-market identification strategy proposed by Kilian. Pork supply shocks are proxied by changes in production, demand shocks by slaughter volume, and precautionary demand shocks by real pork prices. In the second stage, the transmission of these shocks to overall CPI inflation and food CPI inflation is examined using both a linear benchmark model and a nonlinear Markov-switching regression. The Markov-switching framework allows inflation dynamics to differ endogenously between low- and high-volatility regimes, capturing nonlinear pass-through mechanisms that cannot be identified in linear models. In addition, the study investigates the role of policy-specific economic policy uncertainty indices in driving regime transitions, thereby linking pork-market shocks to broader macroeconomic uncertainty.

Key Findings: The empirical results reveal strong state dependence in the inflationary effects of pork-market shocks. In low-volatility inflation regimes, supply shocks and precautionary demand shocks are the primary drivers of inflation, while demand shocks play a limited role. In contrast, during high-volatility regimes, demand shocks and precautionary behavior dominate inflation dynamics, indicating that consumption pressures and expectation-driven responses become more influential when inflation is unstable. Across both regimes, food CPI inflation responds more strongly to pork-market shocks than headline CPI inflation, underscoring pork's role as a key amplifier of food-price pressures. The analysis further shows that supply shocks exhibit delayed effects on inflation, consistent with the long biological production cycle in pork markets, whereas demand and precautionary shocks exert more immediate impacts. Moreover, monetary policy uncertainty emerges as the most important factor triggering transitions between low- and high-volatility inflation regimes, highlighting the interaction between commodity-specific shocks and macroeconomic policy credibility.

Policy Implications: The findings point to the necessity of explicitly state-contingent inflation stabilization policies in China. In low-volatility environments, policy efforts should prioritize supply-side stabilization by enhancing production resilience, improving disease prevention, and strengthening the pork supply chain to mitigate delayed inflationary pressures. In high-volatility regimes, however, demand management and expectation anchoring become more critical, requiring timely policy communication, real-time price monitoring, and measures to curb precautionary and speculative behavior. Strengthening early-warning systems for pork prices and integrating information from futures markets and policy indicators can further improve inflation management. More broadly, the results suggest that effective inflation control in economies where staple food commodities play a central role requires adaptive policy frameworks that recognize nonlinear transmission mechanisms and regime-dependent dynamics.

Keywords: Pork Market; CPI; Food Inflation; SVAR; Markov-Switching; China

JEL Classification Codes: C32; Q11; E52

1. Introduction

Pork is the staple protein in the diets of Chinese residents and constitutes a substantial share of total meat consumption. It is not merely a food item but also a barometer of living costs and dietary culture. The literature indicates that pork prices account for roughly 9% of China's consumer price index (hereafter, CPI) (Ma et al., 2021) and about 12.8% of the food CPI (Bloomberg, 2019), so fluctuations in pork costs can directly affect inflation. From a price-stability and macro-management perspective, pork prices have therefore become a key variable for policymakers. Understanding the quantitative impact of pork price shocks on the overall price level can help the government stabilize inflation and provide forward-looking market intelligence for firms and participants across the pork supply chain.

Traditionally, fluctuations in pork prices are widely believed to be driven by supply (Qiao et al., 2016; Wang et al., 2023; Wang et al., 2023). This is also the main manifestation of the "pig cycle," which refers to cyclical movements in pig prices arising from shifts in supply and demand. These characteristics have been particularly evident in China in recent decades. Since 2000, China's pork industry has displayed relatively regular cycles: a three-year cycle from 2003 to 2006, a four-year cycle from 2006 to 2010, and then five-year and three-year cycles, respectively. However, the pricing mechanism of a mature product market is not completely supply driven.

Following the structural approach proposed by Kilian (2009) for the oil market, demand shocks and product-specific precautionary demand shocks should also be considered alongside supply shocks.

A supply shock reflects unexpected changes in pork production—such as those caused by disease outbreaks (e.g., African swine fever), policy interventions (e.g., slaughter bans), or feed-cost volatility—that directly affect availability; we capture this using the percentage change in pork production. A demand shock reflects unexpected shifts in actual pork consumption, influenced by income levels, food preferences, or prices of substitutes (e.g., beef or chicken); we proxy this with monthly slaughter volume, which reflects immediate market demand from consumers and processors. Precautionary demand in commodity markets typically arises from uncertainty about future supply or prices and leads market participants to stockpile or hedge. Following Kilian (2009), we use the real pork price as a proxy for precautionary demand in the pork market: during periods of heightened uncertainty, real pork prices often rise sharply even when contemporaneous supply or consumption does not fully explain the increase. Overall, China's pork prices appear to be transitioning from a predominantly supply-driven regime to a more complex system influenced by multiple shocks.

To manage the risks and price fluctuations associated with the "pig cycle," the government has implemented a series of policies in recent years. For example, the introduction of live pig futures contracts (listed on the Dalian Commodity Exchange in 2021) and hog insurance tools has helped guide market expectations and reduce farmers' risk exposure. In addition, consumers are encouraged to diversify their protein intake. The structure of food demand in China has indeed shifted (Hovhannisyan & Gould, 2011, 2014). These policies have reduced the impact of pork on the CPI to some extent, especially the upward pressure from high pork prices. Therefore, it is important to investigate the effects of pork price shocks on the CPI from the perspectives of supply, demand, and precautionary (speculative) demand.

Unlike some existing literature that directly uses price changes or events (like Covid-19 and African swine fever [ASF henceforth]) as shocks (Baquedano & Liefert, 2014; Kashyap et al., 2024; Wang et al., 2020; Wang et al., 2023), this paper adopts a more structural and theoretical model to define shocks. Specifically, the shocks in this paper refer to a disturbance term that cannot be predicted from the historical information of itself or other factors. This definition is not only in line with the basic understanding of structural shocks in modern macroeconomics (Kilian, 2009) but also can more effectively identify the dynamic impacts of different types of shocks such as supply, demand and precautionary demand. By estimating a structural vector autoregression (SVAR henceforth) model, this paper extracts the main factors affecting pork prices from multiple dimensions and quantifies their impacts to inflation, respectively. This provides a more convincing empirical basis for understanding the relationship between pork price and inflation.

Furthermore, the impacts of commodity (or pork) shocks on CPI have been found to differ across economic conditions (e.g., high vs. low inflation, high vs. low volatility) (Abbas, 2022; Abbas & Lan, 2020; López-Villavicencio & Pourroy, 2019). When the environment is stable, pass-through tends to be stable as well, and commodity price shocks are less likely to trigger broad reactions. However, once the environment becomes unstable, market expectations are prone to shift—especially because pork prices can serve as an anchor. Residents often regard pork as a representative CPI item, making "self-fulfilling" price-increase expectations easier to ignite. Accordingly, incorporating nonlinearity into the analytical framework not only improves explanatory power for pork-price changes but also better reflects the dynamic features of the real economy.

