Are Agricultural Commodity Prices on a Conventional Wisdom with Inflation?

Ting-Ting Sun, Chi-Wei Su, Ran Tao, and Meng Qin

Abstract

The study investigates the mutual influence between agricultural commodity prices (ACP) and inflation (INF) in China by employing the bootstrap full- and sub-sample rolling-window Granger causality tests. We find that ACP has positive effects on INF, indicating that agricultural commodities play a significant role in stabilizing general price levels, but the higher ACP may create inflationary pressures. However, the negative effects suggest that under the shock of external uncertainty, the rise of ACP is not always regarded as the prime driver of INF. The results are not consistent with Hypothesis 1, which highlights that INF is positively affected by ACP. In turn, we also find positive and negative impacts of INF on ACP, showing that the level of INF can affect the supply and demand of agricultural commodity markets, it can be considered as a factor affecting ACP. The findings support Hypothesis 2 derived from the interaction mechanism. These analyses can assist the Chinese government to understand that ACP is not an effective indicator for forecasting INF. It also can prompt them to pay attention to the transmission effect of price levels on ACP, to maintain the stability of the agricultural commodity market.

Keywords

agricultural commodity prices, inflation, causality, rolling-window

Introduction

The primary target of this study is to investigate whether agricultural commodity prices (ACP) can always be viewed as the prime driver of inflation (INF). Fluctuations in commodity prices since early 2000 have renewed policymakers’ attention to their effects on INF (Sekine & Tsuruga, 2017). Energy or non-energy commodities are crucial inputs to the production process, and their price increases may indicate inflationary pressures (Tule et al., 2019). The role of commodity prices as the main indicator of INF is increasingly important (Fernandez, 2014). Agricultural commodities are closely related to economic activities, because they can reflect the pressure of domestic demand and supply, and have a driving effect on INF (Nguyen et al., 2017; Tule et al., 2019). The spillover effect of the global ACP surge in 2006–2008 has left most countries in a state of high inflation rate (Balcilar & Bekun, 2020). It has become a consensus that rise in ACP is likely to cause INF (Irawati et al., 2019). As agricultural commodities are key inputs in the production process of many goods, changes in ACP are reflected in the marginal cost of production, that is ultimately transmitted to the aggregate price level (Garratt & Petrella, 2019). INF has a significant positive impact on relative price fluctuations of agricultural commodities both in the short- and long-run (Ukoha, 2008). INF positively affects ACP (Goudarzi et al., 2012), and it explains approximately 15% of the change of ACP (Tabakis, 2001). Higher INF generates expectations of rising prices and triggers market speculation and grain storage, thereby reducing the supply of agricultural commodities and causing ACP to rise (Johnson & Song, 1999). Consequently, there is a significant interrelationship between ACP and INF (Balcilar & Bekun, 2020; Ciner, 2011; Okorie & Ohakwe, 2018). The mutual influence indicates that agricultural commodities perform a very important role in government efforts to stabilize general price levels. Also, the level of INF can influence the more susceptible to inflationary pressure from ACP shocks (Gelos & Ustyugova, 2017). In turn, commodity price booms are more likely to occur when the inflation rate is high, which puts upward pressure to prices (Kyrtoua & Labysb, 2006; Pindyck & Rotemberg, 1990). INF has a significant positive impact on relative price fluctuations of agricultural commodities both in the short- and long-run (Ukoha, 2008). INF positively affects ACP (Goudarzi et al., 2012), and it explains approximately 15% of the change of ACP (Tabakis, 2001). Higher INF generates expectations of rising prices and triggers market speculation and grain storage, thereby reducing the supply of agricultural commodities and causing ACP to rise (Johnson & Song, 1999). Consequently, there is a significant interrelationship between ACP and INF (Balcilar & Bekun, 2020; Ciner, 2011; Okorie & Ohakwe, 2018). The mutual influence indicates that agricultural commodities perform a very important role in government efforts to stabilize general price levels. Also, the level of INF can influence the

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The agricultural sector still plays essential roles in the emerging economies (Mariyono, 2019b). For instance, the contribution of Indonesian agricultural sector to employment and national income is about 30% and 12%, respectively (Mariyono, 2019a). Agriculture plays a vital role in the Thai economy as the country is a major exporter of agricultural and food products which generate income for farming households and the labor force (Saiyut et al., 2017). More than 50% of the population in India is still dependent on agriculture for their livelihood (Sasmal, 2015). Due to the rapid change in Chinese economic structure from 1987 to 2017, the agricultural sector has become a more integral component of the whole economy. In the recent years, the role of the agriculture becomes more dominant by its indirect contribution either through the agri-food system or through enhanced linkages with the rest of the economy (Y. Zhang & Diao, 2020). Moreover, INF in emerging markets is often driven by large, persistent changes in agricultural commodity and energy prices (Amstad et al., 2018). China has a huge demand for agricultural commodities, and changes in ACP can have an impact on the overall inflation rate (Wächter, 2016). Since the implementation of economic reforms and opening policies in the late 1970s, ACP has shown a trend of frequent fluctuations (Xie & Wang, 2017). China has experienced a rise in ACP and a high INF level since the end of 2003, which has once again sparked the debate about whether the increase in ACP causes INF (Xin & Wang, 2007). ACP tends to have a strong and sustained impact on INF in countries with a high share of food in the consumption basket (Gelos & Ustyugova, 2017). In China, food prices take up a much higher share of the CPI (C. Zhang et al., 2014), and INF caused by the increase in ACP is more significant (S. Wang, 2013). If ACP increases are sufficiently persistent to influence inflation expectations, producers will raise the price of final goods to offset rising costs, which may lead to higher price levels (Cheung, 2009). Accordingly, the rising ACP has an inflationary effect in China (Zhuang, 2012). However, the degree of the impact of rising ACP on the overall price level has shown an obvious downward trend (X. Q. Wang & Qian, 2004). For instance, with the global economic recession, China has raised the minimum purchase price of agricultural commodities in 2009, which does not significantly increase the general price level (Qin et al., 2009). From 2012 to 2013, ACP in China is at a relatively high level driven by global energy prices, while the inflation rate has declined due to the weaker macroeconomic performance. Besides, speculative trading causes ACP to rise in 2016–2017, but the level of INF exhibits a downward trend due to China’s supply-side structural reform. This shows that in the presence of external uncertainties, INF may be at a low level during the period of high ACP (or INF may be soar during the period of low ACP). Therefore, there may be a negative effect of ACP on INF. In turn, an inflationary shock has a significant effect on commodity prices (Oscorio & Unsal, 2013). The positive causal effect of INF on ACP has been evidenced, because INF causes a reduction in real interest rates, and an increase in demand for physical asset and agricultural commodities, which leads to a rise in ACP (J. Li & Fan, 2005).

