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by

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Abstract

Recent spikes in fertilizer prices, coupled with government interventions by major exporters, have raised global concerns about food security. This study employs a structural vector autoregression model to examine urea price movements in China, the world's largest urea producer and major exporter. Using a heteroskedasticity-based identification approach that allows for a smooth transition in covariances, we decompose urea prices into four structural shocks: supply shocks due to changes in energy prices, demand shocks due to changes in crop prices, export demand shocks, and urea market-specific idiosyncratic shocks unrelated to the preceding three shocks. Findings suggest that rising energy costs and idiosyncratic shocks were the dominant factors behind urea price behavior in China between 2018 and 2023. Conversely, shocks to corn prices and export demand played a minimal role. Importantly, we find limited evidence that reduced exports lowered domestic urea prices, thus questioning the effectiveness of the urea export restriction policies China implemented since October 2021. Furthermore, increased domestic demand associated with the temporary fertilizer reserve program implemented at the end of 2021 contributed to urea price increases in China during the stockpiling period in early 2022, while helping to lower the fertilizer prices in the 2022 summer growing season.

Keywords: fertilizer prices, urea, energy prices, corn prices, export restrictions, policy interventions

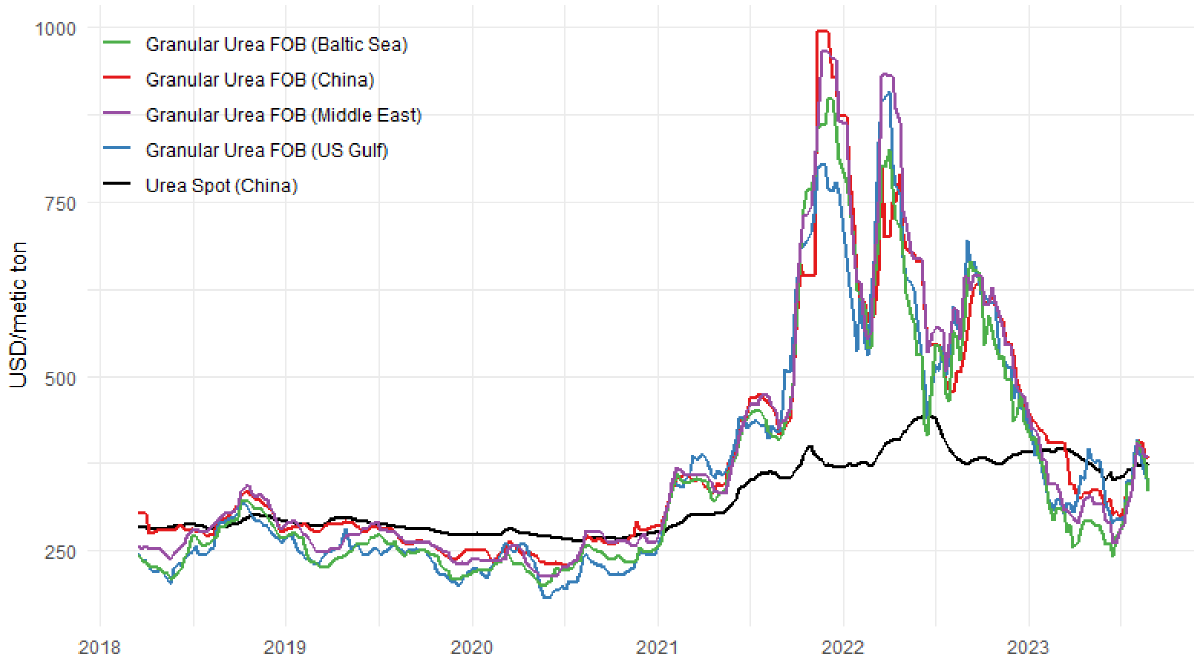
JEL: Q13, Q41, Q18, Q17

1. Introduction

Fertilizer prices have skyrocketed since the end of 2020 and broke new records in 2022. The real prices of major world fertilizers nearly doubled between the end of 2020 and mid-2022, outpacing the increase in grain prices over the same period (Hebebrand and Laborde Debucquet 2023). As fertilizers are essential inputs for major agricultural commodities, high fertilizer prices add fears that farmers would cut back on fertilizer use, leading to lower crop yields, a reduced global food supply, and ultimately, higher food prices, threatening food security in both developed and developing countries. Indeed, estimates from the International Fertilizer Association (IFA) show that in 2022, producers worldwide reduced fertilizer consumption by 5% due to affordability issues, with reduction reaching as high as 25% in Sub-Saharan Africa (IFA 2022).

While the Russia-Ukraine conflict has exacerbated fertilizer supply shortages and price surges, serval pre-existing factors may have also contributed to price increases since the end of 2020. These include rising energy costs, strong demand driven by profitable crop prices, supply disruptions in major producing countries, as well as policy interventions such as export restrictions and national stockpiling programs (Hebebrand and Glauber 2023).

For instance, China, a major fertilizer producer and exporter, implemented a new inspection certificate requirement to ship urea in October 2021, effectively halting exports to “safeguard” domestic supply and lower domestic prices. Later in December 2021, China's National Development and Reform Commission (NDRC) announced a temporary fertilizer reserve program to ensure sufficient domestic supplies for the 2022 summer growing season, supplementing the national off-season fertilizer reserve programs that have been established since 1998. Following these policy interventions, Chinese urea exports fell by 47% in 2022 compared with 2021 (GACC, 2023), and global fertilizer prices continued to climb, with urea prices more than doubling between mid-2021 and the first half of 2022 (WTO 2022). Meanwhile, fertilizer prices in China, although diverging from global trends, reached historical records in mid-2022, as shown in Figure 1.



Source: Data collected from Oilchem

Figure 1. Global urea FOB prices vs. Domestic urea fertilizer prices in China, 2018-2023.

The fertilizer market interventions implemented by China are reminiscent of trade and other policy responses during several recent episodes of price spikes (e.g., rice and corn export bans by India in 2007-2008, and wheat and corn export bans by Russia in 2010-2011)[5]. Governments in exporting countries frequently impose export bans, export quotas, export taxes, or increase domestic reserves to insulate domestic prices from international shocks. Such policies are often cited as contributing factors to global commodity price spikes (Headey and Fan, 2008; Shama 2011; Heady 2011; Martin and Anderson, 2012). However, the impacts of these government interventions on stabilizing domestic prices are often challenged in empirical studies. Previous studies show that while they may initially lower domestic prices, in the longer term, domestic prices tend to return to global levels (e.g. Rude and An 2015; Porteous 2017; Melek,

[5] For further details, see the Food and Fertilizer Export Restriction Tracker developed by Laborde, Mamum, and Parent (2020): https://www.foodsecurityportal.org/tools/COVID-19-food-trade-policy-tracker.

Plante, and Yücel 2017). Additionally, such interventions may lead to market inefficiency and discourage investment in production and infrastructure, negatively affecting domestic producers and consumers (Götz, Glauben, and Brümmer 2013; Svanidze, Götz, and Serebrennikov 2022).

Although the recent fertilizer price spike has garnered significant attention, the relative impact of various contributing factors remains unclear. This paper aims to address this gap by analyzing the interplay between energy costs, crop prices, export demand, and market-specific idiosyncratic shocks in the urea market in China, one of the world's largest producers and exporters of urea fertilizer. We propose a structural vector autoregression (SVAR) model to disentangle the effects of these shocks and measure their relative contributions to historical urea price movements in China. Previous studies on fertilizer prices have primarily focused on the fundamental and speculative drivers of fertilizer prices in the U.S. (Ott 2012; Etienne, Trujillo-Barrera, and Wiggins 2016; Geman and Eleuterio 2013), price transmissions between the U.S. and Middle East markets (Hu and Brorsen 2017), and spatial and vertical price relationships in the U.S. fertilizer industry (Bekkerman, Gumbley, and Brester 2021). However, all these studies predate the recent global food and fertilizer crisis. Given the rapid changes in the fertilizer industry over the past few years, an updated analysis of the drivers of fertilizer price movements is warranted.

In addition to focusing on the recent fertilizer price spike, we contribute to the literature in three important ways. First, despite dominating media headlines, few studies have explored how government interventions such as export restrictions have affected domestic fertilizer prices. This is particularly important in periods of soaring fertilizer and food prices, when major exporters like China try to curb domestic price spikes by restricting international trade and increasing stockpiles. While fertilizer prices in China remained high in 2022 even with these interventions, we are unaware of any empirical analysis quantifying the extent to which these measures influenced domestic prices. Given their intended goal of price stabilization, a thorough investigation of the effectiveness of these policies is needed. We address this gap in the literature by including export demand, proxied by privately collected export port inventory data. Additionally, we consider urea market-specific shocks to capture the impact of China's temporary reserve program implemented in late 2021, which effectively increased domestic demand.

Second, while prior research often focused on the U.S. fertilizer sector, we instead consider China, one of the most important players in the global fertilizer market. In 2021, China was the world's largest producer and consumer, and the third-largest exporter of urea (IFA 2024; Yara International 2022). Notably, China's recent policies, including urea export inspection requirements and the implementation of the temporary fertilizer reserve program, have raised concerns throughout the world, especially for major importers like India and South Korea which heavily rely on Chinese supplies (Reuters 2023 a, b). Our findings hold significant relevance not only for policymakers and market participants within China but also for those operating globally.

Third, unlike previous studies that have primarily relied on reduced-form VAR-type models, we employ a structural VAR model to analyze the impact of energy costs, crop prices, export demand, and market-specific shocks on fertilizer prices. Reduced-form models, while common, are unable to identify the causal relationships between variables, potentially suffering from omitted variable bias due to the failure to incorporate the structural form (Sim 1980). Although methods such as exclusion and sign restrictions have been proposed to identify SVAR models, these approaches rely on assumptions that sometimes may fail to accurately reflect the underlying causal pattern. Recognizing the significant changes in volatility during the sample period, here we instead consider a heteroskedasticity-based identification scheme that accounts for a smooth transition between the covariance regimes developed by Lütkepohl and Netšunajev

(2017). This data-driven approach is particularly advantageous in our case as existing economic theory or empirical evidence on the fertilizer market is limited.

Using weekly data from January 2018 to August 2023, we first estimate an SVAR model that includes four types of shocks: supply shocks due to changes in coal prices, demand shocks related to changes in crop prices, export demand shocks, and market-specific idiosyncratic shocks unrelated to the preceding three shocks. Impulse responses are constructed to understand how each shock affected urea prices in China over the sample period. Additionally, we conduct a historical decomposition and counterfactual analysis to quantify the relative contributions of each of the four shocks on urea price movements over time.

Estimation results reveal that idiosyncratic shocks are the dominant contributors to urea price movements in China over the sample period. However, increases in energy costs also emerged as a dominant factor since late 2021. Focusing on the two recent urea price spikes, we find that the October 2021 spike was primarily driven by a sharp increase in energy prices, while the mid-2022 spike resulted from a combination of elevated energy costs and the increased domestic demand triggered by the national temporary stockpiling program. Interestingly, corn prices and export demand had minimal influence on urea price fluctuations.