This paper models pork price structural shocks using a SVAR and a nonlinear Markov-switching regression to assess their effects under different inflation states. The main empirical findings are as follows. First, in the low-volatility state, supply and precautionary-demand shocks are the primary drivers of inflation, whereas in the high-volatility state, demand and precautionary (speculative) demand dominate. Second, food inflation is more sensitive to pork price shocks than headline CPI, indicating that pork, as a staple, amplifies food-price pressures. Third, supply shocks exhibit lagged effects—consistent with long breeding cycles and market response times—so their transmission to CPI is more time-accumulated. These results highlight the limits of the traditional “pig cycle” view and confirm nonlinear pass-through in China’s inflation dynamics. On this basis, we propose state-contingent policy strategies tailored to prevailing inflation regimes.

The paper is organized as follows. Section 2 reviews the literature. Section 3 describes the methodology. Section 4 presents the data. Section 5 reports the empirical results. Section 6 concludes, and Section 7 discusses the policy implications.

2. Literature Review

The impact of fluctuations in food prices on inflation has always been an important topic of concern both domestically and internationally (Abbas & Lan, 2020; Adjemian et al., 2024; Davidson et al., 2016; Furceri et al., 2016; García-Germán et al., 2016; Peersman, 2022). For example, Abbas and Lan (2020) find the food commodity price pass-through on inflation in China is around 0.044 in the short run and 0.109 in the long run only in the low inflation state, which in is line with theoretical framework in Taylor (2000). They also confirm dynamics in the inflation and find the pass-through is not significant in the high inflation state. In terms of the impact of pork price on inflation, Xin and Wang (2008) studied the causes of inflation in China in 2004 and explored whether the rise in agricultural product prices was the main driving factor. The study has found that as a key component of residents' daily consumption, the rise in pork prices has played a significant role in driving up the current CPI. Furthermore, the rise in pork prices not only directly affects CPI through cost push mechanisms but may also exacerbate inflationary pressures by increasing public expectations of sustained price increases in the future, forming an "expectation behavior" feedback effect (Kikuchi & Nakazono, 2023).

Previous studies have focused on the nonlinearity in the macroeconomic dynamics by using different methods (e.g., Abbas & Lan, 2020; Deluna et al., 2021; Guo, 2013; Hwang & Zhu, 2024). For example, Abbas and Lan (2020) used threshold regression and Markov state transition models to systematically examine the impacts of international commodity prices on inflation under different inflation states. They found that the transmission elasticity of agricultural and energy commodities is more significant in emerging economies such as China in low inflation regime. This discovery validates and extends Taylor's (2000) pass-through theory, which suggests that in low and stable inflation environments, the transmission of input cost shocks to final prices tends to weaken. In addition, inflation targeting policy plays a central role in regulating inflation fluctuations for inflation targeting countries, including China. This system helps achieve price stability by setting clear inflation rate targets or fluctuation ranges, guiding inflation expectations, and enhancing the transparency and foresight of monetary policy (Mishkin & Schmidt-Hebbel, 2001). Hwang and Zhu (2024) further suggest that in countries implementing inflation targeting, the duration of the high inflation phase caused by commodity price shocks is significantly shortened due to the strengthening of the central bank's ability to manage expectations in policy frameworks.

The pig cycle, as a typical price fluctuation phenomenon in agricultural economics, has long been widely concerned about its causes. The traditional theory holds that the pig cycle originates from the biological characteristics of pig production and the time lag effect of market regulation (Coase & Fowler, 1937). When price increases, farmers expand production capacity. However, due to the long breeding cycle of pigs, the increase in supply lags behind demand, thus forming a fluctuation cycle of price capacity price. However, recent studies have shown that the causes of pig cycles are becoming increasingly complex. Qiao et al. (2016) pointed out that as farming methods shift from free range farming to large-scale farming, production decisions gradually become detached from short-term feedback of price signals, leading to market supply no longer responding synchronously to price changes, thereby exacerbating cyclical fluctuations. External shock factors have also become an important factor affecting the pig cycle. Ma et al. (2021) and Wang et al. (2023) have pointed out that the ASF epidemic has led to a significant decrease in stocks, which is the direct cause of an extreme pig cycle since 2018. Besides, Covid-19 not only disrupted the balance between supply and demand but also triggered market panic and intensive policy intervention. It exacerbates the magnitude and persistence of price fluctuations. Similarly, Wang et al. (2020) emphasized from the perspective of COVID-19 that supply chain disruptions have limited the circulation of live pigs in the short term, further driving high pig prices. Bedside, Huang and Xiong (2025) confirm that the newly listed pig futures in China provide a risk management tool for the pig market and have been proven to be effective to a certain extent through empirical analysis. The intervention of financial instruments can also lead to fluctuations in commodity prices, which is also present in other financialized commodities (Chatziantoniou et al., 2021).

3. Methodology

For detecting the impact pork structural shocks on inflation, we use a two-stage method in this paper where we first construct the different pork price shocks by using the identification of structural shocks for oil market from Kilian (2009). Then, we assess the different effects on China's inflation in the second stage under different macroeconomic dynamics. The dynamics are identified via different Markov chains.

3.1 Structural Vector Autoregression (SVAR)

In the SVAR model, typically, the expression for SVAR can be of the matrix form:

$$\boldsymbol{AX_t = B_1X_{t-1} + \cdots B_{12}X_{t-12} + \epsilon_t}$$

where $\mathbf{X_t}$ is a vector with three variables for $\boldsymbol{t = 1, \ldots, n}$: (i) the percentage change in pork production (production), (ii) the monthly slaughter volume (demand), (iii) the real pork price (precautionary); $\boldsymbol{\epsilon_t}$ is a vector of uncorrelated structural shocks and they are given economic meanings in the latter empirical analysis.

The structural VAR can be transformed into a reduced-form VAR:

$$\boldsymbol{X_t = A^{-1}B(L)X_{t-1} + e_t} \tag{1}$$

Where $\boldsymbol{e_t}$ is a vector of correlated errors. The contemporaneous relationships among variables are identified as:

$$\boldsymbol{e_t = \begin{Bmatrix} e_{porduction} \\ e_{demand} \\ e_{precautionary} \end{Bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \epsilon_t} \tag{2}$$

The identification describes that the pork supply does not respond to innovation of pork demand within the same month; the demand would respond to the shock of precautionary demand in pork. The real price of pork is assumed to be affected by production and demand within the same month.

3.2 Effects of Pork Market Shocks on Inflation

3.2.1. Linear Model

The second step is to estimate the effects of three pork structural shocks on China's price levels. Here we also consider the lag of price CPI inflation as the control variable to control impacts from other potential factors. It helps us reduce other influences besides the three shocks we considered.

$$\boldsymbol{inf_t = \alpha + \rho_1\epsilon_{supply_t} + \rho_2\epsilon_{demand_t} + \rho_3\epsilon_{precautionary_t} + \rho_4 inf_{t-1} + u_t} \tag{3}$$

Where $\boldsymbol{inf}$ is the inflation rate of CPI and food CPI. $\boldsymbol{\epsilon_{supply_t}}$, $\boldsymbol{\epsilon_{demand_t}}$ and $\boldsymbol{\epsilon_{precautionary_t}}$ are exogenous shock from SVAR estimation, representing supply, demand and precautionary shocks respectively. $\boldsymbol{inf_{t-1}}$ is the lag of inflation as the control variable. The $\boldsymbol{\rho_i}$ capture the effects of structural shocks on inflation rate.

