Agricultural Supply News as Exogenous Shocks to the Macroeconomy

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Abstract

Changes in anticipated U.S. field crop production are due to weather, pest, and disease shocks. We employ a recently-developed approach that exploits the exogeneity of high-frequency news events to measure the impact of agricultural shocks on both the domestic agricultural sector and the broader economy. Our results indicate that a poor harvest news shock increases the real price of U.S. field crop commodities, but reduces domestic real GDP, industrial production, equity prices, grain exports, global oil production, the price of dry bulk shipping services, and the quantity of food-at-home consumed, while raising stock market volatility, livestock prices, and food-at-home prices. (**JEL Codes**: E31, E32, Q13, Q14)

Introduction

According to the USDA Economic Research Service (USDA, 2024a), agriculture, food, and related industries contributed about 5.6 percent to the U.S. GDP in 2023. Despite that relatively modest contribution, in 2022 these industries employed around 10.4 percent of the U.S. workforce, with a significant portion working in food service, and at eating and drinking places (USDA, 2023a). Moreover, as the ultimate source of our food, agriculture is also the most direct conduit the economy has to the weather: its shocks directly affect food inputs and their quality. So how much do developments in agriculture truly affect the wider economy? How important are they? Because the primary industry in their time was agriculture, classical economists (see, e.g., Ricardo, 1817; Mill, 1848) were concerned with variations of this question, but recent related work is generally limited to wondering how exogenous agricultural events affect commodity markets alone. One way to bound agriculture's importance to our modern economy might be to estimate the correlation between agricultural prices and relevant economic variables, but this approach would suffer from clear endogeneity, as only a portion of the variation in agricultural prices is due to exogenous shocks to the weather, as well are the influence of pests and plant or animal disease. We avoid the endogeneity problem by using high-frequency techniques to identify a series of exogenous USDA agricultural supply news shocks and estimate how they affect a range of commodity market and macroeconomic outcomes.

Agricultural commodities could conceivably influence the U.S. macroeconomy through several channels, most directly through their impact on consumer spending (De Winne & Peersman, 2016). In addition, field crops are vital inputs to the food processing sector, which accounts for about 12 percent of total U.S. industrial production. Grains and oilseeds are key components of animal feed, which Americans consume indirectly as meat, dairy, and eggs; they are also commonly processed into packaged foods for direct consumption. In 2023, Americans spent an average of 11.2 percent of their disposable income on food (USDA, 2024b). Because food consumption is unavoidable, increases in food prices reduce discretionary income, leaving less budget for other spending after covering food and energy bills (Kilian, 2008). Rising food prices can also increase uncertainty about future food costs, prompting consumers to save more and reduce overall spending—a behavior known as "precautionary savings." While this phenomenon has been demonstrated in the context of energy price shocks (Bernanke et al., 1997; Edelstein & Kilian, 2009), it also applies to agricultural commodities. Furthermore, since the mid-2000s, the growing (government-mandated) demand for biofuels like ethanol and biodiesel has increased the use of agricultural commodities for energy production, further linking agricultural markets to the broader economy. Changes in food prices can also influence the broader economy by influencing labor and capital allocation across industries, and policy adjustments. Agricultural markets are closely tied to the financial market, too. A recent study by Cao et al. (2024) finds that USDA reports on agricultural commodity production influence the stock prices of publicly traded companies in the food industry such as food processors, farm machinery producers, and fertilizer manufacturers.

Searching for and exploiting exogeneity

The task of measuring agriculture's causal impacts instead of simple associations, of course, is complicated by the requirement of ensuring the exogeneity of the relevant shocks. Econometric methods commonly used to measure plausible causal effects include randomized controlled trials, difference in differences, regression discontinuity design, natural experiments, and instrumental variables, and more. In finance and macroeconomics, econometricians employ a variety of identification strategies with structural vector autoregressive (SVAR) models to identify exogenous shocks and estimate their impacts: Cholesky decomposition, long-run restrictions, zero and/or sign restrictions, narrative methods, high-frequency identification, and external instruments (see, e.g., Ramey, 2016). Also known as a proxy VAR, the latter approach employs external information to identify structural shocks within the VAR framework (Stock and Watson, 2012; Mertens and Ravn, 2013); we use it in our analysis.