Results from historical decomposition and counterfactual analysis suggest that export restrictions likely had little impact on curbing domestic urea price spikes. Even without these restrictions, urea prices likely would have behaved similarly. This finding challenges the effectiveness of export restrictions as a policy tool. Additionally, we show that the increased domestic demand triggered by the temporary reserve program may have contributed to already higher urea prices during the stockpiling phase in early 2022 but lowered the price in the summer growing season in 2022.

The rest of the paper proceeds as follows. Section 2 provides background on the Chinese urea market and reviews the existing literature. Section 3 details variable selection and the identification strategy for the SVAR model. Section 4 presents the empirical results, followed by a discussion of policy implications in Section 5. The last section concludes the paper.

2. Background and Related Literature

2.1 The Chinese Urea Market

Globally, the production and export of fertilizer are highly concentrated, with just five countries—China, Russia, the United States, India, and Canada—supplying over 60% of global fertilizer nutrient supplies during 2017-2019 (IFA 2022). Notably, China is both the world's largest producer and consumer, accounting for nearly a quarter of fertilizer use and production. Urea, a nitrogen-rich and soil-friendly fertilizer suitable for various crops, is the most widely used nitrogen fertilizer in many countries, including China (Jones and Nti 2022; Hu and Brorsen 2017). In 2021, China was the largest producer and consumer, and the third-largest exporter of urea (IFA 2022). India and South Korea were the largest export destinations for China, accounting for more than half of the country's total urea exports (GACC 2023).

Despite being a major urea exporter, most of China's urea production is for domestic use. In 2020, exports accounted for less than 10% of the country's total urea supply (IEA 2022). According to OilChem (2022), more than 60% of China's domestic urea consumption was for agricultural purposes (direct application or synthetic fertilizers), and the rest was for industrial use. Corn was the largest consumer of nitrogen fertilizer in China, accounting for 23% of the total use in 2018, followed by vegetables (21%), rice (17%), and wheat (16%). Unlike most countries, China's urea production relies heavily on coal (about 75%) instead of natural gas (Reuters 2021).

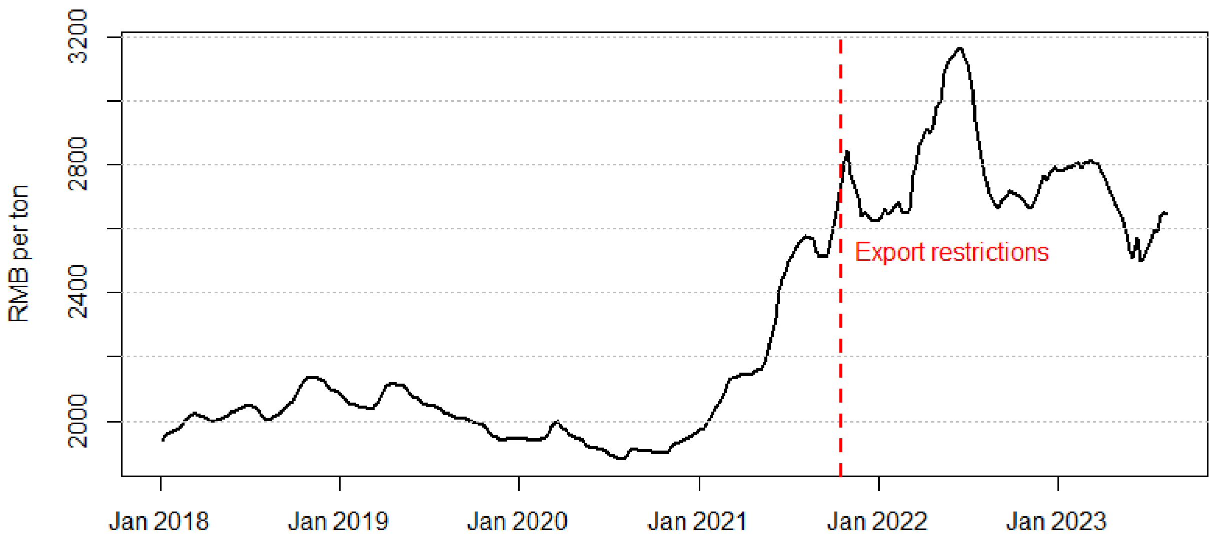
Estimates show that the fertilizer sector accounts for 1-2% of China's total domestic coal consumption (OilChem 2022).

2.2 Policy and Price Changes in the Chinese Urea Market

China's urea industry experienced a significant expansion after 2000. By 2015, annual production soared to 68.6 million metric tons (*mmt*), exceeding domestic consumption by 10 *mmt*. To address this overproduction and environmental concerns, the government launched the "fertilizer zero growth initiative" at the end of 2015. This supply-side reform proved successful, as China's annual urea production dropped to a historical low of 50.0 *mmt* in 2018 and the market supply and demand became more balanced (OilChem 2022). Subsequently, urea prices in China rose from a multi-year low of 1,531 RMB per ton in October 2016 to over 2,000 RMB per ton in 2018.

This study examines China's urea market after 2018, a period following the major supply-side reform. While the selection of the sample period is largely driven by data availability, excluding the earlier years allows us to focus on the factors behind the recent market volatility. Figure 2 plots the weekly Chinese urea prices from January 2018 to August 2023. The data reveals two distinct market regimes: a period of relative stability (2019-2020), followed by a period of increased volatility (2021-2023). From 2019 to 2020, urea prices steadily decreased as producers increased production in response to profitable margins, while industrial and agricultural demand was limited by environmental regulations. The COVID-19 pandemic further dampened demand, driving prices down to a five-year low as both domestic and global consumption contracted.

The period from 2021 to 2022 witnessed a dramatic rise in urea prices due to multiple factors. As the pandemic eased in the first half of 2021, a rapid recovery in industrial and agricultural demand tightened the supply-and-demand conditions for urea both globally and in China. Additionally, a coal supply shortage between July and October 2021 caused a sharp increase in coal prices, a critical input for urea production. This directly affected the urea production costs.



Notes: Data from the Chinese Ministry of Commerce. The red dotted line indicates the beginning of the urea export inspection requirement.

Figure 2: Weekly urea fertilizer spot prices in China, January 2018-August 2023.

To stabilize domestic supply and lower urea prices, the Chinese government implemented two major interventions. First, in October 2021, stricter export controls were imposed by requiring inspection certificates for urea shipments. This measure complicated and lengthened the export inspection process, effectively reducing exports. It is estimated that Chinese urea exports fell by 47% in 2022 compared to 2021 (Hebebrand and Glauber 2023).[6] Second, in December 2021, China launched a temporary fertilizer reserve program of 3 *mmt*, including 1.3 *mmt* of urea, roughly about 25% of the annual production (OilChem 2022). The stockpiling period was set for December 2021 to February 2022, with the release phase between March to May 2022 to ease the supply pressure in the 2022 growing season. It is worth noting that China has already established an "off-season fertilizer reserve" program since 1998, with a stockpiling period running from

[6] Even as of April 2024, when this paper was written, the urea export restrictions have not yet been lifted.

September to May each year for nitrogen fertilizers. Hence, the temporary reserve program overlapped with the existing program by nearly three months, resulting in a surge of additional domestic demand for urea in storage from December 2021 to February 2022.

Finally, the war between Russia and Ukraine that began in February 2022 and the subsequent international sanctions further tightened global fertilizer supplies and increased production costs. In mid-2022, urea prices hit record highs throughout the world.

2.3 Literature on fertilizer prices

Literature on the determinants of fertilizer price movements is relatively limited, with most of the studies focusing on the U.S. market. For instance. Etienne, Trujillo-Barrera, and Wiggins (2016) identified significant linkages between corn and ammonia prices in the U.S., but not between natural gas and ammonia which they attributed to market power. Similarly, Geman and Eleuterio (2013) found a long-term relationship between ammonia and corn prices in the U.S.; however, fertilizer prices do not respond to corn prices in the short term due to market power. Bekkerman, Gumbley, and Brester (2021) investigated the effects of biofuel policies on fertilizer prices in the U.S., finding the equilibrium prices of fertilizers became more influenced by corn prices than by natural gas following the implementation of biofuel policies in the mid-2000s.

For the global market, Hu and Brorsen (2017) analyzed price transmissions between the U.S. and Middle Eastern fertilizer markets, finding that violations of spatial price equilibrium were corrected faster within the U.S. than the international market. Examining global food commodity and fertilizer prices, Ott (2012) found that higher food prices influenced fertilizer prices but not vice versa. Lakkakula (2018) conducted causality tests among five different fertilizer prices collected from the World Bank and found urea prices Granger causes all other fertilizer prices.

Beyond price linkages, previous research also explored how industry structure and trade liberalization affected fertilizer prices. For instance, Hernandez and Torero (2013) analyzed a panel of 38 countries from 1970 to 2002, finding that countries with more concentrated supply tend to have higher urea prices. A 10-percentage point increase in concentration (based on the number of plants and production capacity) would increase urea prices by 8-10%. Renfro (1992) provided evidence from Bangladesh that by reducing subsidies and privatizing the fertilizer sector, farmers benefited from declining fertilizer prices.

Related to Chinese fertilizer markets, Qiao et al. (2003) assessed the potential benefits of China's accession to the World Trade Organization (WTO) to the fertilizer industry. They demonstrated that trade liberalization following China's WTO entry would benefit both domestic fertilizer producers and farmers by enhancing market competition and lowering domestic prices. Li et al. (2013) found that government support policies in China kept fertilizer prices artificially low, contributing to fertilizer overuse and environmental damage.

As noted earlier, several key gaps exist in the literature. First, despite being a major player in the global fertilizer market, China has received limited attention regarding the factors influencing its domestic fertilizer prices. Second, existing research often analyzes determinants of fertilizer prices (e.g., crop demand and input prices) in isolation using reduced-form models. A more comprehensive analysis employing a structural approach is needed to investigate these factors jointly and assess their relative impact. Third, the recent fertilizer price spike has garnered significant media and policy attention, yet no study, to our knowledge, has quantitatively assessed the impact of various factors behind these specific price increases. Lastly, while some research acknowledges the role of government policies in fertilizer markets, few have quantified how interventions such as stockpiling programs or export restrictions impact domestic fertilizer prices.

Our study aims to address these critical gaps in the literature. We investigate the determinants of urea fertilizer price movements in China in 2018-2023 using a structural VAR model identified by heteroskedasticity of structural shocks. By jointly considering input costs, crop prices, and export demand, this structural approach allows us to dissect the key factors driving recent volatility in the Chinese urea market. In particular, we assess the impact of two government interventions implemented during periods of dramatic price fluctuations: the export certification requirement and the temporary fertilizer reserve program. Results from this study can provide valuable insights for both market participants and policymakers in China and globally.

