Deconstructing Urea Fertilizer Price Spikes: The Role of Supply-Demand, Speculation, and Energy Prices

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Abstract

Using weekly data from 2018 to 2022, we conduct historical decomposition and counterfactual analysis based on a SVAR model. We show urea fertilizer price changes are affected mainly by market-specific supply-demand shocks. The energy prices had a minimal impact on urea fertilizer prices during most of the sample period but contributed significantly to the urea price spike in 2021. No evidence suggests precautionary demand measured by inventories and corn price changes led to large fluctuations in urea prices during the sample period.

Key words: urea price, fertilizer market, inventories, corn price, SVAR

JEL: Q13, Q41, Q18, Q17

Introduction

Fertilizer prices have been rising significantly since the end of 2020 and broke new records in 2022. As fertilizers are essential inputs for major agricultural commodities, high fertilizer prices add further to fears over food security in both developed and developing countries. While fertilizer supply shortages fueled by the Ukraine-Russia conflict are a major factor contributing to surging fertilizer prices, soaring fertilizers prices are also driven by serval pre-existing factors, including rising energy costs, strong demand driven by profitable crop prices, reduced production capacity in major producing countries, etc. A better understanding of the causes of fertilizer spikes will have important implications for policymakers and market practitioners.

This paper uses a structural vector autoregression (SVAR) model to decompose Chinese urea fertilizer prices into a set of economic factors and measure their relative contributions to historical urea price movements. Previous studies on fertilizer prices have focused on the price transmissions between natural gas, fertilizer and corn markets (Etienne, Trujillo-Barrera, and Wiggins 2016), price transmissions between the U.S. and Middle East markets (Hu and Wade 2017), and spatial and vertical price relationships in the U.S. fertilizer industry (Bekkerman, Gumbley, and Brester 2021). We contribute to the literature in two ways. First, while previous studies have mainly focused on the U.S. fertilizer market, we investigate the Chinese fertilizer market, as China is one of the world's largest fertilizer producers, users, and major exporters. Second, previous studies depend on reduced form models to investigate the price relationships between fertilizer, agricultural commodity, and energy prices. We instead develop a SVAR model and adopt Rigobon's (2003) heteroskedasticity based identification approach to identify the contemporaneous effects of a set of economic factors, including market-specific net supply shocks, precautionary demand, and grain and energy prices. Limited studies have used inventories to explain fertilizer prices due to data availability, although it is a key explanatory variable for storage commodity prices. Hu and Brorsen (2017) showed that urea markets are thin markets as the major traders in urea markets are large international companies and formula pricing is common. We solve this problem by using privately collected Chinese urea inventory data that are widely used by traders.

Using weekly data from 2018 to 2022, we conduct historical decomposition and counterfactual analysis based on a SVAR model. We show urea fertilizer price changes are affected mainly by net supply shocks. The energy prices had a minimal impact on urea fertilizer prices during most of the sample period but contributed significantly to the urea price spike in 2021. No evidence suggests precautionary demand measured by inventories and corn price changes led to large fluctuations in urea prices during the sample period. The findings of this study will provide valuable insights for policymakers and stakeholders related to the agricultural industry in China.

Related Literature

Hu and Brorsen (2017) showed that the U.S. fertilizer industry is a thinly traded market, and formula pricing is commonly used in the industry. Etienne, Trujillo-Barrera, and Wiggins (2016) discovered significant linkages between the U.S. corn market and the nitrogen fertilizer market. However, they found no significant linkages between U.S. natural gas and nitrogen fertilizer prices, which can be attributed to the market power. Geman and Eleuterio (2016) found a long-term price relationship between ammonia and corn prices in the U.S. markets. However, their results indicated that fertilizer prices do not respond to corn price changes in the short term due to market power in the U.S. fertilizer industry. Bekkerman, Gumbley, and Brester (2021) showed that long-run fertilizer price adjustments became faster, and short-run price dynamics became more responsive to corn markets and less affected by natural gas prices due to biofuel policies.