Using these approaches, economists have identified the importance of various exogenous shocks to the economy. For example, Galí (1999), Fisher (2006), and Justiano, Primiceri, and Tambalotti (2010) explore how technology shocks affect the real business cycle. Sims (1972, 1980), Christiano et al. (1999), and Romer and Romer (2004) contributed to early work focused on the impact of monetary policy, although the identification strategy those shocks has evolved, recently. A common approach is to isolate high-frequency interest rate fluctuations in a tight window around the Federal Reserve's FOMC announcements—or monetary policy "surprises" (Kuttner, 2001; Gürkaynak, Sack, & Swanson, 2005; Gertler & Karadi, 2015; Nakamura & Steinsson, 2018a; Swanson, 2021), and use them to measure how policy choices affect asset prices and the broader macroeconomic landscape. To accomplish a similar goal, Bu, Rogers, and Wu (2021) use two-step regressions proposed by Fama and

MacBeth (1973) to identify a unified series of shocks across monetary policy regimes; Gertler and Karadi (2015) estimate a policy surprise series using asset price movements around FOMC meetings, showing substantial impacts on economic activity and credit scores. Similarly, Coibion et al. (2017) estimate the impact of monetary policy shocks on consumption and income inequality in the United States during the period of 1980-2018 using local projections developed by Jordà (2005).

Similar techniques are used to estimate how government spending and taxes affect the economy. For instance, Ramey and Shapiro (1998) use a narrative approach to examine the impact of spending shocks during major buildups in the United States. They find that a military buildup shock raises the impact of government spending on defense and GDP, while decreasing residential investment and compensation per hour in manufacturing. Blanchard and Perotti (2002) find that government spending shocks have positive effects on private consumption and the GDP, while tax shocks have the opposite effect. Using a different approach (without assuming sluggish responses to fiscal policy shocks), Mountford and Uhlig (2009) produce similar findings. Mertens and Ravn (2013) use a proxy SVAR approach to show that in the post-World War II period government reductions in personal income tax raise GDP, consumption, employment, and labor hours.

As a critical commodity input, researchers have also focused on understanding the effects of oil price shocks. Early work by Hamilton (1983) noted a correlation between disruptions in oil supply and subsequent increases in oil prices in the United States during the period of 1948-1972. Kilian (2009) decomposes oil prices into three factors: oil supply shocks, global demand shocks, and oil demand shocks, and finds that global demand shocks are the primary drivers of oil price fluctuations. A rich deposit of the literature now focuses on oil price shocks (Baumeister and Peersman, 2013; Baumeister and Hamilton, 2019; Caldara, Cavallo, and Iacoviello, 2019). Känzig (2021), for example, constructs a high-frequency oil supply news series, based on production surprises from the Organization of Petroleum Exporting Countries, which he uses as an instrument to identify the related portion of price variation it causes, and then also macroeconomic impact of that news using a proxy SVAR model.

One benefit of identifying these exogenous shocks series is that other researchers can take them off the shelf and exploit their exogeneity to address research questions not pondered by the original econometricians. For example, Bräuning and Ivashina (2020) use monetary policy shocks identified by Gürkaynak, Sack, and Swanson (2005) as instruments to estimate the impact of U.S. monetary policy on loan volumes for emerging market economies. Cloyne et al. (2023) apply Gertler and Karadi's (2015) monetary policy shocks as instruments to estimate their effects on firm investment behavior using a local projection instrumental variable (LP-IV) approach. Bartscher et al. (2022) estimate the effect of Coibion et al.'s (2017) monetary policy shocks on the income and wealth gap between households in the United States.