3. Modeling Urea Fertilizer Market

This paper employs an SVAR model to examine the shocks driving recent urea price spikes in China. In this section, we first outline the economic rationales behind the selection of variables for the SVAR model. Subsequently, we introduce the analytical framework and identification strategy.

3.1 Choice of variables

Coal prices. Urea production is an energy-intensive process that relies heavily on raw energy inputs, such as natural gas and coal. Previous research has typically focused on the impact of natural gas on nitrogen fertilizer prices. However, China relies on coal for approximately three-quarters of its urea production. Hence, we use variations in coal prices to capture shocks to the input costs of urea. In China, anthracite and bituminous coal are the two primary types used for urea production, each contributing to about one-third. While anthracite often commands a price premium due to its superior quality, their prices typically move in tandem.[7] Here, we use anthracite prices throughout this paper and refer to them as "coal prices" for clarity.

Corn prices. As a neutral fertilizer, urea can be used for a variety of crops such as corn,

[7] Appendix A plots the prices for anthracite and bituminous coal in China.

wheat, rice, cotton, and vegetables. Higher crop prices incentivize farmers to use more fertilizer, potentially driving up fertilizer prices. Similar to previous studies (Etienne, Trujillo-Barrera, and Wiggins 2016; Geman and Eleuterio 2013), we employ corn prices to capture urea price variations driven by domestic agricultural demand. Corn is the largest consumer of nitrogen fertilizer in China, and unlike wheat and rice which are affected by price support policies, corn prices are subject to fewer government interventions. Although China previously implemented stockpiling and price supports for corn until 2016, our analysis utilizes data starting from 2018, a period when corn prices are more likely to reflect fundamental supply and demand factors.

Export Demand. A major policy concern regarding the recent global fertilizer supply is the imposition of export restrictions by major exporters (e.g., Kee, Cardell, and Zereyesus 2023; Hebebrand and Glauber 2023). To assess the impact of export restrictions implemented by China, we use port inventories of urea at major Chinese export ports as a proxy for export demand. We opted for export inventories over export quantities for several reasons. First, previous research notes that export shipments typically reflect lagged prices due to ordering and logistics (e.g., Bessler and Babula 1987; Anderson and Garcia 1989). Before October 2021, the typical timeline from winning a urea export bid to loading the shipment took about a month. This involved roughly a week to transport the urea to a port storage facility, followed by another 1-2 weeks for loading depending on port efficiency. However, export inspection requirements implemented since then have added a significant waiting period of 1-2 months. Hence, variations in port inventory can reflect export demand more promptly compared to shipments.

Second, port inventory data offers a crucial advantage in terms of frequency. Unlike export quantity data from China Customs that are released monthly, port inventory data is available weekly. This higher resolution can capture short-term market responses during periods of rapid change, particularly for the recent food and fertilizer crisis. Third, as noted in Appendix B, there exists a significant positive correlation between urea export quantities and both the contemporaneous and lagged urea port inventories. This reinforces the validity of using port inventories as a proxy for export demand.

Prior studies note that inventories may also reflect precautionary speculative demand as market participants buy or sell commodities in anticipation of future price changes (e.g., Kilian and Murphy 2014). In such cases, higher inventories signal increased speculative interest. However, in the present analysis, we only consider inventories at export ports rather than total commercial inventories of fertilizers.[8] While total commercial inventories account for current supply/demand and speculative activities, port inventories should mainly reflect export demand and logistics associated with export shipments.

Urea Prices. Three types of urea prices are available in China: futures, free-on-board (FOB), and spot. We use spot prices in the analysis for two reasons. First, while China launched a urea futures market in August 2019, it only became active in late 2020.[9] Second, while Hu and Brorsen (2017) argued that domestic inland and FOB prices should move in tandem in an efficient market, government interventions after October 2021 caused significant divergence between domestic spot and FOB prices as shown in Figure 1. The higher FOB prices mainly reflected international market trends, rather than the domestic market conditions relevant to our study. Therefore, we rely on domestic spot prices for the analysis.

By construction, the four types of shocks considered in this study hence include (1) coal

[8] We do not explicitly account for storage demand due to data limitations. Commercial inventory data and China's national urea stock levels are not available, hindering the estimation of total storage demand. Additionally, the relatively low liquidity of urea futures prevents us from using futures calendar spreads as a proxy for precautionary demand. In our model setting, the impact of precautionary demand for storage is captured by the urea price residuals as in Killian (2009), which we will discuss in later parts of this section.

[9] Daily trading volume for urea futures contracts can be found in Appendix C.

price shocks, representing supply shocks from changes in input costs, (2) corn price changes, reflecting domestic demand shocks due to changes in crop prices, (3) port inventory shocks, reflecting shocks to export demand, and (4) urea market-specific shocks, or idiosyncratic shocks not captured by the preceding three shocks.

Examples of idiosyncratic shocks include disruptions in production due to maintenance or environmental regulations, shocks to industrial and precautionary inventory demand, and changes in government stockpiling programs. The temporary fertilizer reserve program implemented at the end of 2021 would fall into this category, as it reflects the additional domestic demand due to changes in government policies unrelated to crop price changes. Additionally, the export inspection certificate requirement implemented since October 2021 is captured by the port inventory shock, as it effectively reflects a negative shock to the export demand for urea.

3.2 Data

The sample period considered includes weekly data from January 2018 to August 2023, which is dictated by the availability of port inventory data. Weekly retail urea and anthracite coal prices are obtained from the Chinese Ministry of Commerce. Weekly corn prices are calculated using the average daily settlement prices for the most actively traded corn futures contracts at the Dalian Commodity Exchange (DCE), as agricultural commodity price discovery is typically dominated by the most active futures contracts (Garbade and Silber 1983; Hu et al. 2020). Weekly urea inventories at export ports are purchased from *OilChem*, a leading private oil-chemical commodity information company in China.[10] In total, our sample includes 290 weekly observations.

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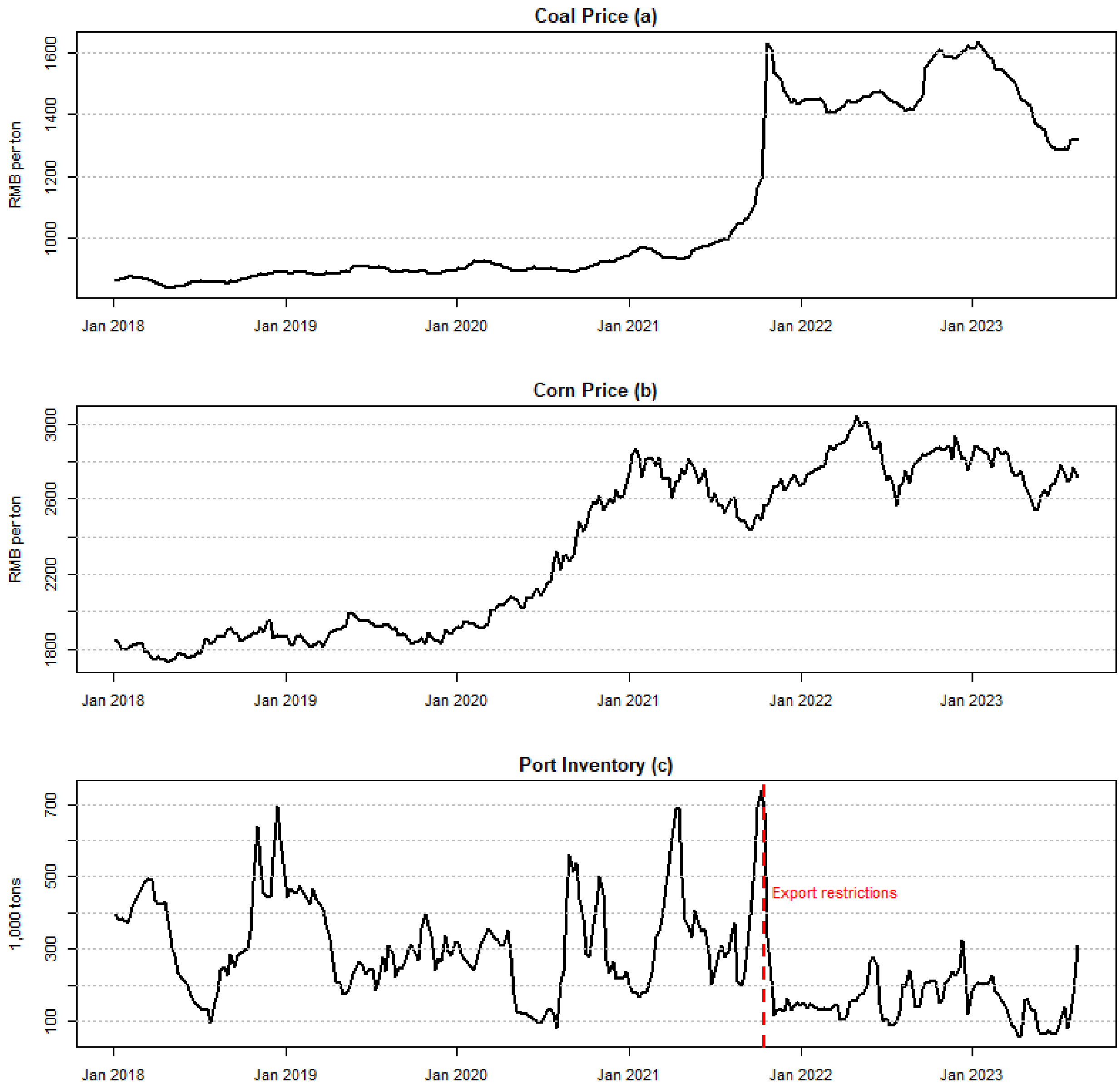
[10] Public data on fertilizer is scare compared to agricultural commodities. Most previous studies rely on fertilizer prices from industrial sources (e.g., Hu and Brorsen 2017, Bekkerman, Gumbley, and Brester 2021). Inventory data from private sources have been increasingly used in the literature. For instance, Kilian (2022) used the global oil inventory data from the Energy Intelligence Group instead of similar data from the Energy Information Association .



Note: the vertical red line indicates the implementation of China's urea export restrictions Port inventory data are from OilChem, corn prices are futures prices from DCE, and coal prices are from the Chinese Ministry of Commerce.

Figure 3. Weekly coal prices (a), corn prices (b), and urea port inventories (c), 2018-2023.

Combining Figure 2 (urea prices) and Figure 3 (prices of corn and coal, and urea port inventories), two key patterns emerge. First, all commodities exhibit shifts in price levels and volatility, a pattern that is crucial for our identification strategy in the SVAR model. In particular, both coal and urea prices started to increase in 2021, with the coal price exhibiting a sharper rise.

Subsequently, both prices became more volatile. Similarly, corn experienced a shift in price level and volatility, but one year earlier in 2020. Second, port inventories plunged after October 15th, 2021, following the implementation of China's export inspection requirement for urea. While this policy lowered exports, it did not impose a complete ban. This is evident from the inventory series—the amount of urea held at the export ports remained well above 100,000 tons for most of the period after the policy change. In certain periods, the inventory surpassed 200,000 tons, suggesting ongoing exports despite the restrictions.