Background

- China was the world’s largest urea producer and a major exporter (#4) during 2018-2021, with a 31% share of global production and 9% share of global exports.
- In China, about 3/4 of urea production used coal as the main feedstock, accounting for 1-2% of total domestic coal consumption. 7% of the coal supply comes from imports.
- About 1/4 urea production used natural gas, accounting for 5% natural gas domestic consumption. More than 40% of the natural gas supply comes from imports.
- 8% of China’s urea was exported during 2018-2021.

- More than **60%** of China's urea domestic consumption was for agricultural purposes (direct application or synthetic fertilizers), and the rest was for industrial use.
- Corn was the largest contributor to China's nitrogen fertilizer use, with a 23% share in 2018, followed by vegetables (21%), rice (17%), and wheat (16%).

Phase 1 (prior to 2018): supply-side reform and decreased production

China's urea production capacity peaked in 2015. In response, the government started a supply-side reform to cut out inefficient capacity. This caused production capacity to drop from 87M tons in 2015 to 75.54M tons in 2018. Consequently, urea prices increased and hit a five-year high by the end of 2021.

Phase 2 (2019-2020): recovered production and weak demand

During this period, urea producers increased production in response to profitable margins, while industrial and agricultural demand was limited by several environmental regulations. Consequently, urea prices steadily decreased. In early 2020, urea prices hit a five-year low due to the COVID-19 pandemic outbreak, which disrupted production and curbed both domestic and global demand.

Phase 3 (2021-2022): multiple shocks and increasingly volatile prices

From 2021 to 2022, Chinese urea prices experienced a run-up and reached a record high due to various market shocks. In the first half of 2021, as the pandemic eased, there was a rapid recovery in industrial and agricultural demand, which led to a historic low in urea inventory. In July 2021, a shortage in coal supply caused a sharp increase in coal prices and drove up the production costs of urea fertilizer. To address domestic demand, China tightened fertilizer export inspections in October 2021. However, the war between Russia and Ukraine in February 2022, coupled with economic sanctions, resulted in reduced fertilizer exports from Russia and caused natural gas prices to soar. This further worsened an already tight global fertilizer supply and production costs, ultimately leading to record-high urea prices in mid-2022.

Econometric Model

To characterize the relationship between factors contributing to variations in urea prices, we introduce the structural vector autoregressive regression (SVAR) model. Next, we describe the identification scheme that is based on changes in variances.

The SVAR model

We consider a reduced-form VAR model of order p,

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

where y_t represents a vector of observable variablesand u_t is a vector of reduced-form shocks that have a constant variance-covariance and zero means. The SVAR model can be obtained by rewriting the reduced-form shocks as a linear combination of the structural shocks,

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

where $u_t = B\epsilon_t$ and ϵ_t is a vector of structural shocks that have zero means and a diagonal variance-covariance matrix. Since structural shocks are instantaneously uncorrelated, the matrix B can be interpreted as the instantaneous 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., $E(\epsilon_t \epsilon_t') = \Sigma_\epsilon = I_K$. 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 $K(K+1)/2$ different elements while B has K^2 different elements. Therefore, at least $K(K-1)/2$ restrictions are required to identify B and accurately define the shocks. A common identification approach relies on exclusion restrictions that specify certain variables as exogenous to the other variables based on economic rationale (e.g., Killian and Murphy 2014, Janzen, Smith, and Carter 2013, Bruno, Büyükşahin, and Robe, 2017). However, these restrictions may be subjective or arbitrary, since more than one set of just-identifying restrictions that lead to identical reduced-forms may exist and cannot be tested against the data (Lütkepohl and Netsunajev, 2017). Here, we adopt a data-driven identification approach, specifically, identification based on changes in variances.