Measuring the importance of agricultural shocks

Many researchers have inquired into the more narrow question—at least when compared to our objective—of how commodity markets incorporate news (see, e.g., Sumner & Mueller, 1989; Fortenbery & Sumner, 1993; Isengildina-Massa et al., 2008; Adjemian, 2012a; Dorfman & Karali, 2015; Adjemian & Irwin, 2018, 2020; Karali, Irwin, & Isengildina-Massa, 2020; Cao & Robe, 2022). Since the Civil War, the U.S. Department of Agriculture (USDA) has collected and reported statistical information about U.S. crop conditions (Adjemian, 2012b). These reports, assembled through both physical and statistical surveys, are published at known, regular intervals (Goyal & Adjemian, 2023); they provide supply-oriented news to agricultural stakeholders, focusing on different aspects of crop production and inventory levels,

[1,2] and USDA reports are prepared under confidential, "lockup" conditions, so the supply information they contain about, e.g., weather, pest, and disease shocks (Peersman, 2022;

Roberts & Schlenker, 2013), is exogenous to the market and can be interpreted as news (Adjemian & Irwin, 2020). That news is reflected in commodity prices as traders digest the new information to reflect updated expectations about fundamentals (Adjemian, 2012b); further down the supply chain, equity prices of food companies (Cao et al., 2024) likewise respond, as do resource allocation decisions by market participants (Gouel, 2020).

Few studies have explored the impact of agricultural shocks on the economy, but we highlight two notable exceptions. De Winne and Peersman (D&P) (2016) use a recursively-identified VAR to study how poor global harvests affect the U.S. macroeconomy. They project the Food and Agriculture Organization (FAO) annual crop production data for 192 countries into a quarterly global harvest index series designed to capture unanticipated changes in aggregate agricultural production. Specifically, they aggregate major field crops (e.g., corn, wheat, rice, and soybeans) into a composite, calorie-weighted commodity production index, following Roberts and Schlenker (2013). Each country's crop production is allocated across quarters based on its specific crop (planting and harvesting) calendar. The authors then seasonally adjust the index and remove trends to isolate unexpected changes in quarterly global agricultural production. They then use a Cholesky decomposition, with the production index ordered before other economic variables in a VAR. Alternatively, they employ a narrative approach, isolating 13 historical events that significantly affected global agricultural commodity prices, to define a quarterly dummy variable instrument in order to estimate their model.

Their findings from impulse response functions indicate that, on average, a poor global harvest shock raises real agricultural commodity prices and the U.S. CPI, but decreases agricultural commodity production, the volume of seeds for planting, global economic activity, the U.S. GDP, and the S&P 500 index. However, their approach has some limitations. First, aggregating each country's crop production across quarters based on planting and harvest seasons may introduce an endogeneity problem: planting decisions in the early months of the crop year in certain countries could affect global field crop prices, which in turn would influence planting decisions in countries where planting occurs later in the year (Haile, Kalkuhl, & von Braun, 2016). Second, the model does not account for country-specific field crop production forecasts, further raising concerns about endogeneity, as expectations can influence resource allocation decisions. Finally, the impact of an aggregate global harvest shock could be less relevant to the U.S. economy than a domestic harvest shock series—the primary tool used in our analysis. A more recent study by Peersman (2022) measures global (although non-European) harvest shocks, building on the index established by De Winne and Peersman (2016), and estimates their impact on European food price inflation using an external instrument VAR. Their results indicate that, on average, changes in global agricultural commodity prices contribute to nearly 30 percent of the volatility in the Harmonized Index of Consumer Prices (HICP) in Europe two years later.

In this article, we employ Känzig's (2021) high-frequency approach and exploit the exogeneity of the news in important USDA publications to estimate their impact on elements of the agricultural sector as well as the broader domestic and global economy. We measure agricultural supply news through changes in major U.S. field crop futures prices, weighted by their share of domestic production, around USDA supply announcements.[3] We scale the USDA supply news series to the mean level of field crop market volatility over the observation period to control for the possibility that volatile prices might be influenced by pre-existing macroeconomic conditions. We employ the news series as an instrument in a proxy SVAR model, developed by Stock and Watson (2012) and Mertens and Ravn (2013), to identify agricultural news shocks.