3.3 The SVAR model

Consider a four-dimensional VAR model $y_t = (\Delta coal, \Delta corn, \Delta port\ inventory, \Delta urea)'$, where $\Delta coal$, $\Delta corn$, $\Delta port\ inventory$, and $\Delta urea$ represent the log differences of coal prices, corn prices, urea port inventory, and urea prices, respectively.[11] The VAR model of order p can be expressed as

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + C x_t + u_t, \tag{1}$$

where u_t is a vector of reduced-form shocks that have a constant variance-covariance and zero means; x_t is a vector of deterministic components that includes seasonal dummies and a dummy variable that accounts for the impact of policy changes, which equals 1 after October 15th, 2021, and 0 otherwise. The SVAR model can be obtained by rewriting the reduced-form shocks as a linear combination of the structural shocks,

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + D x_t + B \varepsilon_t, \tag{2}$$

where $u_t = B\varepsilon_t$ and ε_t is a vector of structural shocks with zero means and a diagonal variance-

[11] We conducted unit root tests and found all price series are non-stationary during the sample period. We estimated the VAR model with all series in levels as suggested by Sim, Stock, and Watson (1990). However, the VAR model was unstable and impulse response functions were explosive. These results are available from the authors upon request.

covariance matrix. The model identifies four structural shocks: coal price shocks that represent unanticipated supply changes due to input cost changes ($\varepsilon_{coal\,price}$); corn price shocks that influence the domestic agricultural demand for urea ($\varepsilon_{corn\,price}$); port inventory shocks that capture innovations to export demand ($\varepsilon_{port\,inventory}$); and idiosyncratic market-specific shocks to the price of urea ($\varepsilon_{urea\,price}$) that cannot be explained by the preceding three shocks.

Since structural shocks are instantaneously uncorrelated, the matrix B can be interpreted as the contemporaneous effects of structural shocks on the observed variables. Without loss of generality, B is chosen such that ε_t has an identity variance-covariance matrix, i.e., $E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon = I_4$. Then, the variance-covariance of the reduced-form shocks is $E(u_t u_t') = \Sigma_u = BB'$. The central goal of an SVAR analysis is to identify matrix B from Σ_u, where Σ_u can be estimated from the data. However, B cannot be uniquely identified without imposing further restrictions, given that Σ_u has $4(4+1)/2$ different elements while B has 4^2 different elements. Therefore, at least $4(4-1)/2$ restrictions are required to identify B and accurately define the shocks.

Traditional identification approaches for SVAR models often rely on exclusion restrictions or sign restrictions (e.g., Janzen, Smith, and Carter 2018, Bruno, Büyükşahin, and Robe 2017, Wiggns and Etienne 2017). Exclusion restrictions assume certain variables have no causal effect on others, while sign restrictions assume positive/negative responses of one variable to another. However, these restrictions may be subjective and lack empirical validation (Lütkepohl and Netšunajev, 2017). The conventional identification approaches are particularly challenging in our case because fertilizer, agricultural commodities, and energy markets are closely linked through the fertilizer industrial supply chain. Assuming one market is independent of the others, or imposing fixed relationships between them, would be overly restrictive. Hence, we adopt a data-driven identification approach, specifically, identification based on changes in variances.

3.3 Heteroskedasticity-based identification

Commodity prices often exhibit phases of high and low volatility, which is known as heteroskedasticity (Bollerslev, 1987). Previous studies that adopted Rigobon's (2003) heteroskedasticity identification approach assume an exogenous change in variance. However, in practice, shifts in volatility are more likely to be a graduate process than a structural change. Hence, we follow Lütkepohl and Netšunajev (2017) and employ an identification scheme via smooth transition covariances. The variance-covariance of reduced-form shocks u_t is assumed to consist of two regimes (Σ_1 and Σ_2), and the transition from one regime to the other is governed by a non-linear function. Specifically,

$$E(u_t u_t') = \Omega_t = \big(1 - G(s_t)\big)\Sigma_1 + G(s_t)\Sigma_2, \tag{3}$$

where $G(\cdot)$ is the transition function and s_t is the transition variable. The two variance-covariance matrices can be decomposed as $\Sigma_1 = BB'$ and $\Sigma_2 = B\Lambda B'$ where Λ = diag ($\lambda_{coal\ price}, \lambda_{corn\ price}, \lambda_{port\ inventory}, \lambda_{urea\ price}$) is a diagonal matrix that captures the change in variance-covariance of structural shocks. In the first regime, the structural shocks have unit variance, while in the second regime, the variances are given by the diagonal elements of Λ. As such, Λ is the ratio of variance of the second regime to that of the first regime. To uniquely identify the structural shocks, it is necessary that all diagonal elements of Λ are distinct, which can be tested using pairwise Wald-type tests (Lütkepohl and Netšunajev 2017).

A deterministic transition variable is plausible when the first and second parts of the sample period are associated with different volatility levels and there is a transition period between the two volatility states. Based on the gradual shifts in the variances as present in Figure 2 and Figure 3, we use time as the transition variable, i.e. $s_t = t$ and a logistic function proposed by Maddala (1977) as the transition function,

$$G(\gamma, c, t) = \frac{1}{1 + e^{-e^{\gamma}(t-c)}}, \tag{4}$$

where γ is the slope of the function and c is the time point of transition. $G(\gamma, c, t)$ depicts the probability of being in each volatility regime and ranges between 0 and 1. When $s_t = t < c$, $G(\gamma, c, t)$ will be close to zero, and $\Omega_t \approx \Sigma_1$. On the other hand, when $s_t = t > c$, $G(\gamma, c, t)$ will be close to one, and $\Omega_t \approx \Sigma_2$.

As shown in Lütkepohl and Netšunajev (2017), the parameters (B, Λ, γ, and c) can be estimated by maximizing the log-likelihood using an iterative algorithm. Given the estimated B, we conduct an impulse response analysis to evaluate the impact of each structural shock and determine their contributions using historical variance decomposition.

4. Empirical Results

4.1 Identification Results

We first estimate a reduced-form VAR model of Equation (1) using the least-squares method. The Akaike information criterion selects a lag length of 2. The resulting estimates are then used to construct the structural VAR representation of the model. Figure 4 plots the estimated transition function, with time as the transition variable ($s_t = t$). The estimated transition function suggests a shift in variance from a lower volatility regime to a higher volatility regime in the middle of 2021, which corresponds to the increased volatility observed in urea prices, as shown in Figure 2.

Table 1 presents parameter estimates for the matrix B and matrix Λ of the structural VAR model. Since the information in matrix B is better conveyed through plots for the impulse responses, we save the discussion on the contemporaneous impacts for later and focus first on the heterogeneity in the estimated relative variances in matrix Λ to check the required conditions for the identification strategy.

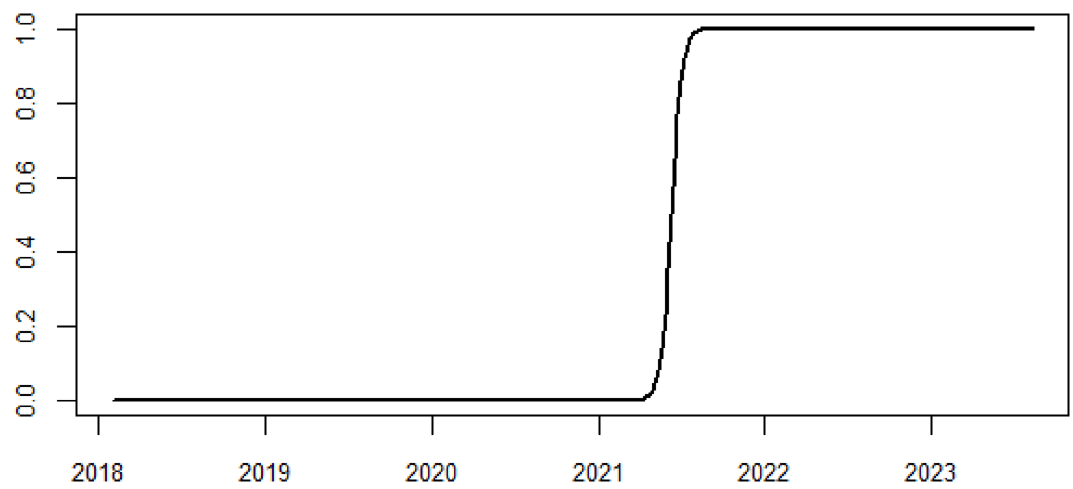


Figure 4. Transition function for the SVAR model ($s_t = t$), 2018-2023.

Table 1. Parameter estimates from the structural vector autoregression model.

Panel (a). Estimated matrix B				Panel (b). Estimated matrix Λ			
				$\lambda_{coal\ price}$	$\lambda_{corn\ price}$	$\lambda_{port\ inventory}$	$\lambda_{urea\ price}$
0.005	0.000	0.000	-0.001	20.185			
(0.000)	(0.000)	(0.000)	(0.001)	(3.393)			
0.000	0.017	0.004	0.000		1.06		
(0.000)	(0.001)	(0.003)	(0.001)		(0.192)		
0.002	-0.071	0.164	0.012			2.078	
(0.006)	(0.035)	(0.015)	(0.012)			(0.368)	
0.001	0.000	0.000	0.004				8.417
(0.000)	(0.000)	(0.000)	(0.000)				(1.545)

Note: B is the matrix associated with structural shocks in Equation (2). Λ is the ratio of variance of the second regime to that of the first regime for Equation (3). Numbers are rounded to the third decimal and standard deviations are presented in the parentheses.

As shown in Table 1, the diagonal elements representing relative variances all exceed 1. This reflects higher volatility across all three commodity returns in the second regime (after mid-2021) compared to the first, and more volatile fluctuations in port inventory due to export restrictions implemented in late 2021. More importantly, the results show apparent heterogeneity in the estimated relative variances, a key requirement for the heteroskedasticity-based identification strategy. To formally confirm this heterogeneity, we conduct pairwise Wald-type tests (Lütkepohl et al. 2021) for each pair of relative variances. As shown in Table 2, all tests reject the null hypothesis of equal variances at the 1% significance level, suggesting that parameters in the structural matrix B are all identified.

Table 2. Tests for equality of relative variances.