The study contributes to the literature in several respects. First, prior studies explore the relationship between ACP and INF. There is sufficient evidence to point out the positive effect of ACP on INF, that is, the increase in ACP is the Granger cause of INF (Balcilar & Bekun, 2020; Garratt & Petrella, 2019; Gelos & Ustyugova, 2017; Irawati et al., 2019; Okorie & Ohakwe, 2018; Tule et al., 2019). Less literature explores the influence of INF on ACP (Akpan & Udoh, 2009; Goudarzi et al., 2012; Guloglu & Nazlioglu, 2013; Taslimi et al., 2012; Ukoha, 2008), indicating that INF can significantly and positively affect ACP. However, the existing empirical evidence on whether ACP has a negative effect on INF is rather limited. Generally, external uncertainty shocks can affect the equilibrium of aggregate supply and demand and may strengthen or weaken the impact of agricultural commodities on general price levels. That is, the relationship between ACP and INF may be positive and negative over time, which is ignored by the existing studies. In short, the increase in ACP may no longer have a pulling effect on INF in the presence of external uncertainties. Therefore, this article can be considered a pioneering effort to investigate whether ACP is always regarded as the prime driver of INF. And then, we fill the gaps in previous studies by exploring the negative influence from ACP to INF.

Second, the Granger causality between ACP and INF could be non-constant. The previous literature has not examined if a structural change could affect this causality. We employ the bootstrap sub-sample rolling-window causality test, to identify the non-constant interaction between ACP and INF. The empirical results point out that there are positive and negative effects of ACP on INF, which are not consistent with Hypothesis 1 derived from the interaction mechanism. The positive impact suggests that agricultural commodities play an important role in stabilizing the price level, but higher ACP may create inflationary pressures. However, the negative impact indicates that under the shock of external uncertainties (e.g., the monetary policy and macroeconomic condition changes, global oil prices, and the exchange rate fluctuations), ACP cannot always be viewed as the prime driving factors of INF. We also find the positive and negative impacts from INF to ACP, which supports Hypothesis 2 derived from the interaction mechanism. Thus, we contribute to the literature by exploring the time-varying interrelationship between ACP and INF and ensuring the reliability and accuracy of our results.

In addition, this study can provide revelations for the Chinese government to ensure an adequate supply of the agricultural commodities to avoid a sharp rise in ACP, which...
is conducive to maintaining the goal of low and stable INF and economic stability. It can give insights for them to focus on the external uncertainties that may affect changes in price levels, and thus cannot always attribute INF to the rise of ACP. Also, the agricultural-related sectors need to pay sufficient attention to the transmission effect of the price level on the agricultural commodity market.

The article has been arranged as follows: First, the “Literature Review” section gives an overview of the relevant studies. We illustrate the theoretical foundation and research hypothesis in the section “Theoretical Analysis and Research Hypothesis” and reveal the test methods of causality in the “Method” section. Next, the “Data” section presents the data used in the study. The “Empirical Results” section explains empirical results. The final section provides conclusive remarks.

**Literature Review**

The inter-linkages between ACP and INF have already been studied, but there is no consensus in the previous literature. Many studies have confirmed the positive causality from ACP to INF. Kowal et al. (2008) believe that the rise in ACP has led to INF. Baek and Koo (2010) suggest that ACP plays a key role in the short- and long-term changes of the U.S. inflation; the increase in ACP leads to the rise in input costs for production, thereby increasing food prices. Okorie and Ohakwe (2018) indicate that about 12% dependency of Nigeria’s inflation on the world prices of its major export is agricultural commodities. Irawati et al. (2019) conclude that prices of major agricultural commodities have a positive and significant impact on INF in Sumatra, that is, if the prices of rice rise by 1%, the inflation rates will increase by 0.116%. Mariyono (2019b) denotes that chili provides a significant contribution to the local and national economy in Indonesia, and it has the potential to trigger INF. Balciolar and Bekun (2020) reveal that there is a positive impact of ACP on INF. In turn, there are several studies that support that INF can affect ACP. Lapp and Smith (1992) find that the relative price variability of agricultural commodities is positively related to INF. Taylor (2000) illustrates that higher INF leads to more frequent price changes, resulting in the increased sensitivity of prices to shocks. Tabakis (2001) evidences that the causal effect from the macroeconomic environment toward agricultural commodities, and reveals a significant role of the INF on ACP. Ukoha (2008) points out that the effect of INF on relative price variability among agricultural commodities is non-neutral, and it explains 64% and 60% of the short-run variations in food crops and cash crops, respectively. Akpan and Udoh (2009) highlight that a positive significant impact of INF on ACP is found, which supports the findings of Lapp and Smith (1992) and Ukoha (2008). Guloglu and Nazlioglu (2013) suggest that the impact of INF on ACP is positive in low-inflation countries, while negative in high-inflation countries.