Our analysis establishes a set of empirical findings regarding the effects of agricultural news both within and beyond U.S. agriculture, reported through volatility-adjusted impulse responses. We show that poor agricultural news generates an immediate rise in the real price of domestic field crop commodities and a reduction in domestic real GDP and industrial production, consistent with D&P's (2016) findings. The core consumer price index (CPI) rises slightly in response to the shock. Financial markets are also affected, with equity prices declining while their implied volatility (VIX) rises. In contrast, D&P (2016) found no significant effect on the VIX from a negative global harvest shock. The bad news shock initially reduces the producer price index for livestock, although that price recovers over time; this observation is in line with the idea that livestock producers trim the size of their herd when they anticipate increases in the cost of feed (Schulz, 2022).

While we do not find that the shock has a significant effect on real ethanol and oil prices, it reduces global oil production. Poor agricultural news also initially increases the quantity of field crop commodities available for export as importers seek supplies ahead of potential shortages, but exports decline over time as the bad harvest materializes; in a similar way, the Baltic Dry Index (BDI) level traces a similar path as the change in exports through the demand it places on dry bulk shipping services. The shock generates an increase in food-at-home prices and a slight decrease in the quantity of food Americans consume at home. Based on the share of farm production in food and beverage products, the impulse responses of food-at-home prices closely match the direct effect that would be expected by the increase in field crop commodity prices we estimate.

We also perform historical decompositions to explore how agricultural supply news shocks contribute to the evolution of U.S. field crop commodity prices, the price Americans pay for food consumed at home, domestic GDP, and S&P 500 index (results for the food-at-home price index, domestic GDP, and the S&P 500 index are provided in Appendix D). Our findings suggest that a substantial portion of the historical variation in field crop commodity prices is closely associated with the USDA harvest news shocks we measure. These shocks also play a role—although to a much smaller degree—in the evolution of food-at-home prices, the U.S. real GDP, and the S&P 500 level. The forecast error variance decompositions further confirm the significant role of domestic agricultural supply news shocks in explaining variations in U.S. real field crop commodity prices, as well as their contributions to U.S. real GDP, core CPI, grain exports, the BDI, and global oil production. Lastly, we examine the pass-through of these shocks to consumer prices, expenditures, economic activity, and monetary policy. The relatively weak evidence suggests that the shocks raise the CPI for food, the CPI for durable goods, labor market tightness, and the federal funds rate, while they decrease household expenditures for nondurables, energy goods and services, services, and global industrial production.

Finally, like identified shocks to monetary policy and oil supply news, the agricultural supply news shocks we estimate can be used in future work as a source of exogeneity for instrumenting purposes, or to isolate causal effects directly. For example, Adjemian, Li, and Jo (2024) decompose food price inflation into data series that represent pressure from the supply and demand sides of the market. They find that, as expected, poor agricultural supply news raises the supply side of the market's contribution to food price inflation.

Methodology

To identify agricultural supply news shocks, we begin by constructing a series of high-frequency surprises around the release of USDA crop production reports. Price reactions of U.S. field crop futures following reveal the supply news component of USDA reports.

Constructing the USDA surprise series

We use U.S. field crop commodity futures prices traded on the Chicago Board of Trade (CBOT) to build the USDA surprise series. These futures contracts trade daily over a number of sequential maturities; their prices reflect expected supply and demand conditions at expiration in each commodity market. Following Känzig (2021), we construct the USDA supply surprise series by measuring the daily returns for U.S. field crop futures prices around the announcement of USDA crop production reports from 1992 to 2023.[4] Surprises for each commodity are calculated using the first principal component of the price changes across the first five maturities nearest expiration, then aggregated into a single domestic surprise series based on production weights. Specifically, individual field crop surprises are calculated as the natural log difference between the daily futures price before and after USDA report publication:

$$Individual\ Crop\ Surprise_{t,d,i}^{h} = 100 \times (lnF_{t,d,i}^{h} - lnF_{t,d-1,i}^{h}), \tag{1}$$

where d, t, and i are the day (or the following trading day), the announcement month, and the commodity, respectively; $F_{t,d,i}^{h}$ is the settlement price of that commodity's h-deferred futures contract maturity, where h=1,…,5.[5] We then apply production weights to each individual commodity's surprises and sum them up according to (2):

$$USDA\ Surprise_{t,d}^{h} = \sum_i Individual\ Crop\ Surprise_{t,d,i}^{h} \times S_{y,i} \tag{2}$$

where $S_{y,i}$ represents the production (weight-based) share of commodity i in year y.[6] The resulting weighted average surprise represents an overall measure of USDA supply news for field crops.

Standard asset pricing theory holds that

$$F_{t,d}^{h} = \mathrm{E}_{t,d}[P_{t+h}] - RP_{t,d}^{h}, \tag{3}$$

where $\mathrm{E}_{t,d}[P_{t+h}]$ represents the expected commodity price conditional on the information available on day d for commodity i and $RP_{t,d}^{h}$ represents a risk premium (Pindyck, 2001). Assuming a constant risk premium within a one-day window around the USDA announcement (i.e., $RP_{t,d}^{h} = RP_{t,d-1}^{h}$), the USDA surprise series can be interpreted as the changes in price expectations for a commodity that are driven by USDA announcements:

$$USDA\ Surprise_{t,d}^{h} = \mathrm{E}_{t,d}[P_{t+h}] - \mathrm{E}_{t,d-1}[P_{t+h}] \tag{4}$$

The surprises in (4) are then combined across all five maturities into a single $USDA\ Surprise_{t,d}$ according to the first principal component.

Selecting the event window size involves a trade-off between capturing the complete response to the USDA announcements and filtering out background noise that could be caused by other news events (Nakamura & Steinsson, 2018a). In our study, we choose a one-day window in equation (1) to capture the relevant price movements associated with the news while minimizing the influence of unrelated market noise. We then aggregate the daily agricultural supply news series, denoted as $USDA\ Surprise_{t,d}$, into a monthly series, denoted as $USDA\ Surprise_{t}$, since the news series is used as an instrument to estimate the effects of agricultural supply news shocks on relevant economic variables available at a monthly frequency. If there is only one USDA announcement in a month, the monthly surprise equals that daily surprise. For months with multiple announcements, like January, March, June, and September, we sum up the daily surprises. For months with no USDA announcements (as in October 2013 and January 2019, when the U.S. federal government shutdown curtailed report publication), we assign a value of zero to the monthly USDA surprise. Finally, to control for the possibility that volatile prices might be influenced by spillover noise from the financial markets, we scale the USDA supply news series to the mean level of field crop market volatility in the data (measured as the long-run conditional volatility of the U.S. real field crop commodity prices, and estimated using the component GARCH model developed by Engle and Lee (1999)); our results are robust to this normalization.

Assessment of the USDA Surprise Series

In this section, we conduct a set of diagnostic tests to evaluate the validity and reliability of our USDA surprise series. These tests include a narrative evaluation, and a placebo check that measures the level of noise in the series.

Narrative account

We present narrative evidence by examining the alignment between the USDA supply news series and the narrative account of selected historical episodes in U.S. agricultural commodity markets. Figure 1 displays the historical surprise series, estimated as the production-weighted average of the first principal component for the changes in the five nearest-to-deliver contracts for major U.S. field crop commodity futures prices around USDA reports from 1992 to 2023 (see individual field crop series and volatility-adjusted series of USDA supply news in Appendix A.2). The figure shows that USDA crop supply news routinely surprises the markets, generating field crop commodity price changes that sometimes over 5%.[7] Market-moving news events and the volatility of the surprise series in general, become more prevalent after 1996, when the farm bill that year offered more flexibility to producers in their crop choices (Westcott & Young, 2004); afterwards, farmers could more efficiently respond to market signals and make production choices based on factors like profitability and consumer preferences, and not be as heavily influenced by subsidy programs. June reports often feature prominently in the surprise series, because June includes USDA's annual AR report that identifies how American producers allocated their cropland (versus how they reported their planting intentions in March), as well as crop production reports for wheat, oats, and rice.