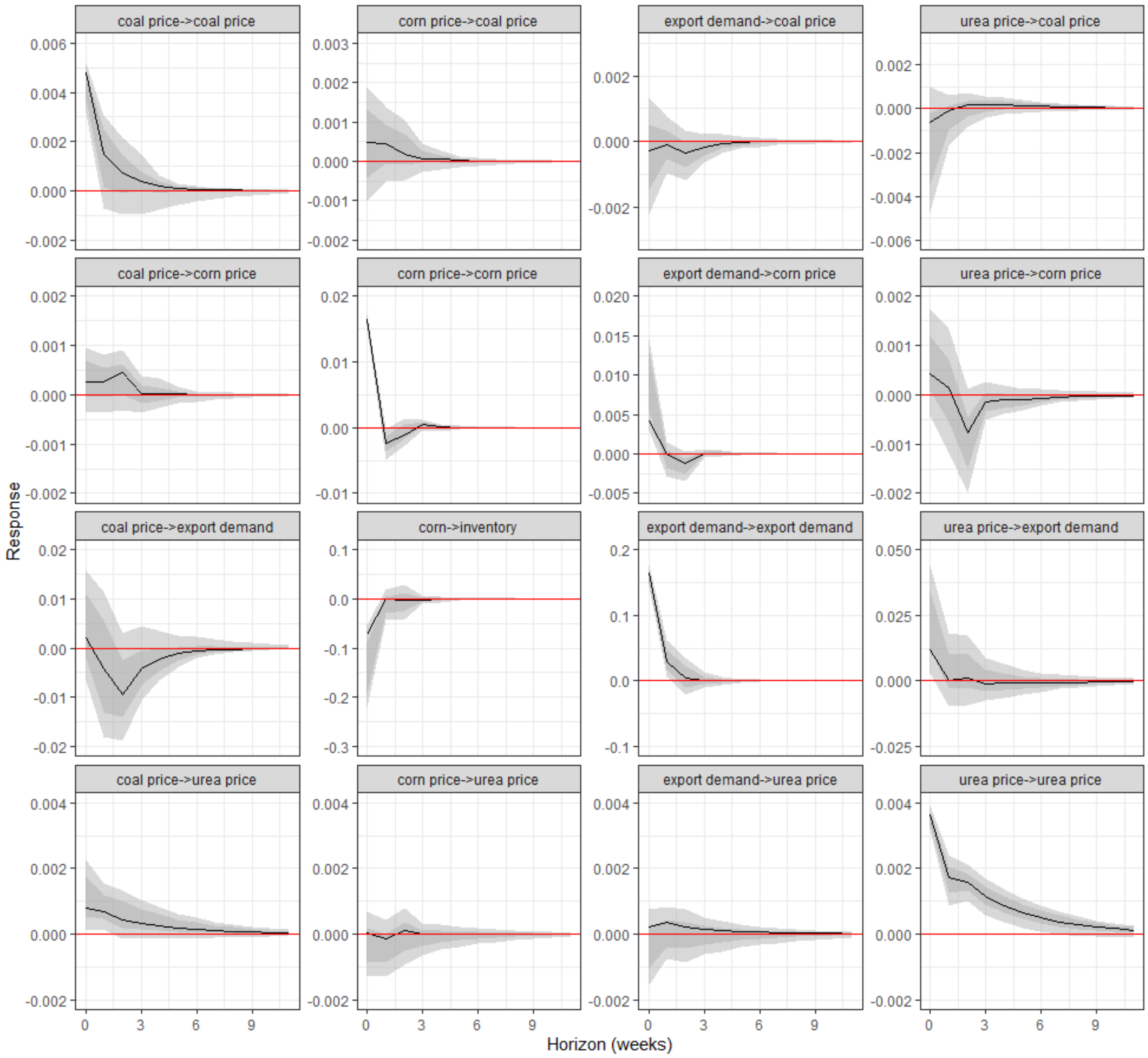
Null hypothesis	Wald Statistic
$\lambda_{coal\ price} = \lambda_{corn\ price}$	31.66***
$\lambda_{coal\ price} = \lambda_{port\ inventory}$	28.13***
$\lambda_{coal\ price} = \lambda_{urea\ price}$	9.92***
$\lambda_{corn\ price} = \lambda_{port\ inventory}$	6.02***
$\lambda_{corn\ price} = \lambda_{urea\ price}$	22.34**
$\lambda_{port\ inventory} = \lambda_{urea\ price}$	15.94***

Note: ** and *** indicate statistical significance at the 5% and 1% levels, respectively. The null hypothesis is the equality of two relative variances between two variables.

4.2 Impulse Response Analysis

Based on estimated parameters and structural shocks from the SVAR model, we next estimate impulse response functions to assess how each variable responds to a one-standard-deviation positive shock in the other variables. To mitigate the impact of heteroskedasticity, the inference is based on a recursive-design wild bootstrap with 2,000 replications (Gonçalves and Kilian 2004). Figure 5 shows impulse responses with 68% and 95% confidence bands.

As can be seen in the top panel of Figure 5, coal prices do not significantly respond to shocks from either the urea or corn market. This aligns with expectations, as coal prices can be viewed as a macroeconomic variable influenced by overall market conditions rather than specific dynamics within the urea and corn markets. Previous SVAR studies relying on recursive identification strategies or parameter restrictions typically assume that macroeconomic variables are contemporaneously exogenous to agricultural market variables (e.g., Janzen, Smith, and Carter, 2013; Bruno, Büyükşahin, and Robe, 2017). Our findings indicate that the data-driven identification strategy employed in the present study can still produce results consistent with economic theory without imposing any restrictions.



Note: confidence bands are constructed using a recursive-design wild bootstrap with 2000 replications. Darker shaded areas represent 95% confidence intervals, and lighter shaded areas represent 68% confidence intervals.

Figure 5. Impulse response functions from the SVAR model with one- and two-standard deviation confidence bands (shock variable→ response variable).

Plots in the second row of Figure 5 show that corn prices do not significantly respond to shocks to input costs as proxied by coal prices. In contrast, a positive shock to export demand, proxied by port inventory, significantly increases corn futures prices. This may happen as increased urea exports reduce the availability of domestic fertilizer supply. In anticipation of higher domestic urea prices and the higher cost of corn production, corn prices increase. A positive shock to urea prices significantly impacts corn prices, again reflecting the effect of increased input costs. However, the effect is only statistically significant at the 68% but not 95% level. The impact also appears to be a temporary overshoot, as the response of corn price changes rapidly decreases and becomes negative within two months, after which they turn indistinguishable from zero.

Export demand (proxied by port inventories) is negatively affected by unanticipated increases in coal prices, suggesting that China's urea exports may decrease when losing production cost advantages. An unexpected increase in domestic corn prices significantly decreases export inventories, as strong domestic demand for fertilizer lowers its availability for exports. Meanwhile, a positive shock to urea prices significantly increases the demand for export inventories. Although we consider domestic urea prices, higher domestic prices are often associated with higher export prices as shown in Figure 1. This implies that higher domestic urea prices are likely to be associated with a more profitable export environment, leading to increased exports.

The bottom panel of Figure 5 presents the effects of the structural shocks on urea prices which are the main interest of the paper. As expected, an unanticipated increase in coal prices has an immediate positive impact on urea prices. Such an impact can last for two weeks, reflecting again the production and logistic time lag. Interestingly, shocks to corn prices do not significantly affect urea prices, which is consistent with Geman and Eleuterio (2013) but contradicts Etienne, Trujillo-Barrera, and Wiggins (2016) and Ott (2012). Notice that our sample period largely coincides with rising corn prices. It appears that during periods of rising agricultural commodity prices, farmers may be less inclined to increase fertilizer use to boost supply, which could lead to lower sale prices and reduced marketing margins.

An unexpected increase in port inventories does not significantly impact urea prices, suggesting that on average, export demand has a minimal influence on domestic urea price changes in China. Even before export restrictions, exports typically accounted for less than 10% of total urea demand in China. The most pronounced and persistent impact on urea prices appears to be market-specific shocks, as illustrated in the lower-left panel of Figure 5. As noted earlier, these idiosyncratic shocks to the urea market encompass supply and demand factors that cannot be explained by changes in input costs, agricultural demand, and exports.

4.3 Historical Decomposition

The impulse response functions only demonstrate the average impact of each structural shock over the sample period. To assess the cumulative contribution of each structural shock to urea price changes at each point in time, in this section we discuss the results from historical decompositions of urea prices, which are presented in Figure 6. By connecting the changes in the contribution of each structural shock to specific events at each time point, we can provide a more detailed explanation for each major price change.

The urea market experienced two notable price spikes during the sample period: one in October 2021 and another in mid-2022 (as shown in Figure 2). Evidence from the first panel of Figure 6 suggests that supply shocks caused by changes in coal prices were the primary contributor to the urea price spike in October 2021. As we use log differences, results indicate that shocks to coal prices may have resulted in a 5% change in urea prices during the sample period. In contrast, coal prices had a smaller impact on the mid-2022 price surge. Notably, apart from October 2021, coal prices also had a relatively large impact on urea prices in late 2022 and at the very end of the sample period (August 2023). For late 2022, Figure 3 suggests that after relatively stable prices in the first half of 2022, coal prices started to rise again toward the end of that year, which likely contributed to the subsequent urea price. Further, it can be seen from Figure 2 that urea prices started to rise again in October 2023, and our results suggest that part of this price increase may be driven by higher production costs.