3.2.2. Markov Switching Method

Linear estimation might be mis-specified due to macroeconomic dynamics. In the macroeconomic analysis, the occurrence of major economic shocks often triggers structural breaks in stochastic processes through dynamic correlations. If this endogenous nonlinear feature is ignored, it will lead to errors in regression models and statistical inference. To avoid misjudging the transmission mechanism of the economic system, it is necessary to conduct a nonlinear model. In the second step, we also conduct a Markov switching model, which is proposed in Hamilton (1989), to create a state-space model. Markov-switching models assume there are various states for estimated variable and model would identify transition probabilities from one state to others, according to a Markov process. This model is particularly suitable for analyzing time series data with nonlinear features, such as inflation. For China's CPI, the state switching model can effectively capture its structural changes under economic cycles, policy adjustments, or external shocks. We estimate the shocks effects in different states endogenously. Econometrically speaking, it relaxes homogeneity assumption on the shock coefficient across stable and unstable environments. The approach also estimates probabilities of switching across states.

Here we propose a two-state first-order Markov-switching dynamic model (MSDR) by extending the benchmark model, distinguishing high volatility state from low volatility state in our context. The MSDR model is widely used in monthly data analysis. The model is present as follows:

$$\begin{aligned} \boldsymbol{inf_t} = \boldsymbol{\alpha_{s_t}} + \boldsymbol{\rho_{1,s_t}\epsilon_{supply_t}} + \boldsymbol{\rho_{2,s_t}\epsilon_{demand_t}} + \boldsymbol{\rho_{3,s_t}\epsilon_{precautionary_t}} \\ + \boldsymbol{\rho_{4,s_t}inf_{t-1}} + \boldsymbol{u_t} \end{aligned} \tag{4}$$

where $\boldsymbol{\alpha_{s,t}}$ and $\boldsymbol{\rho_{i,s_t}}$ refer to the state-variant coefficients of independent variables. $\boldsymbol{u_t}$ is the *IID* but with zero mean and difference variances depended on states. For a Markov process, the transition probabilities are of greater interest. The stochastic state indicator variable $\boldsymbol{s_t} \in \{\boldsymbol{1}, \dots, \boldsymbol{M}\}$, generated by an ergodic M-state Markov chain governed by the transition probability:

$$\boldsymbol{p_{ij}} = \boldsymbol{P_r(s_{t+1} = j|s_{t=i})}, \boldsymbol{\sum_{j=1}^{M} p_{ij} = 1} \, \forall \boldsymbol{i,j} \in \{\boldsymbol{1},\dots,\boldsymbol{M}\}$$

In this case, we assume the states are divided into two states, low and high volatility states. The transitions between states are written in a $\boldsymbol{2 \times 2}$ matrix. For example, $\boldsymbol{p_{11}}$ is the probability of staying in low inflation volatility state in the next period when it has been in the same state currently. Similarly, $\boldsymbol{p_{21}}$ is the probability of moving to low volatility state from high volatility state. If the transition probability closer to 1, it indicates persistence of this state or higher duration. The model is estimated by maximum likelihood procedure.

4. Data

For the SVAR estimation, the dataset includes pork-related variables: pork production, slaughter volume, and pork price. Pork production—proxied by the monthly stock of pigs and sows—and slaughter volume are sourced from the Ministry of Agriculture and Rural Affairs (MARA), representing pork supply and demand, respectively. Pork price data are obtained from the Wind Financial Terminal and consist of weekly national wholesale prices aggregated into monthly averages. The real pork price, deflated by the Consumer Price Index (CPI), is used as a proxy for precautionary demand in the pork market. Additionally, macroeconomic variables—namely the CPI and food CPI—are sourced from the National Bureau of Statistics (NBS) to capture overall inflation dynamics and food price movements.

The dataset comprises monthly observations spanning over 15 years, from January 2009 to November 2024. Furthermore, this study investigates the potential effects of Economic Policy Uncertainty (EPU) indices on inflation transition dynamics. These EPU indices, developed by Huang and Luk (2020), encompass four components: fiscal policy, monetary policy, trade policy, and exchange rate and capital account policy. It should be noted, however, that these indices ceased being updated in June 2022. Descriptive statistics for all variables are summarized in Table 1.

Table 1. Variables and Data Sources

Variables	Time period	Data sources	Note
CPI	2009M1–2024M11	National Bureau of Statistics (NBS)	Consumer price index
Food CPI	2009M1–2024M11	National Bureau of Statistics (NBS)	Consumer price index: Food items
Pork production	2009M1–2024M11	Ministry of Agriculture and Rural Affairs (MARA)	Proxy for pork supply
Slaughter volume	2009M1–2024M11	Ministry of Agriculture and Rural Affairs (MARA)	Proxy for pork demand
Pork price	2009M1–2024M11	Wind Financial Terminal	National wholesale pork price, deflated by the CPI, used as a proxy for Precautionary Demand.
Policy-specific EPU Indices	2009M1–2022M6	Huang & Luk (2020)	Indices covering fiscal, monetary, trade, and exchange rate policies

Source: Authors' compilation.

Table 2 summarizes the statistical characteristics of percentage changes in three key variables in the Chinese pork market. The monthly average change in supply is –0.61%, indicating a general downward trend in inventory over the sample period, accompanied by substantial volatility (maximum value 4.00%, minimum value –9.10%). The extreme negative observations are likely associated with major supply disruptions, such as the African swine fever (ASF) outbreak. The monthly average change in slaughter volume is close to zero (0.01%), suggesting that pork demand is relatively stable on average, although it still exhibits noticeable short-term fluctuations (SD = 0.09). The range of slaughter volume changes spans from –0.28% to 0.28%, which may reflect seasonal demand patterns and short-term supply adjustments. The monthly average change in real pork prices is 2.73%, indicating sustained price increases with relatively low short-term volatility (SD = 0.27), with values ranging from 2.35% to 3.41%.

Table 2. Statistics Summary

	N	Mean	Max	Min	SD
Panel A. Inflation					
CPI Inflation	133	0.13	1.60	-1.20	0.49
Food CPI Inflation	133	0.23	6.70	-4.20	1.89
Panel B. Pork					
Supply	133	-0.61	4.00	-9.10	1.88
Demand	133	0.01	0.28	-0.28	0.09
Precautionary	133	2.73	3.41	2.35	0.27

Source: Authors' calculation.

Unit root and structural break tests were conducted for all variables, with the results reported in Table 3. ADF test results indicate that inflation, pork supply, and pork demand reject the null hypothesis of a unit root at the 1% significance level, while pork precautionary demand does so at the 5% level. Furthermore, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992) fails to reject the null hypothesis of stationarity for all variables, providing additional support for stationarity.

To account for potential structural breaks, the Clemente–Montañés–Reyes test (Clemente et al., 1998) was also employed. Structural breaks are identified in CPI inflation and food CPI inflation at the 5% significance level, with breakpoints occurring in March 2020 (2020M3) and December 2015 (2015M12), respectively. In contrast, no structural breaks are detected in the pork-specific variables.