Variance-based identification

Empirical studies have established that commodity prices undergo phases of volatility and calmness, 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. This is particularly true in our case. Hence, we follow Lütkepohl and Netsunajev (2017) to 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 regimen to the other is governed by a non-linear function. Specifically,

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

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 $(\lambda_1, \dots, \lambda_K)$ 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 Netsunajev, 2017).

We use a deterministic transition variable ($s_t = t$) 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. A deterministic transition variable is plausible when the first and the second parts of the sample periods are associated with different volatility levels and there is a transmission period between the two volatility states. As shown in Lütkepohl and Netsunajev (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 of those structural shocks and determine their contributions using historical variance decomposition.

Choice of Variables

We propose a SVAR model to disentangle the effects of input cost variations, changes in market-specific contemporaneous supply-demand conditions, precautionary demand for physical inventories, and agricultural commodity price changes. In this section, we explicate our rationale for selecting these variables and underscore their significance in our analytical framework.

Input costs

The production of urea is a process that requires a significant amount of energy, obtained through the consumption of raw energy inputs such as natural gas and coal, as well as through the heating and transportation processes (Hu and Brorsen, 2017). In China, a country that heavily relies on coal, approximately three-quarters of the urea produced is made using coal, while the remaining portion uses natural gas. An early study by Etienne, Trujillo-Barrera, and Wiggins (2016) investigated price and volatility transmission between the U.S. natural gas, nitrogen fertilizer, and corn markets and found no significant linkages between natural gas and nitrogen fertilizer prices. They argued that the price transmission between natural gas and fertilizer markets is curbed by the industrial power in the U.S. fertilizer market. In our main analysis, we use coal price variations to capture changes in urea fertilizer input costs, as coal is the main feedstock to produce urea in China. Some market analysts and news reports suggest that the surge in global natural gas prices, fueled by the geopolitical turmoil of a war between Ukraine and Russia, has also contributed to increased urea prices in China. Therefore, in a separate analysis, we replace Chinese coal prices by European natural gas prices to investigate whether shocks to the international energy market have affected the Chinese urea market following the breakout of the war.

Agricultural commodity prices

As a neutral fertilizer, urea can be used for a variety of agricultural products, including corn, wheat, rice, cotton, vegetables, etc.[1] Higher fertilizer prices may contribute to higher crop prices due to increased operating cost. Conversely, higher crop prices incentivize farmers to use more fertilizer, potentially driving up fertilizer prices. Etienne, Trujillo-

[1] Soybeans are not reliant on nitrogen fertilizers.

Barrera, and Wiggins (2016) found significant bi-directional price and volatility transmissions between ammonia fertilizer and corn prices in the U.S., with a stronger influence from corn prices to ammonia fertilizer prices during a period of high corn prices (2006-2014). Similarly, Geman and Eleuterio (2016) found a long-term price relationship between ammonia and corn prices in the U.S. markets. However, their results indicated that fertilizer prices do not respond to corn price changes in the short term due to market power in the U.S. fertilizer industry. Using global food commodity and fertilizer prices, Ott (2012) found that higher food commodities prices influenced fertilizer prices but not vice *versa*. In line with previous studies, we use corn prices to capture urea price variations driven by agricultural demand. While wheat and rice are also major crops that reliant on nitrogen fertilizer, their prices are distorted by price supports. China ended state stockpiling and price support policies for corn in 2016 to allow the market to set prices, but our analysis period starts from 2018.

Contemporaneous supply-demand conditions and precautionary demand

Urea is storable. Classic commodity storage models state that equilibrium prices reflect both contemporaneous supply-demand conditions and the demand driven by the anticipation of future commodity supply shortfalls (Working 1994, Williams and Wright 1991, Deaton and Laroque 1992, 1996). Firms that hold storable physical commodities have an incentive to hoard for futures sales if they expect tighten supply and higher prices, which is typically a speculative activity in physical storable commodity markets. Previous studies that used SVAR models commonly include inventories as an important structural factor to explain storable commodity price dynamics (e.g., Killian and Murphy 2014, Janzen, Smith, and Carter 2013, Janzen et al. 2014, Bruno, Büyükşahin, and Robe, 2017).