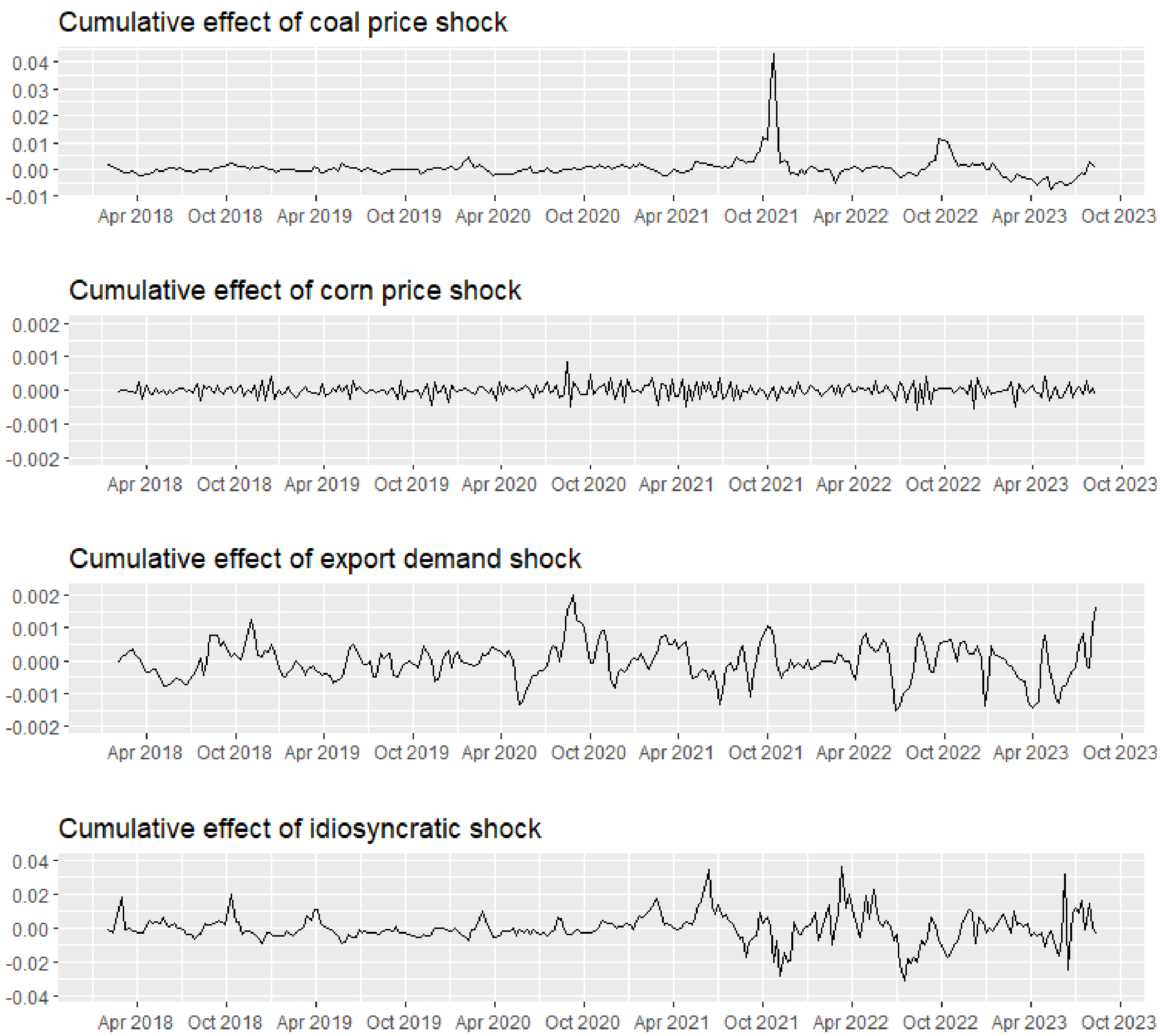


Figure 6. Historical decomposition of urea price changes, January 2018-August 2023

Consistent with the impulse responses, the second panel in Figure 6 shows that demand shocks due to corn price change had minimal impact on urea price movements throughout the sample period. Results suggest that despite large fluctuations in corn prices, shocks to the corn market had no more than a 0.1% impact on urea price changes during the sample period. The largest impact appeared to be around September 2020, before the rapid price run-up.

Turning next to the impact of export demand, results from historical decomposition again show that exports had little influence on urea price changes in China. While its magnitude of impact is slightly higher than that of corn market shocks, its largest impact again occurred around September 2020, at about 0.15%. In particular, the magnitude of contribution from export demand since October 2021 to urea prices is within range, and even smaller than its contribution in some other periods when prices were less volatile. The impact of export shocks from October 2021 to the end of the sample period ranges between -0.015% and 0.018%, a meager impact when compared to the overall price changes of urea.

The bottom panel in Figure 6 suggests that idiosyncratic shocks specific to the urea market (but unrelated to the other three structural shocks) played a key role in driving most of the urea price changes in China over the sample period, including the two large price spikes. The first half of 2021 saw a rapid recovery in agricultural and industrial demand for urea following the temporary relief from the COVID-19 pandemic. Meanwhile, urea inventories were relatively low due to supply disruptions caused by the pandemic in the previous year. The price increase from late 2021 to early 2022 was likely driven by elevated coal prices (discussed earlier) and heightened domestic demand driven by the new temporary fertilizer reserve program. As noted earlier, on December 23rd, 2021, the NRDC announced a temporary fertilizer reserve program aimed at stabilizing the supply for the upcoming summer growing season. The program involved stockpiling fertilizer between December 2021 and February 2022. This period overlapped with the existing off-season reserve program (September to May of the following year), creating unexpectedly strong demand in the market. As depicted in the lower panel of Figure 6, the release of reserved fertilizer did alleviate urea prices during the summer months (June to August) in 2022, but it also contributed to increased urea prices during the reserve period in January-February 2022.

4. 4 Counterfactual Analysis

To better illustrate the impact of each structural shock on urea prices in levels, we next perform a counterfactual analysis assuming the absence of these shocks. We do this by taking two steps. First, we use the standard procedure to remove individual orthogonal shocks from the historical decomposition and then use the sum of the remaining shocks to construct the counterfactual series of demeaned logarithmic urea price changes. Next, to obtain the counterfactual series of demeaned logarithmic urea prices in levels, we take the cumulative sum of the counterfactual series of urea price changes. These counterfactual prices reflect what prices would have been if the respective shock had not occurred. Figure 7 plots the observed demeaned logarithmic urea prices, along with demeaned counterfactual logarithmic price series.

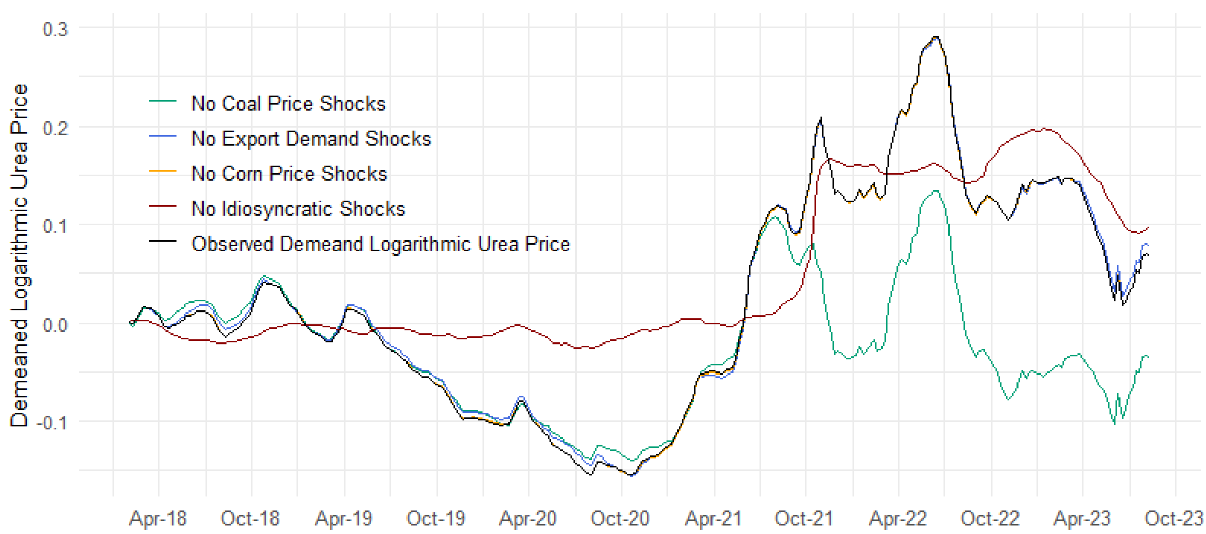


Figure 7. Demeaned counterfactual and actual logarithmic urea prices in China, 2018-2023

As can be seen, the counterfactual urea price sequence assuming no corn price shocks almost overlaps with the actual price sequence, in particular between 2021 and the first half of 2023. A similar pattern is observed in the counterfactual price sequence assuming no export demand shocks. Although urea prices would have been slightly lower in the first half of 2021 in the absence of export demand shocks, the difference between the counterfactual and actual prices is small. Consistent with the results from historical decompositions and impulse responses, the counterfactual analysis suggests that export restrictions implemented through the inspection requirement had a minimal impact on lowering domestic urea prices, raising questions about the effectiveness of the policy.

In contrast, idiosyncratic shocks appeared to be the single most important factor in explaining fluctuations in urea prices before 2021. Without idiosyncratic shocks, urea prices would have remained stable even in the presence of shocks from the corn market, coal prices, and exports. For instance, the price decline observed from October 2018 to October 2021 would not have occurred without idiosyncratic shocks. The difference between the lowest demeaned logarithmic urea price and the counterfactual price, assuming no idiosyncratic shocks, is 0.15, suggesting that urea prices would have been 15% higher without idiosyncratic shocks.

Although idiosyncratic shocks continued to be a major contributor to the two price spikes in 2021 and mid-2022, shocks to coal prices became an important factor since the end of 2021. Specifically, without coal price shocks, the price spikes in 2021 and 2022 would have been approximately 15% lower. Figure 7 also indicates that without idiosyncratic shocks caused by improvements in domestic supply (i.e., the release of urea from the temporary reserve program), urea prices would have been 3%-5% higher after July 2022 when prices began to drop.

5. Policy Implications

Findings from the present study have important implications for exporting countries seeking to mitigate domestic price increases during global price spikes. Two policy instruments were implemented by China to lower urea prices, export restrictions by requiring inspection certificates, and domestic stockpiling through the temporary fertilizer reserve program. The temporary reserve program was announced in December 2021, with the stockpiling period running from December 2021 to February 2022. While the program demonstrated some effectiveness in mitigating domestic urea price volatility during the 2022 summer growing season, findings show that urea prices elevated during the stockpiling period.

The theory of storage (Deaton and Laroque 1996; Williams and Wright 1991) suggests that commodity storage helps reduce price volatility. However, to mitigate the price impact from a temporary stockpiling that would lead to an expected increase in demand, policymakers may consider providing complementary financial or tax support to urea producers to increase domestic supply. Moreover, facilitating access to publicly available urea market supply-demand data by government agencies could provide guidance to market participants and enhance urea market information efficiency. This is particularly crucial considering that the majority of fertilizer market data is currently provided by private firms with additional charges.

In terms of export restrictions, we found limited evidence that it shielded domestic prices from global shocks. While China's export inspection requirements since October 2021 significantly reduced export demand, they had minimal impact on lowering domestic urea prices. Even without these restrictions, counterfactual analysis suggests domestic prices would not have risen significantly, a result consistent with prior studies on the effectiveness of export restrictions (e.g., Rude and An 2015; Porteous 2017; Melek, Plante, and Yücel 2017). While our study did not analyze the impact of China's export restrictions on global urea prices, considering China's role in the global urea market, it likely disrupted the global supply chain and increased uncertainty within the market. As domestic urea prices have significantly declined, returning to pre-2021 levels by early 2024, lifting the restrictions seems advisable.

While our study only considers the immediate effects of export restrictions, their long-term impact is also important. Previous studies show that a lack of clear signals from governments against export restrictions can discourage investment in production and related infrastructure (Götz, Glauben, and Brümmer 2013). The export restrictions remain in effect as of April 2024, and China's urea exports have yet to return to the pre-October 2021 level. Such a prolonged restriction will likely hinder China's supply-side reform in the urea industry to achieve more efficient and cleaner production.

Our findings hold significant implications for countries considering export restrictions and stockpiling to moderate domestic prices. To date, there are still a number of countries implementing fertilizer and food export restrictions. Although export restrictions may appear to be a quick solution, their effectiveness in controlling domestic prices warrants further investigation. Alternative policy options, such as targeted subsidies for fertilizer production (Voegele 2023) or direct assistance to farmers (Ricome, Barreiro-Hurle, and Fall 2024), may be an effective tool to mitigate the impact of domestic price increases without disrupting the fertilizer markets. Regarding domestic stockpiling, our study indicates that it can be effective in moderating domestic prices during the reserve release period. However, the implementation of this strategy should be paired with incentivizes for producers to increase supply during stockpiling periods. Without such incentives, stockpiling risks creating artificial scarcity and potentially driving prices even higher. In the longer term, these policy responses may discourage investment in the fertilizer industry, negatively affecting consumers and producers.