Since the Chinese market reform in 1992, the debate about the relationship between ACP and INF has continued (Xin & Wang, 2007). Most studies focus on the one-way causal analysis, indicating that the positive impact of ACP on INF, or that INF positively affects ACP. X. Q. Wang and Qian (2004) find that a 1% rise in ACP results in a 0.2% increase in INF in China. Ha (2005) holds that the rising ACP causes INF, while Lu and Peng (2002) denote that INF is ahead of the price changes of agricultural commodities, and it causes ACP to rise. J. Li and Fan (2005) also suggest that INF leads to higher prices for agricultural commodities. Cheng et al. (2008) indicate that a 10% rise in pork prices will increase the inflation rate by 0.5%. Y. Chen and Wu (2020) show that a 1% rise in ACP leads to a 0.82% increase in the inflation rate. Furthermore, the bidirectional causality between ACP and INF is expounded in certain investigations. G. Zhao et al. (2008) prove that there is a long-run equilibrium and a dual-direction causal relationship between ACP and INF in China. L. Liu (2009) reveals that the rise of ACP is a contributing factor to INF, and INF has a great impact on the agricultural commodity market. Nie (2012) demonstrates that there is a significant positive mutual causality between ACP and INF. S. Wang (2013) finds that there is a two-way transmission mechanism between the two variables, the rise of ACP causes INF to be more significant. B. Wang and Li (2013) illustrate that although Granger causality exists between the two variables, INF is less affected by ACP shocks. However, the causal link between ACP and INF is not always supported. Zhang et al. (2011) concludes that the key factor of INF is excess liquidity rather than the rise of ACP. Gou (2017) highlights that there is no Granger causality between these two variables, the increase in ACP is only a form of INF. Wei (2019) suggests that the rise of ACP related to supply shortages does not affect China’s price levels.

The previous studies have evidenced a one-way or bilateral causal impact between ACP and INF. However, these studies mainly focus on the positive effect of ACP on INF, or the positive impact from INF to ACP. In contrast, the negative effect of ACP on INF is largely ignored. In general, external uncertainties can affect the equilibrium of aggregate supply and demand in economic activity and may strengthen or weaken the impact of ACP on the general price level. This means that the rise in ACP does not always positively affect the level of INF. There may be a negative effect in the presence of uncertainty shocks, which indicates that ACP is not always regarded as the prime driver of INF. Besides, the existing literature does not consider the structural changes in the time series and ignores unstable parameters in Granger causality test, thus failing to analyze the time-varying correlations between ACP and INF. Therefore, we apply the bootstrap sub-sample rolling-window test to improve the accuracy of the outcomes and obtain the interaction between ACP and INF.
Theoretical Analysis and Research Hypothesis

The Influence Mechanism of ACP on INF

According to the Neo-Keynesian cost-push inflation theory (Batten, 1981), the rise in ACP inevitably pushes up the cost of living for workers and further raises wage levels, thus triggering INF (Hu, 2010). As agricultural commodities are the cost input for most goods production processes, they play an important role in price level by generating supply shocks (C. Zhang et al., 2014). The higher ACP can ultimately be reflected in the price of the related final goods purchased by consumers (Furlong & Ingenito, 1996). Moreover, long-term increases in ACP may lead to changes in overall price levels through expectations. Specifically, if workers realize that ACP continues to rise, they will immediately adjust inflation expectations and demand higher wages (Wei, 2019). To offset the increase in costs caused by the rising ACP, producers will raise the prices of final foods, which is likely to create inflationary pressures (Cheung, 2009). Therefore, the view that ACP is regarded as the main driver of cost-push inflation (Jongwanich & Park, 2009) has been evidenced. However, INF is usually the result of a combination of multiple factors in reality, that is, “hybrid inflation.” Assuming that INF is initially driven by demand, then the excessive demand for agricultural commodities will lead to a rise in the overall price level, which in turn causes wages to increase, thereby formulating the cost-driven inflation. The generation of hybrid inflation can be explained by the extended Phillips curve:

\[ \pi = \pi' + f(u) + bZ, \]  
(1)

where \( \pi \) is the inflation rate, \( e \) represents inflation expectations, and \( u \) denotes unemployment rate, \( f(u) < 0 \). \( Z \) indicates shock of rising production factor costs on the general price level. \( b \) is the price shock coefficient, \( b > 0 \). If \( e = 1 \) and \( Z = 0 \), Equation 1 becomes \( \pi = f(u) \). According to Okun’s Law, Equation 1 can be written as follows:

\[ \pi = \pi'_2 + f(x - x') + bZ, \]  
(2)

where \( x - x' \) represents the deviation of aggregate supply from aggregate demand.

According to Equation 2, increases in wages and other production factor costs inevitably lead to cost-push inflation. Generally, changes in the overall price level are affected by the conditions of aggregate supply and demand. We can further apply the supply-demand equilibrium to analyze the formation of INF. From a macroeconomic perspective, the impact of demand factors on the price level is achieved by the supply and demand conditions in the labor market affecting wage changes. When the demand for agricultural commodities increases, producers will expand their demand for labor. With unchanging labor supply, the increased demand for labor will cause the demand curve to shift to the upper right and push up the wages, thereby leading to an increase in the overall price level. Accordingly, when ACP rises, the cost of production factors (i.e., wage levels) increases from \( Z_1 \) to \( Z_2 \), and the inflation rate will rise from \( \pi_1 \) to \( \pi_2 \). Through the above analysis, we can conclude that INF is positively affected by ACP.

The Influence Mechanism of INF on ACP

Two main explanations of the influence mechanism of INF on ACP have been identified. One perspective focuses on the supply side, which can explain that INF positively affects ACP. Commodity price booms are more likely to occur when the inflation rate is high (Kyrtsous & Labysb, 2006; Pindyck & Rotemberg, 1990). INF has a significant positive impact on relative price fluctuations of agricultural commodities both in the short- and long-run (Ukoha, 2008). Theoretically based on profit maximization, INF causes input (e.g., machinery, fertilizers, and oil) prices to increase, which will lead to a decrease in agricultural production and a shift in the supply curve to the upper left. And then, in the case of unchanging demand, a decrease in supply will cause ACP to rise. Another perspective is derived from the income effect; this can explain the negative impact of INF on ACP. Specifically, INF causes people’s purchasing power to decline (real income decreases) so that demand will decrease. In the case of unchanging supply, the demand curve shifts to the lower left, which in turn leads to a decrease in ACP.

Summarizing the above analyses, we put forward the following Hypotheses 1 and 2.