There are two methods used in the literature to capture changes in inventory conditions. The first is to obtain physical inventory levels directly. Typically, inventory data can be obtained from official sources such as the Energy Information Administration (EIA) for energy commodities or the United States Department of Agriculture (USDA) for agricultural commodities. However, inventory data for physical commodities are also available from industrial sources. For instance, Kilian (2022) advocates using the global oil inventory series provided by the Energy Intelligence Group instead of similar data from the EIA. Compared to agricultural output commodities, fertilizer market data are not widely recorded by government agencies. For example, Hu and Brorsen (2017) as well as Bekkerman, Gumbley, and Brester (2021) had to depend on urea fertilizer price data for the U.S. inland markets and import ports from an industrial source given that the USDA fertilizer price data are only available at the national level. Since there is no official Chinese urea inventory data, we obtain urea producer inventories from *OilChem*, a leading energy and petrochemical commodity data service provider in China[2]. As indicated by *OilChem*, the data series are gathered from more than 99% of the urea producers in China.

Another widely used method to capture inventory fluctuations of storable commodities is by using futures market calendar spreads as a proxy (e.g. Janzen, Smith, and Carter 2013, Bruno, Büyükşahin, and Robe, 2017). The slope of the futures forward curve reflects the marginal cost of storage, which increases with the level of storage (Fama and French, 1987). However, we do not choose to use urea futures calendar spreads for two reasons. First, China's urea futures trading at Zhengzhou Commodity Exchange only started in August 2019, and since our analysis ends in December 2022, a large proportion of our sample period will be associated with an immature urea futures market. Besides, our identification scheme depends on changes in variances, so it is important to include sufficiently long periods for both tranquil and volatile regimes to achieve identification. However, much of the time periods after August 2019 are associated with high volatility in the markets examined (coal, urea, and corn).

Data

The data used in this analysis were obtained from different sources. Urea fertilizer and coal prices are weekly retail urea and anthracite prices published by the Chinese Ministry of Commerce. Corn prices are weekly average prices calculated using daily settlement prices for the most actively traded corn futures contracts at the DCE in each month[3]. Natural gas

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[2] Our data are not commercial inventories typically used in the literature as they only cover inventories held by urea producers. We did not find available Chinese urea commercial inventory data. However, producer inventories are widely tracked by market participants.

[3] Nearby futures contracts are not always the most liquid contracts in Chinese futures markets. See Xie and An (2022) for relevant discussion.

prices are the rolling nearby weekly average European TTF natural gas futures prices. Weekly urea inventory data are purchased from *OilChem* and include physical inventories held by more than 99% of Chinese producers in China. The analysis covers the period from January 2018 to December 2022, which is determined by the availability of inventory data.

Model estimation

We consider a four-dimensional VAR model with the vector of variables $y_t = (\Delta coal, \Delta corn, inventory, \Delta urea)'$, where $\Delta coal, \Delta corn, \Delta urea$ are log differences of deseasonalized coal, corn, and urea prices, respectively; $inventory$ is the linearly detrended and deseasonalized urea producer inventory level in natural logarithm form[4]. The Akaike Information Criterion (AIC) suggests including only 1 lag in the VAR system. However, to account for residual serial correlation, we estimate a VAR model with 4 lags.

Previous SVAR studies on commodity price dynamics typically use a recursive identification scheme or rely on exclusion restrictions that specify certain variables as exogenous to the other variables based on economic rationale (e.g., Killian and Murphy 2014, Janzen, Smith, and Carter 2013, Bruno, Büyükşahin, and Robe, 2017). However, conventional identification approach is challenging in our case because fertilizer, agricultural commodities and energy markets are linked by the fertilizer industrial supply chain. It would be too restrictive to assume that one market is exogenous to the other two markets[5]. Hence, we estimate an unrestricted SVAR model and depend on a data-driven identification scheme.