Table 3. Unit Root and Structural Break Tests

	ADF test	KPSS test	Clemente test	
Variable	**Test statistics**	**Test statistics**	**Test statistics**	**Breakpoint**
CPI Inflation	-9.635***	0.049	-9.442**	2020M3
Food CPI Inflation	-8.518***	0.044	-8.070**	2015M12
Supply	-4.798***	0.073	-2.450	
Demand	-14.435***	0.046	-1.734	
Precautionary	-2.890**	0.221	-3.065	

Source: Authors' calculation.
*Note: ADF tests the null hypothesis of a unit root, while KPSS tests the null of stationarity. Lag length selection is based on the Bayesian Information Criterion (BIC). Structural breaks are identified using the Clemente–Montañés–Reyes test. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

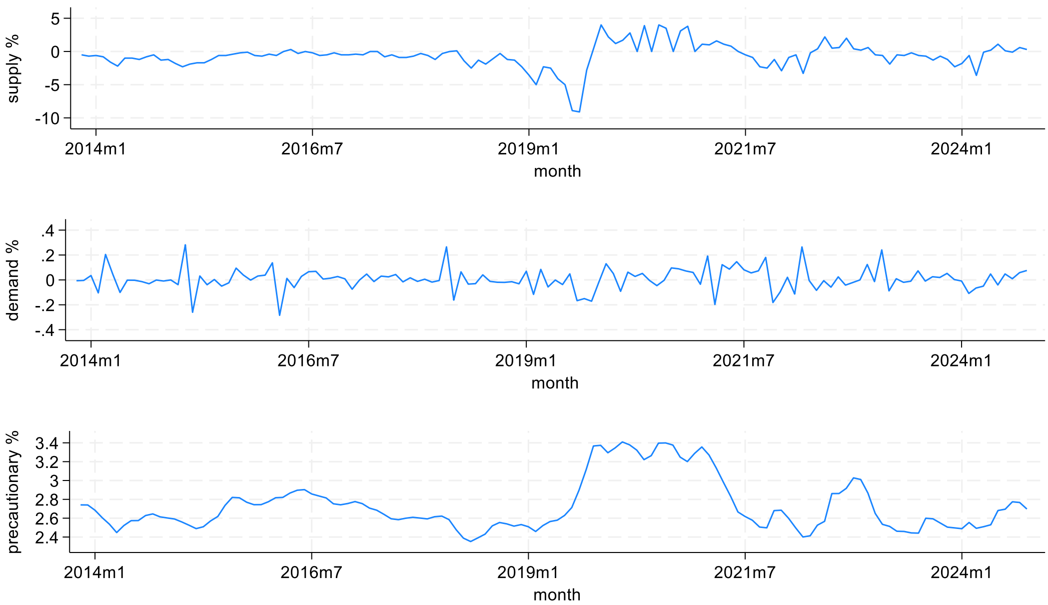


Figure 1. Pork Market Dynamics in China: Supply, Demand, and Real Prices
Source: Authors' compilation based on data from the Ministry of Agriculture and Rural Affairs (MARA) and Wind Financial Terminal.
Note: The vertical axis reports the monthly percentage change (%) in pork supply, pork demand, and real pork prices (proxy for precautionary demand), respectively. The horizontal axis denotes time (months), covering January 2014 to November 2024.

Figure 1 depicts the monthly percentage changes in pork supply, demand, and real pork prices in China over the period 2014–2024. The first subgraph shows that pork supply experienced pronounced fluctuations and sharp declines after 2019, with the lowest observations approaching -10%. These extreme movements are likely associated with major supply disruptions, most notably the African swine fever (ASF) outbreak, which led to a substantial reduction in pig inventories. From the second half of 2020 onward, supply gradually recovered, and fluctuations became more moderate, possibly reflecting policy intervention and market adjustment. The middle subgraph indicates that pork demand is relatively stable on average, with short-term fluctuations remaining limited in magnitude. Monthly changes range between approximately -0.28% and 0.28%, suggesting that demand variations are primarily driven by seasonal factors—such as holiday-related consumption—or short-term adjustments during supply tightness. The third subgraph illustrates that real pork prices increased sharply following the COVID-19 outbreak, peaking at around 3.4%, before declining after 2021 and eventually stabilizing. This pattern suggests that heightened price pressures coincided with periods of supply–demand imbalance and elevated market uncertainty.

5. Empirical Results

The empirical findings are presented in two parts, following the two-step methodology outlined in Section 3. In the first stage, a SVAR model is estimated to identify structural shocks within the pork market. This section reports the statistical summaries and graphical representations of these shocks, while the associated Impulse Response Functions (IRFs) are provided in the Appendix. In the second stage, the analysis evaluates the impacts of different pork-market structural shocks on both overall CPI inflation and food CPI inflation, utilizing a linear benchmark alongside a nonlinear Markov-switching model.

5.1 Structural Shocks in Chinese Pork Market

Figure 2 illustrates the identified structural shocks in the pork industry, derived from the SVAR model estimation in Equation (1). These shocks are categorized into three distinct types: supply, demand, and precautionary shocks. Each panel corresponds to a specific shock and depicts its estimated values over the sample period.

The supply shock (top panel) is typically associated with factors affecting pork production and the supply chain, such as disease outbreaks, fluctuations in feed costs, and policy interventions. Notably, the results reveal that the African Swine Fever (ASF) outbreak in 2019 led to a substantial negative supply shock, which severely constrained pork production and market availability.

The demand shock (middle panel) captures shifts in consumer demand for pork, influenced by economic conditions, consumer preferences, or the prices of substitute goods. The COVID-19 pandemic had a significant impact on demand dynamics, driven by income fluctuations, mobility restrictions, and evolving consumer behaviors.

Precautionary shocks (bottom panel), which reflect market participants' responses to uncertainty, exhibited extreme values primarily during the COVID-19 period. This suggests that heightened uncertainty during the pandemic led to excessive market concerns, which were subsequently transmitted to prices through speculative behavior and precautionary inventory adjustments.