We describe five example episodes to illustrate how our series of USDA supply surprises aligns with real-world events and identify each of them in the figure: October 2008, January 2009, June 2009, June 2010, and June 2021. The October 10, 2008, WASDE report indicated a significant increase in corn and soybean production, surpassing the September forecast by 128 million bushels and 49 million bushels, respectively (USDA, 2008).[8] As a consequence, prices for both commodities fell that month. Similarly, the WASDE report released on January 12, 2009 raised corn and soybean production estimates by 81 million bushels and 39 million bushels, respectively, compared to the previous month, resulting in a decline in commodity price expectations (USDA, 2009a).[9] In June of the same year, the June

1 Grain Stocks and AR reports revealed that corn stocks and acreage surpassed expectations (Good, 2009). The estimated corn stocks were 238 million bushels higher than the previous year, while the projected acreage for corn in 2009 was approximately 87.035 million acres, indicating a 1.035 million-acre increase compared to the previous year's acreage and a rise of 2.049 million acres than the figures reported in the March PP report (USDA, 2009b;2009c).[10] The following year's June WASDE report instead caused a spike in corn prices, because the higher expected use of corn coupled with lower beginning stocks resulted in a decrease in projected 2010/11 corn ending stocks by 245 million bushels (USDA, 2010).[11] Finally, the June, 2021 GS report revealed a significant reduction in corn and soybean stocks—with corn down by 18 percent, and soybean stocks down 44 percent compared to the previous year—raising U.S. field crop commodity prices (USDA, 2021).[12]

(Figure 1. Historical series of USDA supply surprises, 1992-2023)

Placebo evaluation: background noise in USDA supply news

Our high-frequency identification approach may be confounded by the potential influence of other news that is not related to agricultural commodity markets during the daily window around the USDA news publication, given that liquid commodity markets incorporate government news in a far shorter timespan (Adjemian & Irwin, 2018). As a result, that noise may bias our measurement of USDA news series. To assess the magnitude of this potential problem, we compare changes in the U.S. field crop commodity futures prices around USDA report release days to changes on control days that do not involve the publication of USDA supply news. For control days, we use the same weekday one week (7 days) after the monthly WASDE report announcement, provided that the day is not a holiday. In the case of a holiday, the target trading day is delayed by one business day (see Appendix table A.2).

Figure 2 compares the changes in U.S. field crop commodity futures prices around USDA announcements with those on control days. Price changes on announcement days are more volatile than on control days—the distribution for the latter is narrower. Specifically, the variance of weighted field crop prices is found to be twice as high on announcement days than on control days. A Brown-Forsythe (1974) test to assess the statistical significance of the difference between the two groups confirms that this difference is statistically significant.[13] Similar analyses for individual commodities indicate that the gap between announcement and control days is even higher for the most important domestic field crops: corn, oats, and soybeans. On the other hand, the gap is less pronounced for rice and wheat, as shown in the figures in Appendix B.2.

(Figure 2. Comparing the USDA announcement to control days)

Empirical Approach

One challenge with interpreting the USDA surprise series directly as a shock is that it may only capture a portion of the exogenous shock of interest as well as measurement errors (Stock & Watson, 2018). Therefore, we use it as an instrument for the shock in this study—specifically, as an external instrument in a proxy SVAR model of the agricultural commodity market. As a result, we identify a structural agricultural supply news shock following the method developed by Stock and Watson (2012) and Mertens and Ravn (2013).[14] An external instrument must satisfy two conditions: it should be correlated only with the shock of interest (relevance) and uncorrelated with other structural shocks (contemporaneous exogeneity).