Estimation results

See tables 1-2 and figures 2 – 4.

Concluding Remarks

-Urea prices are mainly affected by market-specific supply demand.

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[4] We conducted unit root tests and found all price series are non-stationary during the sample period. We also tried using all series in levels as suggested by Sim, Stock, and Watson (1990), however, the VAR model was unstable and impulse response functions were explosive. To save space, these results are available upon request.

[5] For example, we imposed the restriction that the coal price, as a macroeconomic factor, is not contemporaneously affected by the other two markets. However, the likelihood ratio test developed by Lanne et al. (2010) suggested that the model was overrestricted at the 5% significant level.

-Low producer inventory contrite to the price run-up in 2021, but not afterward.

-The urea fertilizer market is affected by the tail-risk of coal prices. Coal prices have limited impact on urea fertilizer price changes during most of the sample period but contributed significantly to the urea price spike occurred in late 2021.

-In the short-term, corn price changes have no significant influence on urea price variations. Farmers' income was negatively affected because despite the increase in input costs, the corn prices did not rise accordingly.

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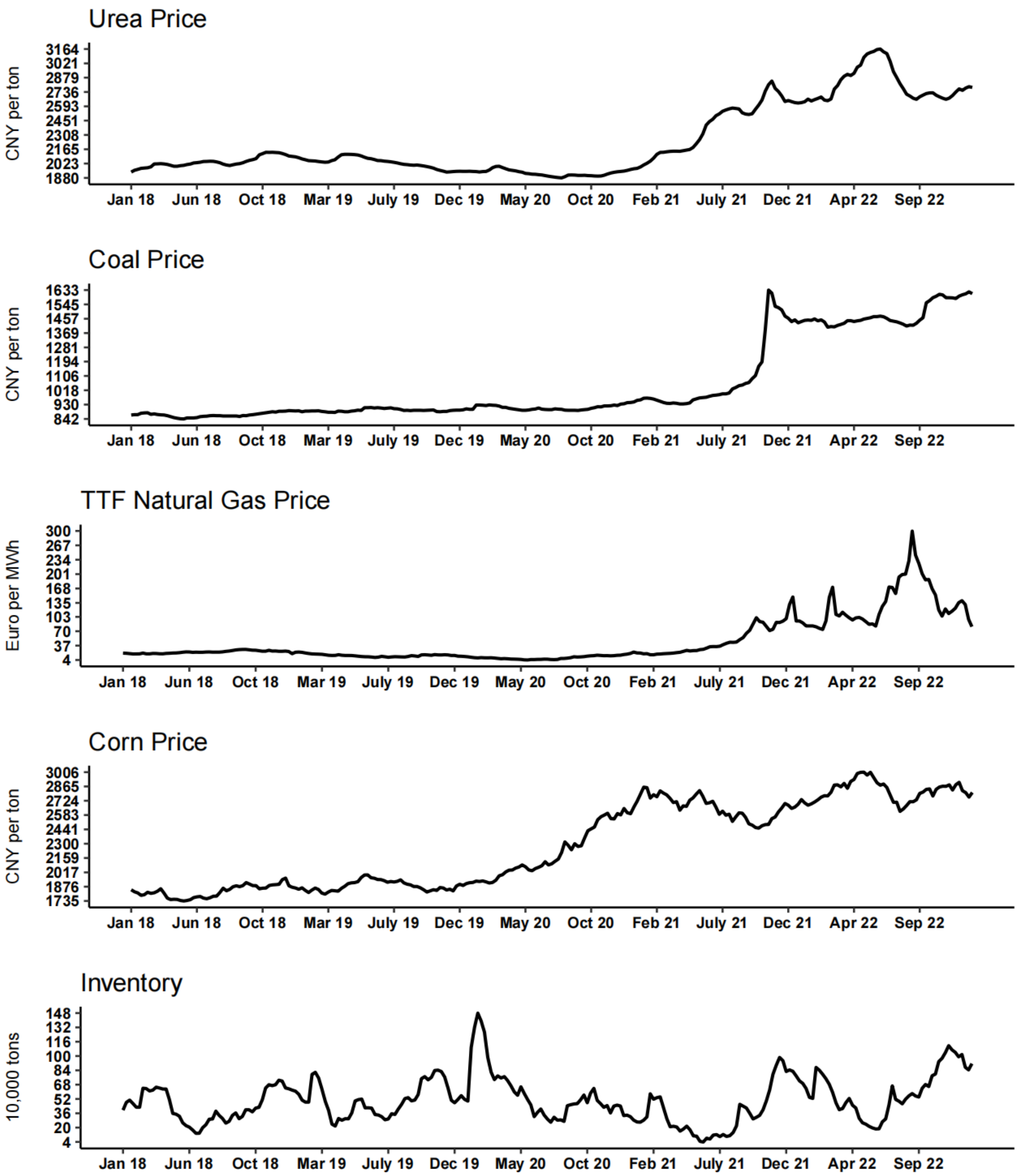