**Hypothesis 1:** The increase in ACP causes INF to rise, indicating that ACP has a positive effect on INF.

**Hypothesis 2:** INF has both positive and negative impacts on ACP, suggesting that ACP is significantly affected by INF.

Method

Bootstrap Full-Sample Causality Test

The statistical value of Granger causality test in conventional vector autoregression (VAR) models cannot follow the standard asymptotic distribution. To avoid the incorrect results, Shukur and Mantalos (1997) use the critical values based on the residual bootstrap (RB) method and enhance the correctness of the causality test. In addition, they find that RB method is more suitable for standard asymptotic tests, even in a small sample. In particular, they suggest that small sample corrected likelihood ratio (LR) tests present relatively better power and size properties (Shukur & Mantalos, 2000). In the study, we apply the RB-based modified-LR statistic to
test the causal relationship between ACP and INF. The VAR $(p)$ system with two variables is constructed as Equation 3:

$$Z_t = \beta_0 + \beta_1 Z_{t-1} + \cdots + \beta_p Z_{t-p} + \mu_t \text{ where } t = 1, 2, \ldots, T,$$

where $p$ is selected based on the Schwarz Information Criterion (SIC), which indicates an optimal lag order. The bivariate VAR $(p)$ system can split $Z$ into ACP and INF, that is, $Z_t = (ACP_t, INF_t)$. Besides, ACP and INF may have certain relationships with crude oil prices (COP), which in turn affects the inter-linkages between the two variables (C. W. Su et al., 2020a; C. W. Su, Qin, Tao, Nicoleta-Claudia, & Oana-Ramona, 2020). COP can positively influence agricultural commodity markets through the input channel (Paris, 2018), the continued rise in COP has a significant impact on INF in the long-run (Mukhtarov et al., 2012). Also, COP has positive and significant impacts on INF in the long-run (Mukhtarov et al., 2012). Then, we choose the COP as a control variable, and rewrite Equation 4 as follows:

$$
\begin{bmatrix}
ACP_t \\
INF_t \\
\end{bmatrix} = \begin{bmatrix}
\beta_{10} \\
\beta_{20} \\
\end{bmatrix} + \begin{bmatrix}
\beta_{11}(L) & \beta_{12}(L) & \beta_{13}(L) \\
\beta_{21}(L) & \beta_{22}(L) & \beta_{23}(L) \\
\end{bmatrix} \begin{bmatrix}
ACP_{t-1} \\
INF_{t-1} \\
COP_{t-1} \\
\end{bmatrix} + \begin{bmatrix}
\mu_{1t} \\
\mu_{2t} \\
\end{bmatrix},
$$

where $\mu_t = (\mu_{1t}, \mu_{2t})'$ is a white-noise process.

And then, we can examine the null hypothesis that there is no causal effect of INF on ACP by imposing the restriction where $\beta_{1,k} = 0$ for $k = 1, 2, \ldots, p$. Likewise, the inverse null hypothesis that there is no causal impact of ACP on INF ($\beta_{2,k} = 0$ for $k = 1, 2, \ldots, p$) can be tested. If the first hypothesis is rejected, it means that INF has a significant causal impact on ACP. Conversely, there is a significant causal effect of ACP on INF when the second hypothesis is rejected.

**Parameter Stability Test**

One of the assumptions for the full-sample test in VAR models is that the parameters are constant, which is usually unrealistic. If the parameters are time-varying, this means that the full-sample test is unreliable. Thus, we examine parameter stability by using the $Sup-F$, $Ave-F$, and $Exp-F$ tests (Andrews, 1993; Andrews & Ploberger, 1994). The $Sup-F$ test is able to examine structural changes in parameters, $Ave-F$ and $Exp-F$ tests can be used to prove whether parameters change gradually over time. In addition, we apply the $L_c$ statistics test developed by Nyblom (1989) and Hansen (1992), to check whether the parameters conform a random walk process in the long run. By performing these stability tests, the time-varying interaction between ACP and INF can be evidenced if the parameters are unstable. Hence, we will employ the sub-sample test to explore the mutual influence between the two-time series.

**Bootstrap Sub-Sample Rolling-Window Causality Test**

This method can separate the full-time series into small samples according to the width of the rolling-window (Balcilar et al., 2010; C. W. Su et al., 2020b). Choosing the appropriate width is complicated, and if it is small, the robustness of the results may not be guaranteed. A large one can enhance the correctness of the results, but it may decrease the times of scrolls. Therefore, Pesaran and Timmermann (2005) ascertain that this width cannot be less than 20 if the parameters in the VAR system are unstable. Then, we show the specific way: Let the length of the full-time sample be $H$, and the sample length be $w$. The terminal of each sub-sample is $w + 1, \ldots, H$ and we can get $H - w + 1$ sub-sample. Next, we obtain the sub-sample causal relationship test results.

$$N_{b} \sum_{k=1}^{p} \beta_{12,k}^{*}$$ and $N_{b} \sum_{k=1}^{p} \beta_{21,k}^{*}$ are mean values based on a large number of estimates, which suggests the impact of INF on ACP and the influence from ACP to INF, respectively. $N_{b}$ is the rate of recurrence of bootstrap repetition. $\beta_{12,k}$ and $\beta_{21,k}$ are parameters from Equation 4. We consider the 90% confidence interval, and the associated lower and upper limits are the 5th and 95th quantiles of $\beta_{12,k}$ and $\beta_{21,k}$, respectively (Balcilar et al., 2010; C. W. Su, Qin, Tao, Shao, et al., 2020).