6. Conclusions

Recent spikes in fertilizer prices have heightened global concerns about food security. Major fertilizer-exporting countries intervened by imposing export restrictions or stockpiling to secure domestic supplies and mitigate price increases. This study focuses on urea in China, one of the major players in the global urea market. Using a structural vector autoregression model, we decompose Chinese urea price movements between January 2018 and August 2023 into four structural shocks: supply shocks due to coal price changes, domestic demand shocks due to changes in crop prices, shocks to export demand, and urea market-specific idiosyncratic shocks not captured by the preceding three shocks. Identification is achieved through a heteroskedasticity-based approach that allows for a smooth transition in covariances.

Results suggest that idiosyncratic shocks from changes in domestic supply and demand conditions consistently had a large impact on Chinese urea price fluctuations throughout the sample period. Supply shocks due to changes in coal prices also had a large impact starting from late 2021. In particular, the urea price spikes observed in 2021 and 2022 were largely driven by these two factors—urea prices in China would have been 15% lower in the absence of either of the two shocks. In contrast, variations in corn prices and export demand had a minimal impact on urea price changes. Overall, our results suggest that input cost changes and supply/demand factors unrelated to input cost, export demand, and crop prices are the primary drivers of urea price behavior in China since 2018.

Our results further highlight that government interventions in exporting countries during periods of rapid price volatility may fail to achieve the goal of insulting domestic prices from the global market. As demonstrated in the present study, the impact of export restrictions on lowering domestic urea prices in China is minimal. Further, while the temporary fertilizer reserve program may have helped to lower urea prices during the growing season in 2022, it significantly increased urea prices between late 2021 and February 2022. Further studies are needed to quantify the impact of these policies on the global fertilizer markets, as well as investigate the long-term impact of these policies both domestically and internationally.

References

Anderson, M., & Garcia, P. (1989). Exchange rate uncertainty and the demand for US soybeans. *American Journal of Agricultural Economics*, *71*(3), 721-729.

Bekkerman, A., Gumbley, T., & Brester, G. W. (2021). The Impacts of Biofuel Policies on Spatial and Vertical Price Relationships in the US Fertilizer Industry. *Applied Economic Perspectives and Policy*, *43*(2), 802-822.

Bessler, D. A., & Babula, R. A. (1987). Forecasting wheat exports: Do exchange rates matter? *Journal of Business & Economic Statistics*, *5*(3), 397-406.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. *Review of Economics and Statistics*, 542-547.

Bruno, V. G., Büyükşahin, B., & Robe, M. A. (2017). The financialization of food?. *American Journal of Agricultural Economics, 99*(1), 243-264.

Deaton, A., & Laroque, G. (1996). Competitive storage and commodity price dynamics. *Journal of Political Economy*, *104*(5), 896-923.

Etienne, X. L., Trujillo-Barrera, A., & Wiggins, S. (2016). Price and volatility transmissions between natural gas, fertilizer, and corn markets. *Agricultural Finance Review*, *76*(1), 151-171.

Garbade, K. D., & Silber, W. L. (1983). Futures contracts on commodities with multiple varieties: An analysis of premiums and discounts. *Journal of Business*, 249-272.

Geman, H., & Eleuterio, P. V. (2013). Investing in fertilizer–mining companies in times of food scarcity. *Resources Policy*, *38*(4), 470-480.

General Administration of Customs of the People's Republic of China (GACC). (2023). Statistics Database. http://stats.customs.gov.cn/ (accessed 15 December 2023).

Gonçalves, S., & Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, *123*(1), 89-120.

Götz, L., Glauben, T., & Brümmer, B. (2013). Wheat export restrictions and domestic market effects in Russia and Ukraine during the food crisis. *Food Policy*, *38*, 214-226.

Headey, D. (2011). Rethinking the global food crisis: The role of trade shocks. *Food Policy*, *36*(2), 136-146.

Headey, D., & Fan, S. (2008). Anatomy of a crisis: the causes and consequences of surging food prices. *Agricultural economics*, *39*, 375-391.

Hebebrand, C., & Glauber, J. W. (2023). The Russia-Ukraine war after a year: Impacts on fertilizer production, prices, and trade flows. *The Russia-Ukraine Conflict and Global Food Security: Section One: A Conflict with Global* Consequences (Chapter 8, pp. 43-47). International Food Policy Research Institute (IFPRI). Washington, DC

Hebebrand, C., & Laborde Debucquet, D. (2023). High fertilizer prices contribute to rising global food security concerns. *The Russia-Ukraine Conflict and Global Food Security: Section One: A Conflict with Global Consequences (Chapter 7, pp. 38-42).* International Food Policy Research Institute (IFPRI). Washington, DC

Hernandez, M. A., & Torero, M. (2013). Market concentration and pricing behavior in the fertilizer industry: a global approach. *Agricultural Economics*, *44*(6), 723-734.

Hu, Z., & Brorsen, B. W. (2017). Spatial price transmission and efficiency in the urea market. *Agribusiness*, *33*(1), 98-115.

Hu, Z., Mallory, M., Serra, T., & Garcia, P. (2020). Measuring price discovery between nearby and deferred contracts in storable and nonstorable commodity futures markets. *Agricultural*

Economics, *51*(6), 825-840.
IFA. (2022). IFA Short Term Outlook Report 2022-2023. https://www.fertilizer.org/resource/public-summary-short-term-fertilizer-outlook-2022-2023/ (accessed 13 March 2023).
IFA. (2024). Fertilizer and raw materials statistics in the world. https://www.fertilizer.org/market-intelligence/ifastat/ (accessed 13 March 2024).
IEA. (2022). Production, consumption, and trade of urea in selected countries and regions. https://www.iea.org/data-and-statistics/charts/production-consumption-and-trade-of-urea-in-selected-countries-and-regions-2020 (accessed 13 March 2023).
Janzen, J. P., Smith, A., & Carter, C. A. (2018). Commodity price comovement and financial speculation: the case of cotton. *American Journal of Agricultural Economics*, *100*(1), 264-285.
Jones, K., & Nti, F. (2022). Impacts and repercussions of price increases on the global fertilizer market. *USDA Foreign Agricultural Service.*
Kee, J., Cardell, L., & Zereyesus, Y. A. (2023). Global Fertilizer Market Challenged by Russia's Invasion of Ukraine. *Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America*, *2023*.
Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053-1069.
Kilian, L. (2022). Facts and fiction in oil market modeling. *Energy Economics, 110*, 105973.
Kilian, L., & Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied econometrics*, *29*(3), 454-478.
Laborde Debucquet, D., Mamun, A., & Parent, M. (2020). *Documentation for the COVID-19 food trade policy tracker: Tracking government responses affecting global food markets during the COVID-19 crisis* (Vol. 1). Intl Food Policy Res Inst. https://www.foodsecurityportal.org/tools/COVID-19-food-trade-policy-tracker.
Lakkakula, P. (2018). Testing causality among five fertilizer prices. *Applied Economics Letters*, *25*(9), 601-606.
Li, Y., Zhang, W., Ma, L., Huang, G., Oenema, O., Zhang, F., & Dou, Z. (2013). An analysis of China's fertilizer policies: impacts on the industry, food security, and the environment. *Journal of Environmental Quality*, *42*(4), 972-981.
Lütkepohl, H., & Netšunajev, A. (2017). Structural vector autoregressions with heteroskedasticity: A review of different volatility models. *Econometrics and Statistics*, 1, 2-18.
Lütkepohl, H., Meitz, M., Netšunajev, A., & Saikkonen, P. (2021). Testing identification via heteroskedasticity in structural vector autoregressive models. *The Econometrics Journal*, *24*(1), 1-22.
MADDALA, G. S. (1977). "Self-Selectivity Problems in Econometric Models," in Applications of Statistics. Ed.: PARUCHURI R. KRISHNAIAH. Amsterdam: North- Holland, 1977, pp. 351-66.
Martin, W., & Anderson, K. (2012). Export restrictions and price insulation during commodity price booms. *American Journal of Agricultural Economics*, *94*(2), 422-427.
Melek, N. Ç., Plante, M., & Yücel, M. K. (2017). *The US shale oil boom, the oil export ban, and the economy: A general equilibrium analysis* (No. w23818). National Bureau of Economic Research.
OilChem. (2022). *Oilchem 2021-2022 Urea Market Annuel Report*. https://en.oilchem.net/

(accessed 13 March 2023).
Ott, H. (2012). Fertilizer markets and their interplay with commodity and food prices. *Report for the European Commission Joint Research Centre, Brussels*.
Porteous, O. (2017). Empirical effects of short-term export bans: The case of African maize. *Food Policy*, *71*, 17-26.
Qiao, F., Lohmar, B., Huang, J., Rozelle, S., & Zhang, L. (2003). Producer benefits from input market and trade liberalization: the case of fertilizer in China. *American Journal of Agricultural Economics*, *85*(5), 1223-1227.
Renfro, R. Z. (1992). Fertilizer price and subsidy policies in Bangladesh. *World Development*, *20*(3), 437-455.
Reuters. (2021). China's urea futures hit limit up on energy regulations, soaring coal prices. https://www.reuters.com/article/idUSL1N2QI0TQ (accessed 13 March 2023).
Reuters. (2023a). South Korea to Consult China Over Urea Export Delays. https://www.reuters.com/world/asia-pacific/south-korea-consult-china-over-urea-export-delays-2023-12-04/ (accessed 13 December 2023).
Reuters. (2023b). China slows fertilizer exports, raising industry concerns in India. https://www.reuters.com/markets/commodities/china-slows-fertiliser-exports-raising-industry-concerns-india-2023-09-08/ (accessed 13 December 2023).
Ricome, A., Barreiro-Hurle, J., & Fall, C. S. (2024). Government fertilizer subsidies, input use, and income: The case of Senegal. *Food Policy*, *124*, 102623.
Rigobon, R. (2003). On the measurement of the international propagation of shocks: is the transmission stable?. *Journal of International Economics*, *61*(2), 261-283.
Rude, J., & An, H. (2015). Explaining grain and oilseed price volatility: The role of export restrictions. *Food Policy*, *57*, 83-92.
Shama, R. (2011). *Food export restrictions: Review of the 2007-2010 experience and considerations for disciplining restrictive measures* (pp. 1-12). Rome: FAO.
Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48.
Svanidze, M., Götz, L., & Serebrennikov, D. (2022). The influence of Russia's 2010/2011 wheat export ban on spatial market integration and transaction costs of grain markets. *Applied Economic Perspectives and Policy*, *44*(2), 1083-1099.
Voegele, J. (2023). How to manage the world's fertilizers to avoid a prolonged food crisis. World Bank Blogs. https://blogs.worldbank.org/en/voices/how-manage-worlds-fertilizers-avoid-prolonged-food-crisis (accessed 24 March 2024).
Wiggins, S., & Etienne, X. L. (2017). Turbulent times: Uncovering the origins of US natural gas price fluctuations since deregulation. *Energy Economics*, *64*, 196-205.
Williams, J. C., & Wright, B. D. (1991). *Storage and commodity markets*. Cambridge University Press.
WTO (2022). WTO Report on International Trade and Trade Organizations. https://www.wto.org/english/news_e/news22_e/igo_14nov22_e.pdf (accessed 20 March 2024).
Yara International. (2022). Fertilizer Industry Handbook 2022. https://www.yara.com/siteassets/investors/057-reports-and-presentations/other/2022/fertilizer-industry-handbook-2022-with-notes.pdf (accessed 13 March 2023).