In addition to our main identification method, again following Känzig (2021), we also present alternative approaches for identifying the impacts of agricultural supply news shocks. First, we apply a heteroskedasticity-based identification that filters out background noise in USDA supply surprises caused by other shocks during the event window (Rigobon, 2003; Rigobon & Sack, 2004; Nakamura & Steinsson, 2018a); this approach allows us to isolate the true impact of agricultural supply news by comparing price movements in U.S. field crop commodity futures during event windows around USDA reports to similar windows that do not contain any USDA announcements (Känzig, 2021). Next, we employ Jordà's (2005) local projection method in place of the proxy SVAR to directly estimate the impulse responses to USDA news shocks. While the high-frequency identification approach helps address the endogeneity issue, it is accompanied by a trade-off of reduced statistical power (Nakamura & Steinsson, 2018a). Furthermore, the surprise series explains only a small portion of field crop commodity prices, and future outcome variables are likely to be influenced by numerous other shocks. As a result, it is difficult to directly estimate the impact of high-frequency USDA supply surprises on the future outcome variables. By exploring these alternative methods, we provide a comprehensive and robust analysis of the effects of agricultural supply news shocks.

Conceptual model

We specify the reduced-form VAR (p) model

$$y_t = \alpha + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \quad (5)$$

where p represents the lag order, y_t represents a $n \times 1$ vector of endogenous variables, u_t represents a $n \times 1$ vector of reduced-form innovations with covariance matrix $Var(u_t) = \sum$, α is an $n \times 1$ vector of constants, and $A_1, \dots, A_p$ are $n \times n$ coefficient matrices.

The vector of endogenous variables, y_t, include 14 variables: the real price of U.S. field crop commodities, domestic real GDP, industrial production, core CPI, equity prices, the VIX, the producer price index for livestock, domestic grain exports, the Baltic Dry Index (BDI), the real price of ethanol, the real price of oil, global oil production, the quantity of food-at-home that Americans consume, and the price of that food.

We propose that the reduced-form innovations in (5) are linked to structural shocks through a linear mapping such that

$$u_t = B\varepsilon_t, \quad (6)$$

where B represents a non-singular, $n \times n$ structural impact matrix and ε_t is a $n \times 1$ vector of structural shocks. The structural shocks are not mutually correlated (i.e., $Var(\varepsilon_t) = \Omega$ is diagonal). Based on the linear mapping of the shocks (i.e., the “invertibility” assumption), we obtain

$$\sum \ = B\Omega B'. \tag{7}$$

Without loss of generality, we order the agricultural supply news shock as the first shock in the VAR model (i.e., $\varepsilon_{1,t}$). Since our focus is on the impacts of exogenous agricultural supply news shocks and the first variable in y_t is U.S. real field crop commodity price, we seek to identify the structural vector of interest, b_1, which represents the first column of B.[15]

Identification with external instruments

We identify the structural vector of interest using external instruments, also known as proxies, by assuming that the background noise in the USDA supply surprise series is marginal. Let z_t represent our external instrument, which in this study is the USDA surprise series. To estimate the coefficients of b_1, the following conditions must be satisfied:

$$\mathbb{E}\left[z_t \varepsilon_{1,t}\right] = \theta \neq 0 \tag{8}$$

$$\mathbb{E}\left[z_t \varepsilon_{2:n,t}\right] = 0, \tag{9}$$

where $\varepsilon_{1,t}$ represents the agricultural supply news shock and $\varepsilon_{2:n,t}$ represents an $(n-1) \times 1$ vector of the other structural shocks. Equation (8) implies that the external instrumental variable is correlated with exogenous agricultural commodity price shocks (relevance condition). Equation (9) establishes that the instrument is not correlated with other structural shocks (contemporaneous exogeneity).