**Data**

The study is undertaken to examine the bidirectional causality between ACP and INF covering the period from 2007:M1 to 2020:M2. China experienced high growth and low inflationary pressures from 2003 to 2007 (T. Y. Liu et al., 2017). A unilateral structural INF gradually emerged in early 2007, which is primarily driven by rising food prices (J. H. Liu & Yang, 2008). During the global financial crisis from 2007 to mid-2008, prices of major agricultural commodities such as corn and soybeans more than doubled (Fowowe, 2016; Pal & Mitra, 2017), dominating the rise in food prices (C. Zhang et al., 2014). Over the same period, the outbreak of blue ear disease (Porcine Reproductive and Respiratory Syndrome, PRRS), is an immediate cause of the shortage of pork supply (Q. Zhang & Reed, 2008). Rising pork prices have accelerated food prices increase, further triggering INF. As agricultural commodities are the cost input for most food production processes, they play an important role in food prices by generating supply shocks (C. Zhang et al., 2014). Moreover, food...
prices account for nearly one-third of the weight in the calculation of China’s consumer prices; this means that ACP may be an important driver of INF. We use ACP index to reflect the trend of China’s agricultural commodity market, which is a fixed base index calculated by the weighted average method. More precisely, the ACP index is a weighted average of prices for five primary commodities group: corn, rice, wheat, soybean, and cotton. INF is most widely measured by the changes in CPI (Amstad et al., 2018), which is one of the main economic indicators for macroeconomic analysis (Y. Chen & Wu, 2020). We use the percentage of monthly CPI change to represent the level of INF, which is provided by the Statistical Bureau of the People’s Republic of China. Besides, in early 2000, due to the continued increase in global demand, the COP has shown a significant upward trend (S. T. Chen et al., 2010). Demand shocks from the crude oil market usually have a long-term impact on China’s INF (L. Zhao et al., 2016). Moreover, because crude oil is a very important input in the transportation and production process of agricultural commodities, ACP is affected by COP fluctuations (C. Zhang & Qu, 2015). Thus, we choose the COP to reflect the global supply and demand situation of the oil market, which is published by the U.S. Energy Information Administration. Figure 1 highlights the trends of ACP and INF.

We can observe that the level of INF does not always increase with ACP, and vice versa. China has experienced both ACP increases and inflationary pressures from 2007 to mid-2008. Due to the uncertainty shocks caused by the global financial crisis (C. W. Su, Huang, et al., 2021), the prices of major agricultural commodities have surged unprecedentedly, and ACP in China has inevitably risen as well. INF starts to accelerate sharply in the first half of 2007, which is mainly driven by rising food prices. Moreover, the spread of blue ear disease has led to a huge pork shortage, and rising pork prices are a significant driver of INF. Since 2010, the prices of cereals, vegetables, and other agricultural commodities rise sharply; the higher ACP triggers a new round of INF. From 2012 to 2014, ACP exhibits an upward trend, while INF is at a relatively low level. In the second half of 2012, the grain-producing regions of the Midwestern United States have experienced high temperatures and severe drought, resulting in a decrease in the production of corn, soybeans, and other grains. The shortage of global agricultural commodity supply and China’s growing demand have contributed to driving ACP to rise. However, as prudent and neutral monetary policy maintains appropriate liquidity and reduces the possibility of inflation risk, the price level is relatively stable. From August 2015 to December 2016, the formation of the exchange rate central parity mechanism led to a depreciation of the renminbi (RMB). This has increased the import prices of agricultural commodities; thus, ACP exhibits an upward trend. In contrast, INF is at a relatively low level in 2015–2016 due to the weak macroeconomic performance. The Sino-U.S. trade friction severely affected China’s imports of the U.S. agricultural commodities in 2017–2018. To stabilize ACP, China gradually shifted agricultural imports to Brazil, Uruguay, and other South American countries. The diversified import channels have increased the supply of agricultural commodities and led to a downward trend in ACP. Meanwhile, the inflation rate was at a slower pace in 2017 and remained steady in 2018, which was mainly due to stable food prices. However, due to the spread of African swine fever, increased pork demand during the Lunar New Year holidays and the ongoing outbreak of the Corona Virus Disease 2019 (COVID-19), the level of INF accelerated in 2019–2020.

Figure 1. The trends of ACP and INF. Note. ACP = agricultural commodity prices; INF = inflation.
full-sample test results are reported in Table 2. The optimal lag order is chosen to be 2. Based on Equation 4, the bivariate VAR system with ACP and INF, COP satisfy the platykurtic distribution. Meanwhile, as the kurtosis is less than 3, ACP and COP are stationary, we convert ACP and COP by taking natural loga-

Empirical Results

Based on Equation 4, the bivariate VAR system with ACP and INF is used to test the full-sample causal relationship. According to SIC, the optimal lag order is chosen to be 2. The full-sample test results are reported in Table 2. The $p$ values point out that there is no significant interrelationship between ACP and INF, suggesting that ACP cannot affect INF, and vice versa. These are not supported by the previous studies (Garratt & Petrella, 2019; Goudarzi et al., 2012; Irawati et al., 2019), and also inconsistent with Hypotheses 1 and 2.

The full-sample estimation in the bivariate VAR system assumes that the parameters are constant over time. Nevertheless, due to structural mutations in the VAR model, the parameters may not be constant, and the causality between ACP and INF may exhibit time-varying characteristics (Balcilar & Ozdemir, 2013; C. W. Su, Qin, et al., 2021).

![Table 1. Descriptive Statistics for ACP, INF, and COP.](image)

| Statistics | ACP | INF | COP |
|------------|-----|-----|-----|
| Mean       | 153.826 | 0.242 | 73.423 |
| Median     | 159.205 | 0.140 | 71.015 |
| Maximum    | 181.480 | 2.600 | 133.880 |
| Minimum    | 108.920 | −1.100 | 30.320 |
| SD         | 20.603 | 0.547 | 22.740 |
| Skewness   | −0.623 | 0.691 | 0.274 |
| Kurtosis   | 2.282 | 4.387 | 2.178 |
| Jarque–Bera | 13.602*** | 25.249*** | 6.430*** |
| Observations | 158 | 158 | 158 |

Note. ACP = agricultural commodity prices; INF = inflation; COP = crude oil prices.

***Denotes significance at the 1% level.

Obviously, the interrelationship between ACP and INF is complex and changes over time.