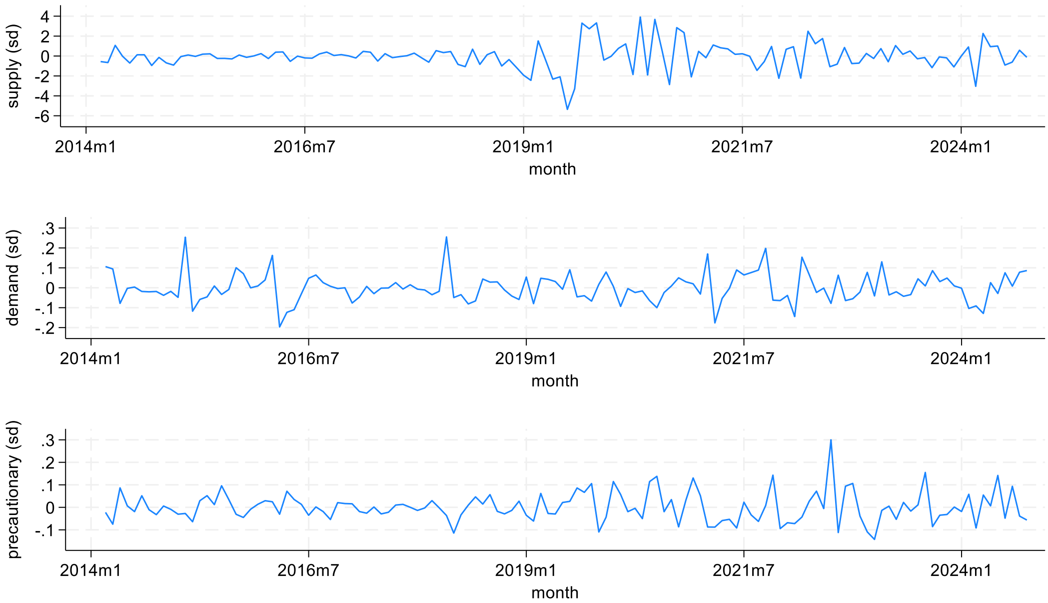


Figure 2. Structural Shocks in the Chinese Pork Market
Source: Authors' calculation.
Note: The vertical axis shows the estimated structural shocks identified from the SVAR model, measured in standard deviation units. Positive (negative) values indicate expansionary (contractionary) shocks. The horizontal axis denotes time (months).

5.2 The Impacts of Pork Shocks

Table 4 presents the results of the linear regression based on Equation (3), illustrating the varying impacts of structural shocks on China's CPI and food CPI inflation. The linear estimation indicates that both demand shocks and precautionary shocks exert significant positive impacts on both inflation measures, with the magnitude of these effects being considerably stronger for food CPI inflation (6.885 and 14.544, respectively). This suggests that shifts in market demand and heightened uncertainty are primary drivers of food price fluctuations. Conversely, supply shocks do not exhibit a statistically significant impact on either CPI or food CPI in the linear model. This lack of significance may stem from the weaker short-term effects of supply disruptions or the limitations of a linear framework in capturing the dynamic adjustments inherent in the supply chain. The model's goodness of fit further supports these observations, with an R^2 of 0.305 for food CPI inflation—exceeding the 0.202 for overall CPI inflation—indicating that pork-related shocks are more effective in explaining variations in food prices.

Table 4. Linear Estimation Results

Variable	CPI inflation	Food CPI inflation
L. Inflation	0.188*	0.324***
	(2.30)	(4.22)
Supply Shock	-0.003	-0.064
	(-0.10)	(-0.59)
Demand Shock	1.916***	6.885***
	(3.48)	(3.45)
Precautionary Shock	2.982***	14.544***
	(4.74)	(6.32)

Variable	CPI inflation	Food CPI inflation
Constant	0.091*	0.113
	(2.25)	(0.79)
R^2	0.202	0.305
BIC	173.7	503.5

Source: Authors' calculation.
*Note: The dependent variables are CPI inflation and food CPI inflation. Heteroskedasticity-robust t-statistics are reported in parentheses. "L." denotes the lag operator. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

The nonlinear estimation results are summarized in Table 5, where parameters are estimated across two distinct regimes: low-volatility and high-volatility states. In the low-volatility state (State 1), the estimated variances (σ_1) are 0.10 for CPI inflation and 0.99 for food CPI inflation. Within this regime, both supply shocks and precautionary shocks significantly influence inflation, whereas demand shocks appear insignificant. Specifically, supply shocks exert a negative impact on both inflation measures, suggesting that supply-side factors contribute to price stabilization during periods of low volatility. In contrast, precautionary shocks maintain a positive impact, indicating that market hedging or precautionary behavior can still drive price increases even in a stable environment. However, the duration of State 1 is relatively brief, averaging 2.67 months for overall inflation and 4.45 months for food inflation, suggesting a high propensity for transitioning into the high-volatility regime.

In the high-volatility state (State 2), demand and precautionary shocks emerge as the predominant drivers of inflation. Lagged inflation—representing inflation persistence—shows a significant positive impact, implying that inflation is more difficult to mitigate during highly volatile periods. While the immediate coefficients for supply shocks are not significant in this state, further analysis (available in the Appendix) reveals significant lagged effects after approximately five months. During this regime, the impact of demand shocks becomes highly significant, identifying consumption growth as a key driver of price escalations. Furthermore, the influence of precautionary demand is amplified, particularly in its effect on food inflation. The expected duration for State 2 is longer for overall inflation (approximately 5.40 months), indicating a persistent difficulty in restoring price stability once high volatility is triggered. Food inflation, despite its high volatility, exhibits a faster recovery rate with an expected duration of 2.54 months in the high-volatility state.

Table 5. Markov-Switching Estimation Results

Variable	Inflation	Food inflation
State 1		
L. Inflation	-0.278**	-0.198
	(-2.86)	(-1.50)
Supply Shock	-0.199***	-0.449*
	(-4.45)	(-2.48)
Demand Shock	-0.247	1.812
	(-0.33)	(0.68)
Precautionary Shock	2.254*	10.811***
	(2.37)	(3.93)
Constant	-0.082	-0.722*
	(-1.20)	(-2.40)
σ_1	0.10	0.99

Variable	Inflation	Food inflation
State 2		
L. Inflation	0.403***	0.707***
	(3.70)	(7.93)
Supply Shock	0.040	-0.087
	(1.21)	(-0.77)
Demand Shock	2.202***	4.515*
	(3.61)	(2.11)
Precautionary Shock	2.956***	12.933***
	(4.02)	(4.97)
Constant	0.180***	0.613***
	(4.06)	(3.46)
σ_2	0.52	1.44
P_{12}	0.37	0.22
P_{21}	0.19	0.61
dur_1	2.67	4.45
dur_2	5.40	2.54

Source: Authors' calculation.
Note: State 1 and State 2 correspond to the low- and high-volatility inflation regimes, respectively. σ_i denotes the state-dependent variance, P_{ij} represents the transition probability from state i *to state* j*, and dur_i indicates the expected duration of state* i*. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

Table 6 reports the long run effects of different shocks for CPI inflation and food CPI inflation. Similar with estimation in Table 5, the results indicate significant heterogeneity in the long-term mean growth rates across different states. In the low volatility state (State 1), supply shocks have a significant effect on inflation and food inflation (-0.156 and -0.375). Precautionary demand exerts a positive effect on inflation, with a significantly amplified impact observed in food inflation (1.764 and 9.028). The demand shock did not pass the significance test in this state. However, in the high volatility zone (State 2), the impact of demand shocks on inflation rise to 1.723, and food inflation reached 3.770. The precautionary shock amplifies inflationary pressures in this state, with its effect on CPI inflation rising to 2.314, while the impact on food CPI inflation surges markedly to 10.800. Supply shock has no significant impact in State 2. Overall, the response of food inflation to precautionary shocks far exceeds inflation in both states. The results also reveal that during low volatility state, attention should be paid to the sustained transmission of supply shocks, while during high volatility state, priority should be given to controlling demand sides.