Appendix A

Figure A1 presents weekly Chinese bituminous and anthracite coal prices from January 2018 to July 2023. As can be seen, the two prices move in tandem.

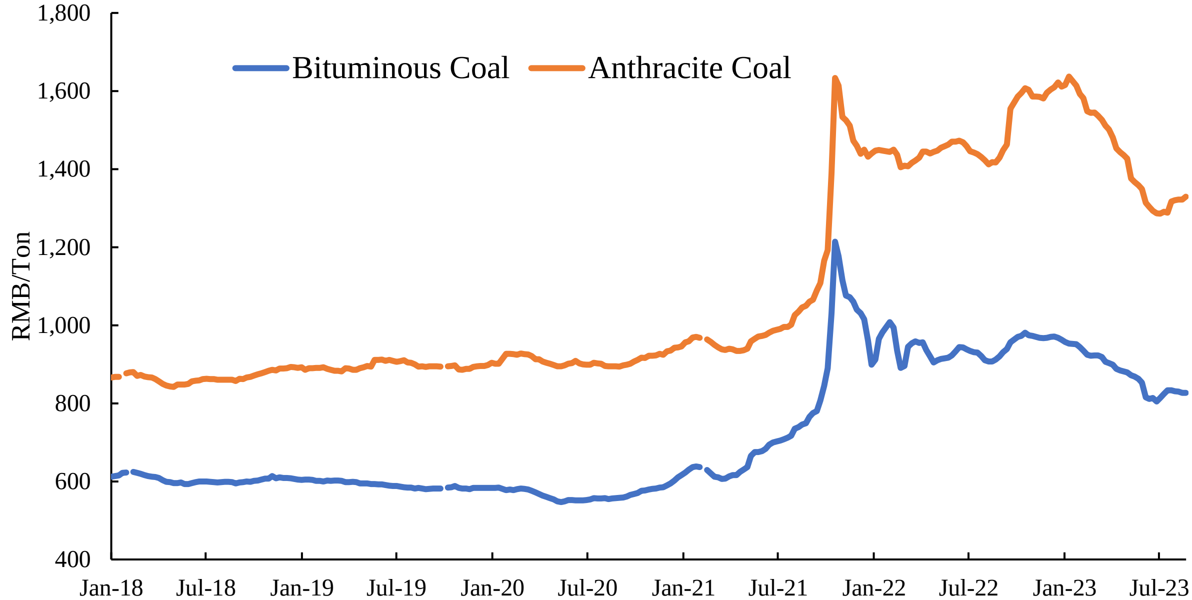


Figure A1. Weekly Chinese bituminous and anthracite coal prices, January 2018-August 2023

Appendix B

This appendix examines the contemporaneous and lead-lag relationships between urea export shipments and port inventories.

Figure B1 compares monthly urea export quantities released by China Customs and monthly urea inventories at export ports calculated based on weekly data collected by *Oilchem*, for the period from January 2018 to August 2023. As can be seen, the two series largely trend together. The correlation between the two series is 0.43.

Table B1 (see next page) presents parameter estimates for the VAR model using logarithmic differences for monthly urea export quantities and inventories, with lags selected based on the Akaike Information Criterion (AIC). Lagged port inventories significantly lead export quantities up to the second lag, reflecting the quick turnaround period. In contrast, lagged export quantities are mostly non-significant in the port inventory equation.

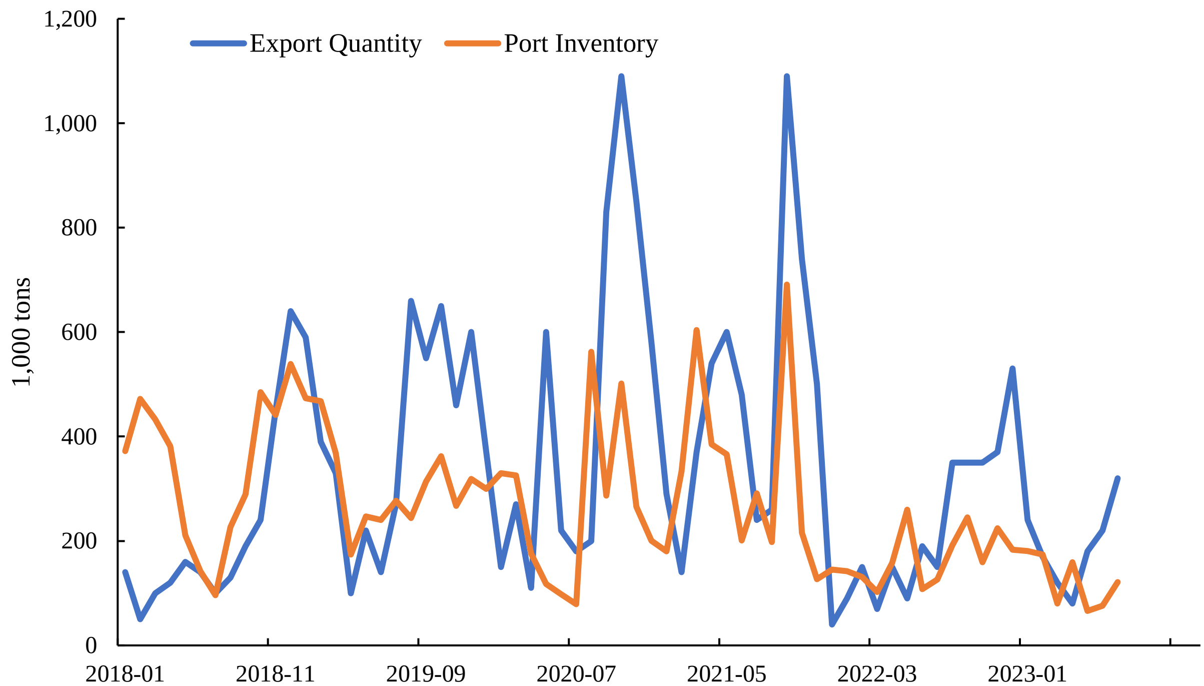


Figure B1. Monthly Chinese urea export quantities and port inventories, January 2018-July 2023

Table B1. VAR parameter estimates for export quantities and port inventories

	Equations	
	$\Delta export$	$\Delta inventory$
$\Delta export_{t-1}$	-0.428**	-0.022
	(0.136)	(0.109)
$\Delta export_{t-2}$	-0.048	0.001
	(0.143)	(0.114)
$\Delta export_{t-3}$	-0.172	0.219*
	(0.136)	(0.109)
$\Delta export_{t-4}$	-0.281*	0.021
	(0.125)	(0.100)
$\Delta inventory_{t-1}$	**0.596****	-0.316*
	(0.172)	(0.138)
$\Delta inventory_{t-2}$	**0.436***	-0.052
	(0.190)	(0.152)
$\Delta inventory_{t-3}$	-0.093	-0.351*
	(0.206)	(0.165)
$\Delta inventory_{t-4}$	-0.093	-0.353*
	(0.192)	(0.153)
$intercept$	0.041	-0.035
	(0.078)	(0.063)

Notes: Asterisks * and ** denote significance at the 5% and 1% levels. Standard errors are provided in the parentheses.

Appendix C

This Appendix presents the daily trading volume of the urea futures contract traded in China. The trading volume for each contract maturity is plotted.

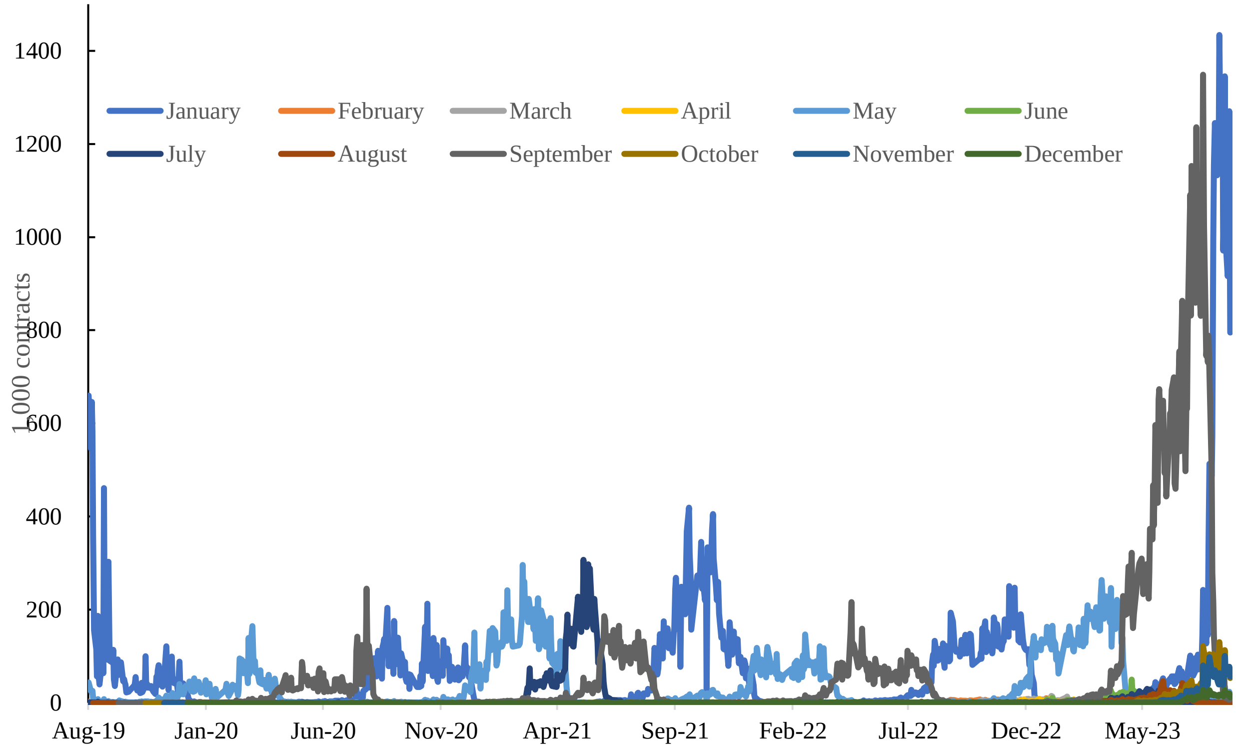


Figure C1. Daily trading volume for each contract month for urea futures in China