Table 1 reports descriptive statistics. The averages of ACP, INF, and COP suggest that they are centered at the 153.826, 0.242, and 73.423 levels, respectively. The skewness in INF and COP is positive. INF has a kurtosis greater than 3, which means the sequence satisfies the leptokurtic distribution. Meanwhile, as the kurtosis is less than 3, ACP and COP satisfy the platykurtic distribution. In addition, the Jarque–Bera index indicates that ACP, INF, and COP are non-normally distributed at the significance level of 1%. Thereby, it is not suitable to apply the conventional Granger causality test. Then, we apply the RB method to solve the potential non-normal distribution problem in the three variables. In summary, the interrelationship between ACP and INF may exhibit time-varying characteristics (Balcilar & Ozdemir, 2013; C. W. Su, Qin, et al., 2021).

![Table 2. Full-Sample Granger Causality Tests.](image)

| Tests | Bootstrap LR test | Ave-F | Exp-F | Sup-F |
|-------|-------------------|-------|-------|-------|
| $H_0$: ACP does not Granger cause INF | 3.681 | .220 | .959 | .640 |
| $H_0$: INF does not Granger cause ACP | Statistics | $p$ values | Statistics | $p$ values |

Note. To calculate $p$ values using 10,000 bootstrap repetitions. ACP = agricultural commodity prices; INF = inflation; LR = likelihood ratio.

Then, to ensure the reliability of the causal analysis, we use $Sup-F$, Ave-$F$, and Exp-$F$ tests to examine the parameter stability in the VAR model with ACP and INF. Besides, the $L_c$ test is employed as well to make Granger causality tests more reliable. Table 3 reports the corresponding results.

The $Sup-F$ test indicates that ACP, INF, and the VAR model have structural mutations at a significance level of 1%. The Ave-$F$ and Exp-$F$ tests highlight that at the 1% significance level, the parameters in INF can gradually change over time. The time-varying parameters in the VAR model can be proved through the Ave-$F$ and Exp-$F$ tests at the 5% and 1% significance levels, respectively. Also, the null hypothesis of the $L_c$ test can be rejected at the 10% significance level, revealing that the parameters in the VAR system do not follow a random walk process. Therefore, through the parameter stability test, we can conclude that the parameters in the entire VAR process are time-varying. The Granger causality relationship between ACP and INF is non-constant, so the bootstrap full-sample method does not apply to the study. Then, to analyze the time-varying mutual influence between ACP and INF and address the problem of the structural change, we perform the bootstrap sub-sample rolling-window causality test. Besides, to evidence the robustness of the empirical analysis, we use the sizes of 20, 28, and 32 months to explore the causality, and the results are consistent with the 24-month rolling-window. Therefore, we choose the rolling-window width as 24 months, which can enhance the reliability of the causal analysis results. Moreover, the direction of the impact from ACP to INF (or the impact of INF on ACP) can be acquired.

Figures 2 and 3 highlight the bootstrap $p$ values and the orientation of ACP impact on INF, respectively. ACP Granger causes INF during the periods of 2009:M12–2010:M4, 2010:M10–2011:M12, 2012:M10–2013:M9, 2016:M10–2017:M2, and 2017:M10–2018:M2 at the significance level of 10%. The positive effects (2009:M12–2010:M4, 2010:M10–2011:M12, and 2017:M10–2018:M2) and negative impacts (2012:M10–2013:M9 and 2016:M10–2017:M2) exist from ACP to INF. The positive effects of ACP on INF, indicating that higher ACP may put upward pressure on the price level, and a rise in ACP will increase the possibility of INF. The global economic recession in 2009 causes a substantial increase in prices of bulk commodities such as agricultural commodities (Food and Agriculture Organization,
During the period 2009:M12–2010:M4, speculators enter the Chinese agricultural commodity market to speculate on garlic, ginger, and mung beans, which has increased demand for agricultural commodities. However, due to the severe weather conditions in Northern China since October 2009, the supply of agricultural commodities has been reduced, resulting in an upward trend in ACP (Nie, 2012; Z. Zhang et al., 2011). These factors ultimately have caused ACP to be at a relatively high level, forming inflationary pressures. Furthermore, prices for major agricultural commodities (wheat, maize, sorghum, and barley) dominate the increase in food prices (C. Zhang et al., 2014). Besides, higher pork prices due to several years of swine disease pandemics since 2009 have been another major factor behind the acceleration in INF (Funke et al., 2015). This round of INF is mainly driven by rising food prices that are dominated by ACP. Thus, we can prove the positive impact of ACP on INF during this period.

In China, the agriculture sector is a labor-intensive industry. The labor market is in short supply during the period 2010:M10–2011:M12, resulting in an increase in the wage level of laborers, which inevitably has led to a rise in the production cost of commodities. That is, the prices of labor-intensive commodities such as agricultural commodities are higher than those of other commodities (T. Y. Liu et al., 2017), especially the prices of vegetables have risen significantly (J. Su, 2011). In addition, since 2011, the government has strictly regulated the real estate market, curbing speculative demand. This has caused most of the capital to flow into the agricultural commodity market, which increases the demand for agricultural commodities and leads to a rise in ACP. The price of energy or non-energy commodities has proved to be effective information for forecasting INF (Ciner, 2011; De Nicola et al., 2016). As agricultural commodities are an important factor input in the production process, the rise of ACP has created inflationary pressures during this period. Therefore, China has experienced cost-push inflation led by rising ACP, the positive effect of ACP on INF can be evidenced.

China imports more than $115 billion of agricultural commodities in 2017, and 60% of all soybeans traded on the global market (Carvalho et al., 2019). Besides, total grain output in China has reached 618 million tons, among the three major cereal crops grown, the self-sufficiency ratios of wheat, rice, and corn are about 95%. Sufficient supply of agricultural commodities leads ACP to decline during the period 2017:M10–2018:M2. Meanwhile, the inflation rate is less than 2% for 10 straight months from March 2017 to February 2018. There are two ways to explain the relatively low level of INF. First, prices of pork, aquatic products, and

### Table 3. The Results of Parameter Stability Test.

| Tests   | Statistics | p value | Statistics | p value | Statistics | p value |
|---------|------------|---------|------------|---------|------------|---------|
| Sup-F   | 61.519***  | .000    | 34.373***  | .000    | 65.287***  | .000    |
| Ave-F   | 13.886***  | .002    | 25.091***  | .000    | 17.916**   | .015    |
| Exp-F   | 26.051***  | .000    | 15.059***  | .000    | 27.954***  | .000    |
| $L_c$   |            |         |            |         | 2.607*     | .068    |

Note. To calculate p values using 10,000 bootstrap repetitions. ACP = agricultural commodity prices; INF = inflation; VAR = vector autoregression. ***, **, and * denote significance at the 1%, 5% and 10% levels, respectively.
fresh vegetables have declined due to sufficient supply, the decrease in food prices causes a drop in consumer prices. Second, because COP has positive and significant impacts on INF (Mukhtarov et al., 2019), the lower INF is also dragged down by the decline of COP. Global oil demand is weak and COP drops in the second half of 2017. Thereby, the level of INF decreases during the period of low ACP, the positive effect of ACP on INF can be proved.