Figure 1. Plots for weekly commodity prices and urea inventories, January 2018 to December 2022

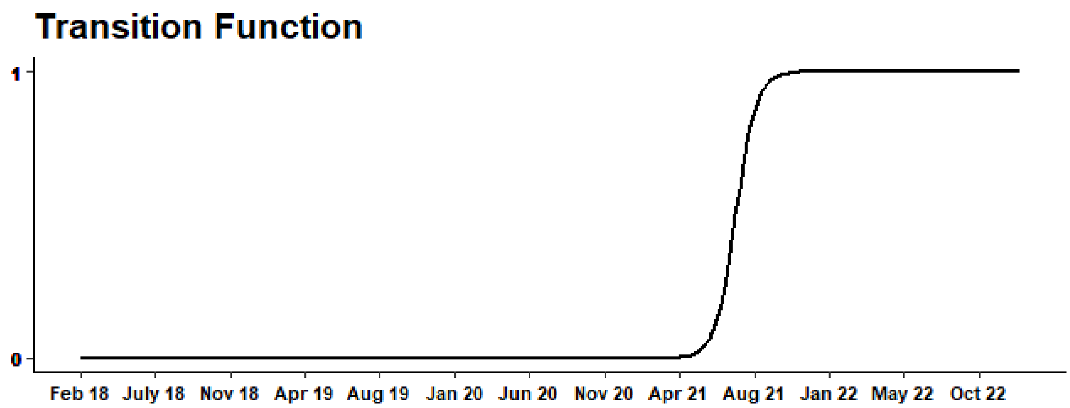

Figure 2. Transition function for the SVAR model

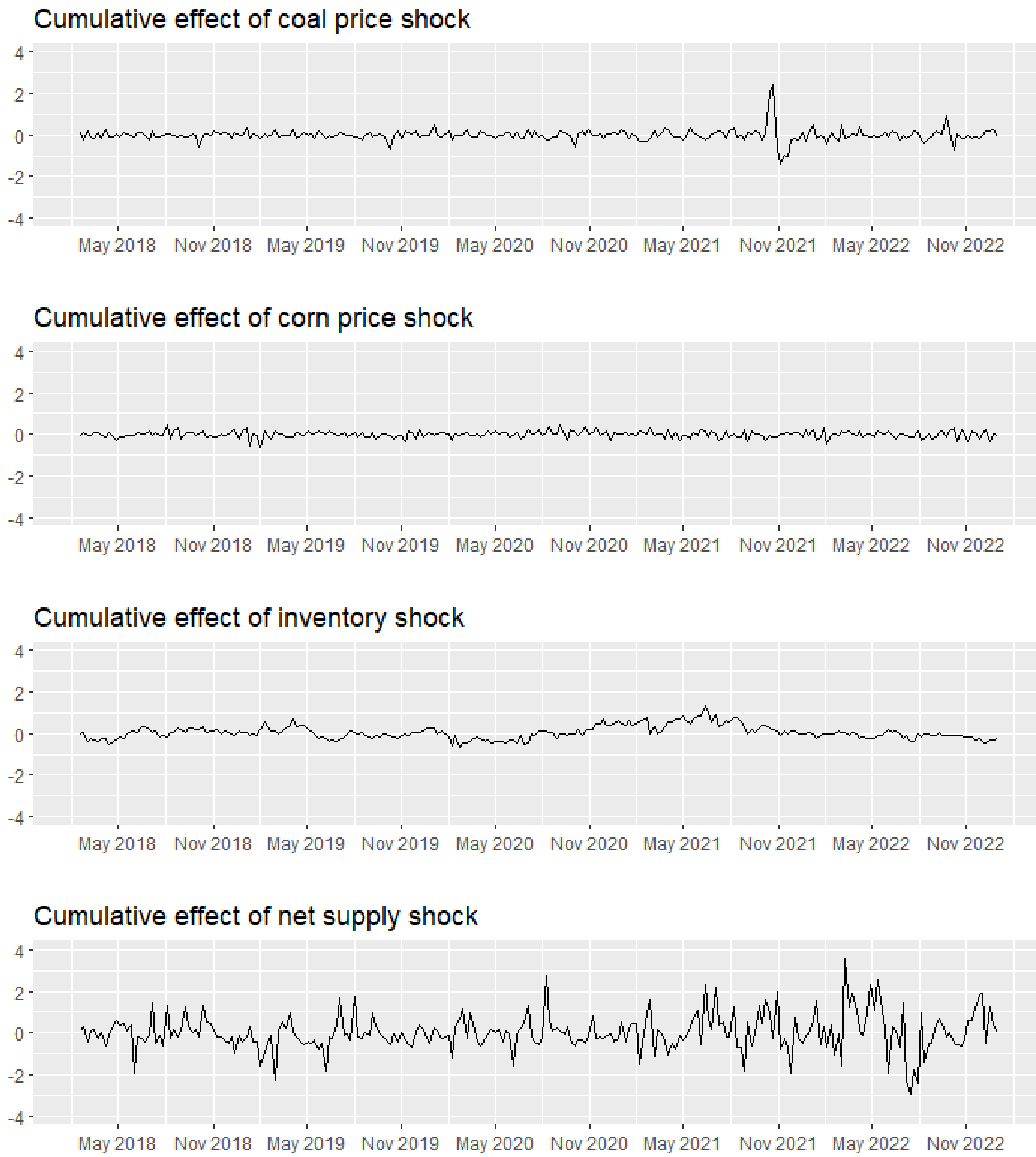

Figure 3. Historical decomposition of urea price changes

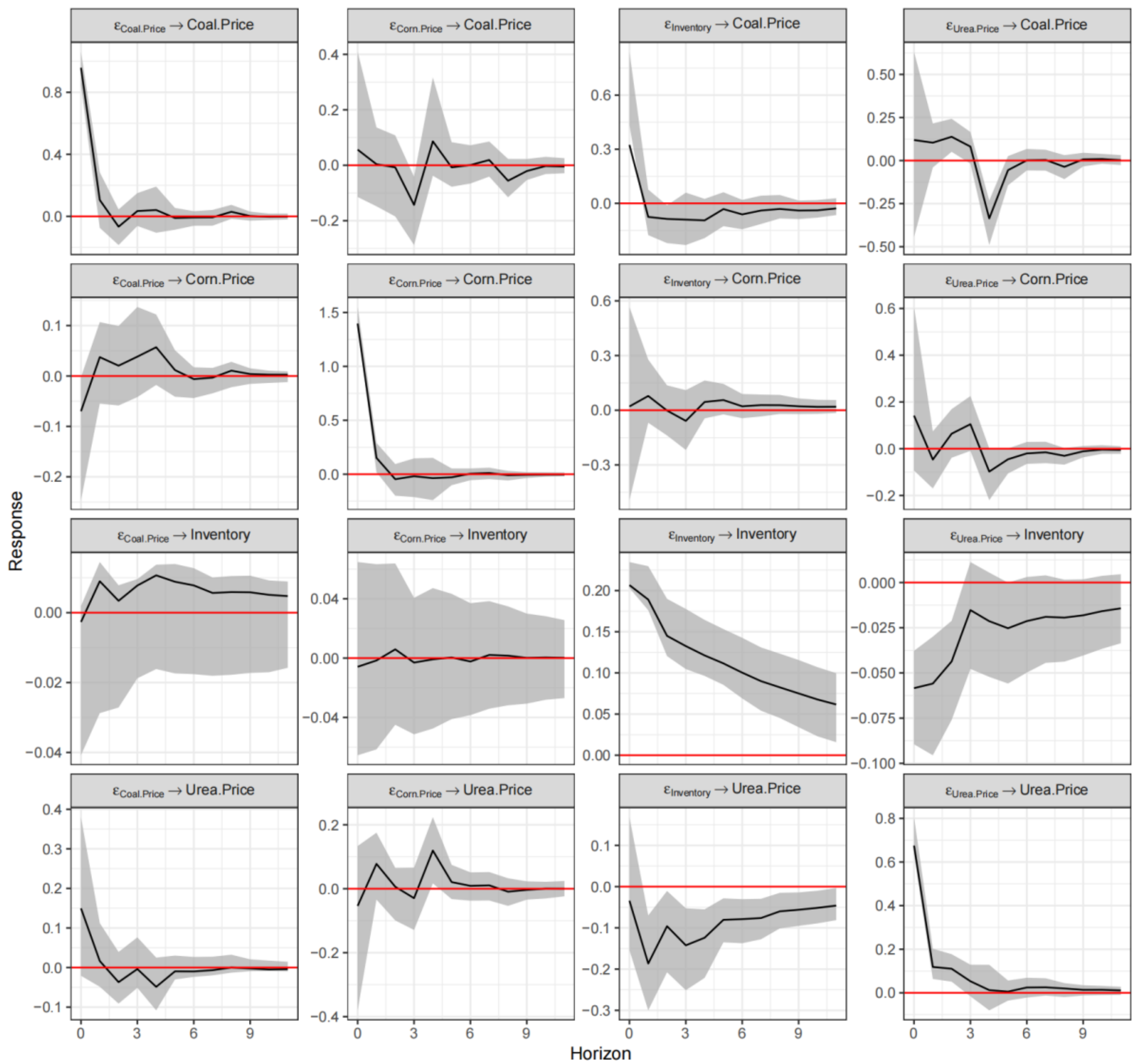

Figure 4. Impulse response functions from the SVAR model

Table 1. Structural Vector Autoregression Model Parameter Estimates

						λ_1	λ_2	λ_3	λ_4
B	0.959	0.056	0.324	0.119	Λ	7.620			
	(0.055)	(0.112)	(0.089)	(0.169)		(1.450)			
	-0.070	1.397	0.021	0.142			1.177		
	(0.078)	(0.080)	(0.244)	(0.188)			(0.238)		
	-0.003	-0.006	0.207	-0.058				0.435	
	(0.010)	(0.028)	(0.013)	(0.012)				(0.093)	
	0.150	-0.054	-0.034	0.675					2.986
	(0.087)	(0.123)	(0.076)	(0.046)					(0.610)

Table 2. Tests for Equality of λ_i for the SVAR Model

	Wald Statistic
$\lambda_1=\lambda_2$	19.23^{***}
$\lambda_1=\lambda_3$	24.45^{***}
$\lambda_1=\lambda_4$	8.68^{***}
$\lambda_2=\lambda_3$	8.39^{***}
$\lambda_2=\lambda_4$	7.65^{**}
$\lambda_3=\lambda_4$	17.11^{***}