Table 6. Long-Run Effects of Structural Shocks

Variable	Inflation	Food inflation
State 1		
Supply Shock	-0.156***	-0.375**
	(-4.74)	(-2.29)
Demand Shock	-0.194	1.512
	(-0.34)	(0.66)
Precautionary Shock	1.764**	9.028***
	(2.21)	(3.10)
State 2		
Supply Shock	0.041	-0.073

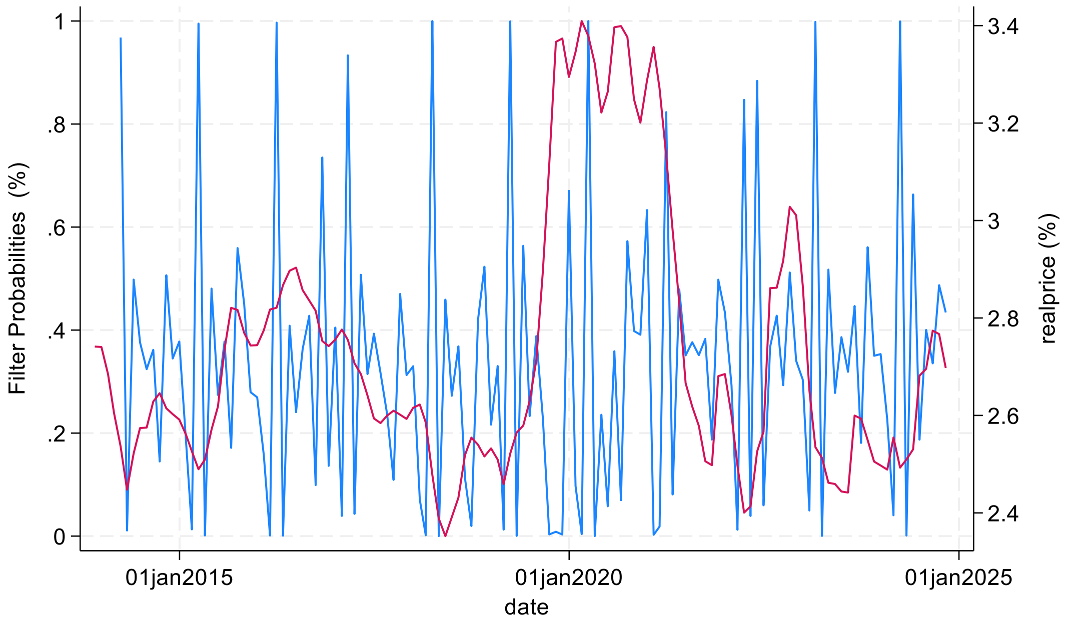
Variable	Inflation	Food inflation
	(1.21)	(-0.77)
Demand Shock	1.723***	3.770**
	(3.51)	(2.11)
Precautionary Shock	2.314***	10.800***
	(3.88)	(4.30)

Source: Authors' calculation.

*Note: Long-run effects are computed as $\rho_i/(1-\rho_4)$ based on Equation (4), where ρ_i denotes the state-dependent shock coefficient and ρ_4 is the coefficient on lagged inflation in the Markov-switching model. Test statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

In the Markov switching model, filter probability represents the posterior conditional probability of the economic variable being in state i based on time t and all previous observed information. According to Panel A in Figure 3, it finds that the volatility of CPI inflation in China exhibits significant regional heterogeneity. For CPI inflation, the filtered probability during the sample period shows that it remained in a low volatility state for the long term before 2019. However, after 2019, especially during the COVID-19, the probability from low volatility state to high volatility state increased significantly. This dynamic can be attributed to the supply chain disruption caused by the impact of the epidemic and the frequent policy interventions of the central bank (such as targeted liquidity injection). They intensified the frequency of regional system switching by changing market expectations and policy transmission paths. In Panel B, the filtering probability of food CPI inflation shows a characteristic of high volatility zone dominance. This heterogeneity stems from the sustained impact of supply shocks in agricultural products: the pig cycle, climate disturbances, and transportation cost fluctuations collectively constitute strong seasonal effects and cycles. The filter probability graph aligns the estimated duration in Table 5, 4.45 months in the low volatility state and 2.54 months in the high volatility state.

Panel A. CPI inflation



Panel B. Food CPI inflation

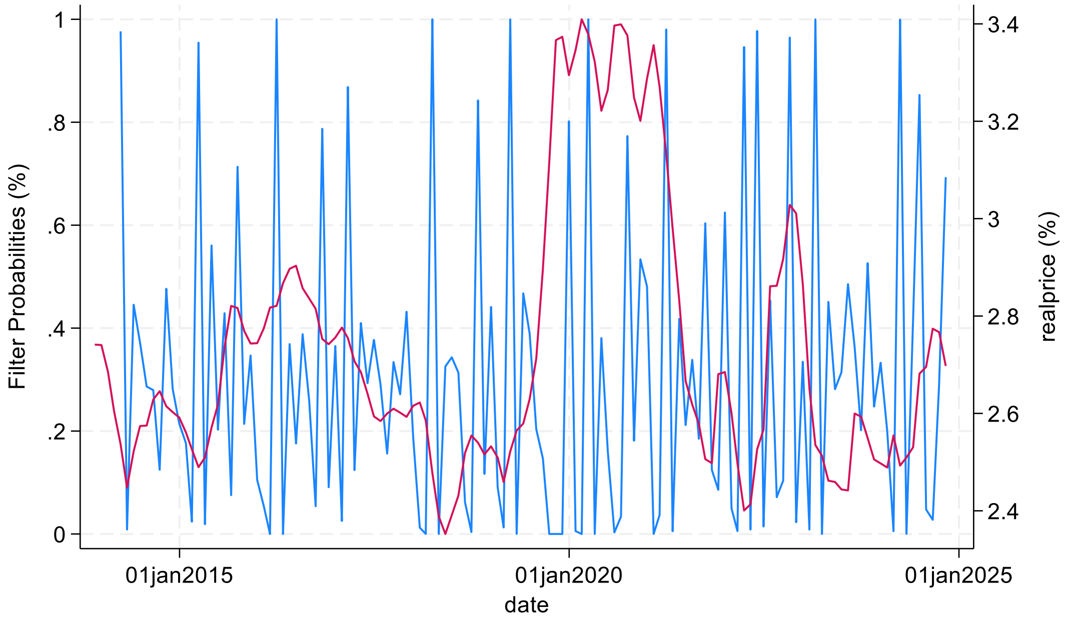


Figure 3. State Probabilities from the Markov-Switching Inflation Model
Source: Authors' calculations.
Note: The vertical axis reports the filtered probability (0–1) (100%) that CPI inflation is in the low-volatility regime. The horizontal axis denotes time.