However, the view cannot always be supported, which can be seen in the negative effect of ACP on INF. Major grain-producing regions, such as the United States and Russia, have experienced high temperatures and severe droughts in the second half of 2012, which has led to a decrease in agricultural production and a reduction in global stocks. As the main source of China’s imports of the agricultural commodity, the U.S. agricultural exports to China have averaged $25.9 billion per year in 2012–2013 (Gale et al., 2015). Furthermore, the United States has pricing power over the export prices of agricultural commodities, which has a great impact on ACP. Meanwhile, the geopolitical events linked to oil-producing countries like Libya and Yemen again push the COP above $100 per barrel in 2012 (Kumar, 2017), and the rising COP increases ACP by pushing the costs of production (Cabrera & Schulz, 2016; Pal & Mitra, 2017). These factors have caused ACP to rise rapidly during the period 2012:M10–2013:M9. Nevertheless, INF has experienced a downward trend. To stabilize ACP and consumer prices, China has continuously promoted the diversification of agricultural imports, to ensure domestic demand for agricultural commodities. For instance, China Oil & Foodstuffs Corporation has signed a memorandum of understanding with Ukr Land Farming Public Limited company (ULF) in December 2012, which states that 3 million tons of corn are exported to China. Besides, China sets the tone of monetary policy as prudent and neutral, avoiding excessive liquidity injections. China’s economy has been stuck in a protracted weak recovery, easing from 7.9% in the fourth quarter of 2012 to 7.5% growth in the second quarter of 2013. The prudent monetary policy is conducive to the stability of the price level, and the slow economic growth reduces the possibility of inflation risk. Accordingly, the negative impact of running from ACP to INF is demonstrated.

ACP is strongly influenced by exchange rates and more responsive to its changes (Hatzenbuehler et al., 2016). The RMB has experienced a long-term and significant depreciation from August 2016 to January 2017, which has increased the import prices of agricultural commodities. Over the same period, the Sino-U.S. trade situation has changed during the Trump presidential election, inducing speculative capital to enter agricultural commodity markets to obtain benefits. Speculative trading has increased demand for agricultural commodities (Miščekča et al., 2019), while the depreciation of RMB has reduced the supply. These factors have caused ACP to rise slightly during the period 2016:M10–2017:M2. However, the inflation rate is far below the government’s 3% annual target. Since the second half of 2016, China maintains the prudent and stable monetary policy, refraining from excessive money supply to prevent inflationary risks, curbing asset bubbles, and guarding against economic and financial risks. This monetary policy reduces the possibility of INF and causes inflation rate to decline. Besides, China’s supply-side structural reform has delivered initial results, lowering costs of labor and capital, and cutting electricity tariff and gas fee by nearly 100 billion yuan, respectively. Therefore, INF remains at a low level during the period of high ACP, we can prove the negative impact of ACP on INF. The results do not always support Hypothesis 1, which highlights that INF is positively affected by ACP.

Figures 4 and 5 highlight the bootstrap p values and the orientation of INF impact on ACP, respectively. INF Granger causes ACP during the periods of 2010:M5–2010:M8, 2013:M7–2013:M12, 2015:M5–2015:M8, and 2019:M6–2019:M12 at the significance level of 10%. The positive effect (2015:M5–2015:M8) and negative impacts (2010:M5–2010:M8, 2013:M7–2013:M12 and 2019:M6–2019:M12) exist from INF to ACP. The positive influence from INF to ACP suggests that macroeconomic performance affects the stability of the agricultural commodity market, and lower INF levels may cause ACP to decline. Due to sluggish demand, weak exports, and flagging investment, China’s economic growth is slow in 2015 (C. W. Su, Sun et al., 2021). In this economic situation, INF is at a relatively low level during the period 2015:M5–2015:M8, and ACP exhibits a downward trend. Due to the abundant supply of seasonal harvests of some agricultural commodities, the prices of fruits, eggs, and vegetables have declined. Besides, the total import value of China’s agricultural commodities from other countries, such as India, Ukraine, and Russia, reaches $22.8 billion, which has significantly increased the supply of agricultural commodities. Moreover, the continued decline in global oil prices has also led to a decrease in ACP during this period. COP can influence the fluctuations in ACP (Mitchell, 2008), mainly because crude oil is an important cost input in
the production of agricultural commodities (Kumar, 2017). That is, the lower price level has inevitably transmitted to ACP through the cost of production factors. Under the situation of weak aggregate demand, the oversupply of the agricultural commodity market and the decline of COP further lead to lower ACP. Therefore, we can evidence that INF has a positive influence on ACP during this period.

However, under the shock of external uncertainty, INF does not always cause ACP to change in the same direction. As the easing of the global financial crisis during the period 2010:M5–2010:M8, China adopts moderately loose monetary policies to ensure sufficient liquidity and promotes economic recovery (C. W. Su et al., 2016). This loose monetary policy increases aggregate demand, which in turn causes price levels to rise, and INF has emerged since May 2010 (Wu et al., 2011). At the same time China has conducted price adjustments, electricity, water, and gas have increased simultaneously, thus accelerating the emergence of INF (T. Y. Liu et al., 2017). Nevertheless, due to the expansion of imports and the increase in domestic production, the supply of agricultural commodities has increased significantly, leading to a slight decline in ACP during this period. In 2010, the value of imports of agricultural commodities has reached S$1.4 billion, and total agricultural production has maintained an annual average increase of roughly 13%. This, in turn, lowers food production costs and reduces the impacts of INF. Thereby, ACP decreases during the period of high INF, and the negative influence from INF to ACP can be proved.