5.3 What Drives the Regime Switching

Based on the significant states transition of inflation in China (low volatility and high volatility states), here we also aim to systematically identify the key economic policy uncertainty (EPU henceforth) factors driving the transition of inflation states, including the heterogeneous effects of fiscal policy, monetary policy, trade policy, exchange rate policy. We use the filtered probability of low inflation volatility state as the dependent variable and these four policy shocks as independent variables. Following Basher et al. (2018), we use arcsine function to transfer dependent variable as it values 0 to 1. The regression is estimated as follows:

$$\begin{aligned} arc\sqrt{p_t} = \mu_0 + \mu_1 EPU_{fiscal_{t-i}} + \mu_2 EPU_{monetary_{t-i}} + \mu_3 EPU_{trade_{t-i}} \\ + \mu_4 EPU_{ex_{t-i}} + \varepsilon_t \end{aligned} \quad (5)$$

Where p_t is the filter probability in the low inflation volatility state estimated from Equation 4. EPU is the policy-specific EPU indices, including four aspects of macroeconomic policy uncertainties. As the lag in effect of macroeconomic policy, we include the lag terms of each EPU index in the model, rather than use the contemptuous term in the estimation.

The impacts of policy-specific EPU indices on the filter probability of low volatility state are presented in Table 7. The results show that the transition of fiscal policy to inflation has a significant negative impact, and the increased uncertainty of fiscal expansion reduces the probability of low volatility. Monetary policy shocks also have a negative impact, with larger estimators. An increase in the monetary policy index would significantly decrease the probability of being in the low volatility state eventually, rather than other EPU indices. The trade policy uncertainty index only has a negative impact on the probability of being in the low volatility state for CPI inflation, with the value at -0.094. The heterogeneity between estimation for CPI inflation and food inflation may be raised by the proportion of imported and exported goods. As an important agricultural and populous country, the main food sources in China are product domestically. The overall price level is more susceptible to the influence of trade policies due to many import and export transactions. Different from other EPU indices, exchange rate and capital account policy uncertainty index affects the filter probability positively. The increased instability of exchange rate policies is due to stabilize or strengthened capital controls, ultimately helping to maintain a low volatility state. Although policy tool adjustments may increase operational instability (policy uncertainty increases), they ultimately reduce economic and financial stability risks by isolating external risks Beirne and Friedrich, (2017). Thus, an increased in exchange rate policy uncertainty index would increase the probability of staying in the stable state. Overall, Monetary policy uncertainty is a key driver of inflation transition. The goal of monetary policy directly anchors inflation stability. The increasing monetary policy uncertainty would destabilize expectations and reduces confidence in the central bank's ability to control inflation. This uncertainty makes households and firms more reactive to economic shocks, amplifying inflation fluctuations. As a result, even small disturbances can trigger a shift from a low to high volatility regime in inflation.

Table 7. Drivers of Inflation Regime Switching

Variable	Inflation	Food inflation
Fiscal policy	-0.158*	-0.215*
	(-1.78)	(-2.18)
Monetary policy	-0.359**	-0.389**
	(-3.15)	(-3.08)
Trade policy	-0.094*	-0.082
	(-1.91)	(-1.50)
Exchange rate and capital account policy	0.175*	0.191*
	(2.45)	(2.42)
Constant	2.654***	2.882***
	(3.98)	(3.90)
R^2	0.156	0.159
BIC	89.2	109.8

Source: Authors' calculation.

*Note: The dependent variable is the filtered probability of being in the low-volatility inflation state, transformed using the arcsine function. Lagged values of policy-specific economic policy uncertainty (EPU) indices are included. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

6. Conclusion

This paper examines the nonlinear impacts of pork-market structural shocks on inflation in China, employing a structural vector autoregression (SVAR) model combined with a Markov-switching framework to capture state-dependent dynamics. The analysis distinguishes the roles of supply, demand, and precautionary demand shocks in shaping inflation outcomes across different volatility regimes.

The empirical results yield three main findings. First, the transmission mechanisms of pork price shocks vary markedly across inflation states: supply shocks and precautionary demand shocks play a dominant role in the low-volatility state, whereas demand shocks and precautionary (speculative) demand become the primary drivers during high-volatility states. Second, food CPI responds more strongly to pork price shocks than headline CPI, highlighting pork's central role as a staple commodity that amplifies inflationary pressures within the food sector. Third, supply shocks exhibit delayed effects on inflation due to the long biological production cycle of pork, underscoring the importance of time-accumulated transmission in price dynamics.

These findings challenge the traditional "pig cycle" narrative by demonstrating the increasing complexity of China's pork market, where inflation dynamics are shaped by the interaction of supply disruptions, demand fluctuations, and precautionary behavior. More broadly, the results underscore the necessity of state-dependent policy frameworks: supply-side stabilization is particularly relevant in low-volatility environments, while managing demand pressures and inflation expectations becomes more critical during periods of heightened volatility. Overall, this study provides a nuanced understanding of pork-related inflation dynamics in China and offers a coherent analytical basis for designing adaptive and state-sensitive inflation management strategies.

7. Policy Implications

Based on the identified nonlinear effects of pork-market shocks on inflation, this study highlights the importance of adopting state-dependent policy responses rather than uniform stabilization measures. Under low-inflation-volatility states, policy efforts should prioritize supply-side stabilization by supporting farmers in expanding production capacity, improving breeding efficiency, and enhancing resilience along the pork supply chain. Such measures help mitigate delayed inflationary pressures arising from supply disruptions associated with the long biological production cycle of pork.

In contrast, during high-inflation-volatility states, greater attention should be paid to demand-side management and expectation stabilization. Policy instruments such as temporary consumption subsidies, encouragement of protein substitution, and clear communication strategies can help prevent demand shocks and precautionary behavior from further amplifying price pressures. These targeted interventions are crucial for avoiding the inefficiencies associated with "one-size-fits-all" policies and underscore the need for an effective mechanism to identify prevailing inflation regimes in real time.

Moreover, given the prominent role of precautionary and expectation-driven shocks—particularly in high-volatility environments—the findings support strengthening price early-warning and monitoring systems. Integrating information from futures markets, statistical indicators, and predictive analytics can improve the early detection of abnormal price movements in pork markets. Finally, establishing a core food basket monitoring framework, with pork as a central component, would provide a more robust empirical basis for inflation surveillance and enhance policymakers' capacity to stabilize food prices and overall inflation dynamics.

More broadly, the state-dependent policy framework developed in this study offers a transferable reference for emerging Asian economies, where food staples play a central role in consumption baskets and inflation dynamics, and where similar supply shocks, demand fluctuations, and expectation-driven behaviors pose recurring challenges to price stability.

8. Acknowledgments

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10. Appendix

In the appendix, we include the impulse response of SVAR estimation of Equation 2. The results are presented in Figure A1. To validate the reliability of our identified pork market structural shocks and their transmission to inflation, we conduct a robustness check by incorporating CPI inflation directly into the SVAR model as an endogenous variable. We maintain the recursive identification strategy, allowing inflation to respond contemporaneously to pork supply, demand, and precautionary (price) shocks, while assuming pork variables are not contemporaneously affected by inflation. The results are presented in Figure A2. As the robustness check of second stage, we conduct the Markov switching regression with more lags and the results are presented in Table A1.