China has implemented a prudent monetary policy, which is conducive to the stability of the overall price level. The average inflation rate is less than 3% during the period 2013:M7–2013:M12. However, ACP has experienced an upward trend in the second half of 2013; we can explain it from two sides. First, China imports 63.38 million tons of soybeans in 2013, accounting for 80% of the domestic soybean market. Thus, the high external dependence of agricultural commodities makes ACP more susceptible to external factors, such as oil price shocks (C. Zhang & Qu, 2015). China has become the global largest net oil importer since September 2013. Meanwhile, the continuous geopolitical uncertainty in oil-producing countries has contributed to rising COP, which has led to an increase in ACP (C. W. Su et al., 2019). Second, the investor trading behavior is a key determinant of various asset prices, including ACP (Tao et al., 2021; Zhou et al., 2019). Financial speculative capital flows into agricultural commodity markets to gain benefits, which increases the demand for agricultural commodities and leads to a rise in ACP. Accordingly, ACP soars during the period of low INF, we can evidence that INF has a negative influence on ACP.

After June 2019, pork prices rise further due to a sharp decline in hog stock as a result of the spread of African swine fever. As of November 2019, consumer inflation climbs to nearly 8-year peaks as pork prices doubled. Over the same period, pork remains in high demand as China prepares to celebrate the Lunar New Year, the peak consumption period for the meat. Besides, pork prices drive beef and mutton prices up, and fruit prices also keep rising. These factors lead to higher consumer price and trigger a new round of INF during the period 2019:M6–2019:M12. Generally, the higher INF is reflected in agricultural commodity markets, and may usually put upward pressure on ACP. However, there is a decline in ACP. First, agricultural output plays an important role in stabilizing the price level. China has achieved a bumper grain harvest for 15 consecutive years, with per capita grain possession exceeding 470 kilograms. Second, with the easing of Sino-U.S. trade friction, China’s imports of agricultural commodities from the United States increased significantly in December 2019, filling the domestic agricultural supply-and-demand gap. Adequate stocks of agricultural commodities increase market supply; thus, ACP shows a downward trend. Third, due to the impact of geopolitical tensions in the second half of 2019, oil supply exceeds demand, leading to a decline in COP. ACP is more closely associated with oil price shocks (C. Zhang & Qu, 2015), and a drop in COP has reduced ACP. Therefore, we can evidence that INF has a negative influence on ACP during this period.

In summary, the empirical results evidence that there are both positive and negative impacts from ACP to INF. ACP can significantly and positively affect INF during some periods, which indicates the rise in ACP will increase the possibility of INF, and higher ACP may create inflationary pressures. While in other periods, this view cannot be supported, mainly due to the external uncertainties (e.g., the monetary policy and macroeconomic condition changes, global oil prices, and the exchange rate fluctuations) may influence the equilibrium of aggregate supply and demand. Thus, ACP cannot always be viewed as the prime driving factors of INF. The results are not consistent with Hypothesis 1, which indicates a positive influence from ACP to INF. In turn, INF has both positive and negative impacts on ACP, suggesting that INF does not always cause ACP to change in

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**Figure 5.** Bootstrap estimates of the sum of the rolling-window coefficients for the impact of INF on ACP.

*Note. INF = inflation; ACP = agricultural commodity prices.*
the same direction under the external shocks. The findings are supported by Hypothesis 2, which demonstrates that ACP is significantly affected by INF.

Conclusion
This article examines the time-varying mutual influence between ACP and INF in China, to prove whether or not ACP can always be regarded as the prime driver of INF by applying the sub-sample causality test. The empirical results indicate that there are positive and negative effects of ACP on INF. The positive causal effect states that the higher ACP may put upward pressure on the price level, and an increase in ACP is more likely to cause INF. However, this view cannot be held by the negative impacts. Due to the shock of external uncertainty, ACP cannot always be viewed as the prime driving factors of INF. The results do not always support Hypothesis 1, which suggests a positive effect of ACP on INF. In addition, we also find the positive and negative impacts of INF on ACP, showing that INF levels may affect the supply and demand of agricultural commodity markets, which can be considered as a factor affecting ACP. The findings are consistent with Hypothesis 2, which states that ACP is significantly affected by INF. Through the mutual influence between ACP and INF, we can conclude that ACP should not always be regarded as the prime driver of INF in China. In the presence of external uncertainties, the rise in ACP may no longer have a pulling effect on INF. In addition, as the agricultural commodity market is also affected by other internal (e.g., domestic agricultural production) and external (e.g., global oil price fluctuations) factors, ACP does not always increase as INF levels rise.

Understanding the interaction mechanism between ACP and INF can give practical implications to the Chinese government. First, to maintain the goal of low and stable INF, it is necessary to avoid a sharp rise in ACP. The related sectors need to ensure adequate domestic grain production and supply, and implement the strategy of diversification of agricultural commodity import markets, which is conducive to the stability of ACP. Second, external uncertainties can affect the equilibrium of aggregate supply and demand, and may weaken the pulling effect of ACP on general price levels. This means that the rise of ACP does not always lead to INF. Therefore, in China, ACP should not always be considered as an effective indicator of INF. The government needs to focus on the impact of external uncertainties, such as macroeconomic performance and global oil price fluctuations, on price levels changes. Third, the level of INF can affect the conditions of supply and demand in agricultural commodity markets. This highlights the need for the Chinese policy-making authorities to maintain the stability of the price level to reduce the transmission effect on the agricultural commodity market. In addition, the mutual influence between ACP and INF could be a fruitful area for future study. This article contributes to the literature by exploring the time-varying interrelationship between ACP and INF. Moreover, we intend to examine the ability of ACP to predict INF in other countries (e.g., Indonesia, India, Thailand, and Nepal) in future studies.

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