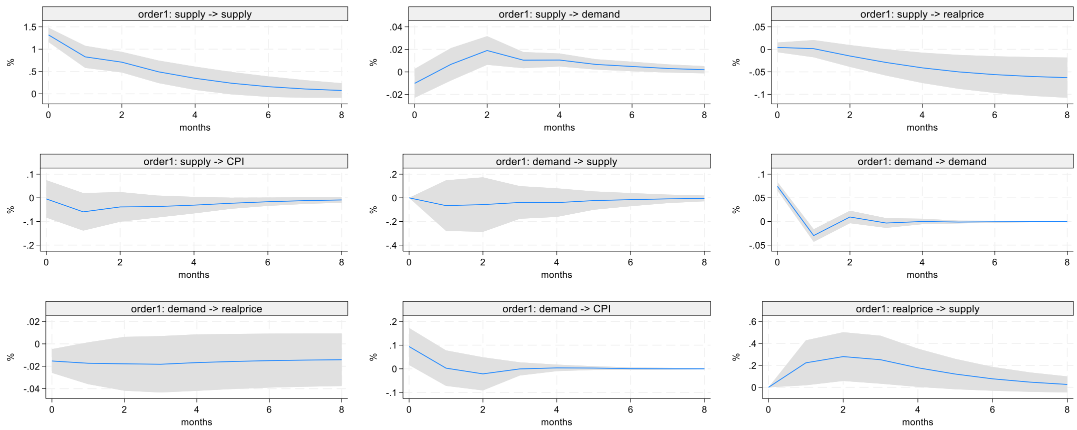

Figure A1. Impulse Response Functions from the SVAR Model
Source: Authors' calculation.
Note: The vertical axis shows the percentage response of each variable to a one-standard-deviation structural shock. Shaded areas indicate 95% confidence intervals. The horizontal axis is measured in months.

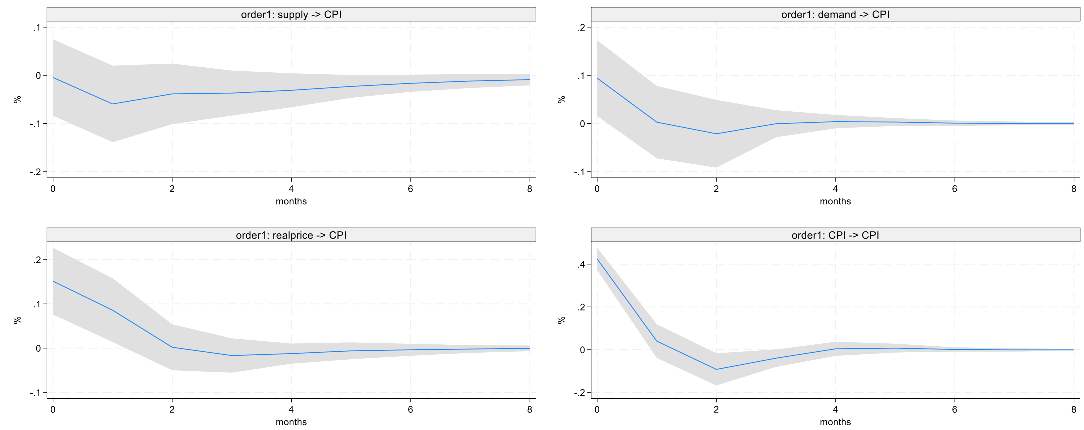

Figure A2. Inflation Responses to Pork Market Structural Shocks
Source: Authors' calculation.
Note: The vertical axis represents the percentage-point change in CPI inflation and food CPI inflation following each identified pork market shock. The horizontal axis is measured in months.

Table A1. Markov-Switching Estimation with Additional Lags

	Inflation		**Food inflation**	
	State1	State2	State1	State2
L.CPI	-0.164***	-0.129	-0.278***	0.431***
	(-8.01)	(-1.23)	(-147.51)	(4.04)
Supply Shock	-0.117***	0.039	0.087***	0.027
	(-13.91)	(1.32)	(39.42)	(0.27)
L.Supply Shock	-0.176***	-0.036	-0.119***	-0.100
	(-24.54)	(-1.13)	(-50.62)	(-0.91)
L2.Supply Shock	-0.108***	-0.014	-0.232***	0.088
	(-22.34)	(-0.47)	(-60.59)	(0.93)
L3.Supply Shock	0.028***	0.047	-0.145***	0.158
	(3.54)	(1.65)	(-55.65)	(1.54)
L4.Supply Shock	-0.104***	-0.034	-0.295***	-0.191*
	(-16.33)	(-1.13)	(-66.40)	(-2.03)
L5.Supply Shock	-0.102***	-0.021	-0.153***	-0.066
	(-23.11)	(-0.65)	(-47.22)	(-0.59)
L6.Supply Shock	-0.091***	-0.087**	-0.557***	-0.239*
	(-12.36)	(-2.97)	(-203.85)	(-2.38)
Demand Shock	2.403***	2.692***	12.974***	10.274***
	(13.66)	(5.07)	(255.14)	(5.57)
L.Demand Shock	-0.221*	0.940	5.001***	-0.188
	(-2.32)	(1.41)	(120.67)	(-0.08)
L2.Demand Shock	0.402***	-0.479	7.806***	1.245
	(4.31)	(-0.73)	(79.81)	(0.73)
L3.Demand Shock	-0.119	-1.174	9.651***	-2.095
	(-0.88)	(-1.64)	(127.32)	(-1.17)
L4.Demand Shock	-1.083***	1.218	4.096***	2.436
	(-10.80)	(1.84)	(72.45)	(1.36)
L5.Demand Shock	0.108	1.346	5.722***	2.364
	(1.37)	(1.95)	(89.42)	(1.17)
L6.Demand Shock	0.827***	0.792	6.086***	2.903
	(7.29)	(1.33)	(86.79)	(1.68)
Precautionary Shock	2.711***	2.416***	15.490***	12.565***

	Inflation		**Food inflation**	
	State1	State2	State1	State2
	(21.27)	(3.84)	(228.13)	(5.53)
L.Precautionary Shock	1.789***	2.263**	13.032***	-0.431
	(15.75)	(2.96)	(175.98)	(-0.17)
L2.Precautionary Shock	1.386***	1.414	6.987***	-0.984
	(17.49)	(1.74)	(126.66)	(-0.41)
L3.Precautionary Shock	-1.218***	-0.203	1.759***	-1.978
	(-6.76)	(-0.22)	(22.67)	(-0.91)
L4.Precautionary Shock	-0.960***	0.227	1.312***	0.748
	(-9.57)	(0.28)	(21.70)	(0.37)
L5.Precautionary Shock	0.001	0.165	3.780***	-0.393
	(0.01)	(0.23)	(42.05)	(-0.20)
L6.Precautionary Shock	-0.330	2.686***	3.062***	10.015***
	(-1.87)	(4.43)	(41.67)	(4.65)
constant	-0.148***	0.333***	-0.833***	0.528***
	(-17.40)	(6.60)	(-183.18)	(4.30)
lnsigma	-3.530***	-1.136***	-4.207***	0.086
	(-21.05)	(-13.58)	(-31.44)	(1.17)
P_{12}	0.43		0.70	
P_{21}		0.22		0.21
dur_1	2.32		1.43	
dur_2		4.63		4.74

Source: Authors' calculation.

*Note: The table reports Markov-switching estimation results with additional lags of structural shocks. State 1 and State 2 correspond to low- and high-volatility regimes. L. denotes the lag operator. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*