Results

First-stage regression fit

The external instruments approach we use relies on two key assumptions: instrument relevance and exogeneity. Weak correlation between the instrument and the shocks of interest can lead to biased results. To address this, we generate a series of related USDA supply news instruments using futures price changes from a single or a series of commodity futures expirations (for the weighted field crop commodity price), and we verify the strength of each instrument using an F-test in the first stage of the VAR, and report those results in table 1. Note that the "comp." column represents a composite model that spans the expirations over the first five maturities of the term structure. The first stage F-statistic should ideally be above a threshold value of 10 (Stock & Yogo, 2005). Our instruments yield first-stage F-statistics over about 16, with the composite instrument showing a first-stage F-statistic of 16.93 and a robust F-statistic of 18.70. These results support the relevance of our instrument. For exogeneity, we test autocorrelation, forecastability, and correlation with other shocks. The results indicate that our proxy is not correlated to itself, is not predicted by previous observations of the economic variables we study and is uncorrelated with other measured shocks (see Appendix B for details).

(Table 1. F-test results in the first stage of the VAR)

Baseline model results

Our baseline model, estimated with the external instrument, includes 14 variables: U.S. real field crop commodity price (weighted by domestic production share), U.S. real GDP, U.S. industrial production, core CPI, S&P 500 index, the VIX, U.S. grain exports, BDI, U.S. PPI for livestock, U.S. real ethanol price, real oil price, global oil production, quantity of food-at-home that Americans consume, and the U.S. food-at-home price index (refer to Appendix C for the sources and definitions of the data). The sample period spans from January 1992 to December 2023. Figure 3 shows our estimates of the dynamic response of the baseline variables to an agricultural supply news shock normalized to increase the production-weighted real price of field crops by a single standard deviation; because it raises prices, a convenient way to think about the normalized shock is representing poor news about the coming harvest.

Since we transform our baseline variables into natural logarithms, the results in the figure can be interpreted as percentage changes following the shock. Also, the variables are seasonally adjusted using the X-13ARIMA-SEATS Seasonal Adjustment Program. Impulse response functions to a shock of a single standard deviation in the U.S. real field crop commodity prices are plotted over a fifty-month horizon, with 68 and 90 percent confidence bands generated from 10,000 bootstrap replications. We specify a lag order of 12, since the data are monthly. As the external instrument is scaled by the average long-run conditional volatility from the component GARCH model, the figure reflects volatility-adjusted impulse responses.

Impulse response functions in the figure generally align with our expectations. In response to the shock, the first panel shows that the U.S. real field crop commodity price rise immediately by 2.3 percent and remains elevated over a year, as production adjusts. This outcome is intuitive because supply and inventory level recovery from a less abundant harvest takes at least a full growing season. On the other hand, the shock lowers domestic real GDP and industrial production for about three years (at the 90 percent confidence level); at its trough, the mean estimated decrease reaches about 0.26 percent for real GDP and approximately 0.41 percent for industrial production. This is anticipated because agriculture, food, and related industries collectively represent around 5 percent of the U.S. GDP (USDA, 2024b), and U.S. food manufacturing comprises roughly 10-13 percent of industrial production (Board of Governors of the Federal Reserve System, 2024). Its magnitude is also consistent with prior literature; D&P (2016) estimate that a one standard deviation shock that decreases global agricultural commodity production reduces U.S. real GDP by 0.28 percent and global industrial production by around 0.4 percent at its trough.

The shock also raises core CPI slightly for a few months. D&P (2016) argue that rising food commodity prices indirectly raise core inflation by raising energy costs and production expenses, which can be passed on to consumers through higher prices for non-food and non-energy goods. In response to the shock, the S&P 500 index decreases to a trough of about 1.3 percent at about a one-year horizon, consistent with the findings of D&P (2016), while implied stock market volatility increases and peaks at about a four percent rise after half a year. Although these findings are statistically significant, D&P's (2016) corresponding results are not. In the figure, poor field crop supply news raises immediate grain exports—perhaps as importers seek supplies ahead of a potentially poor harvest—but reduces the amount of exported grain after about a year, consistent with dwindling supplies of grain following the harvest. Similarly, global bulk shipping prices trace a similar response, following the demand exports place on bulk shipping services. At a single standard deviation of significance, the livestock price decreases in the short-run, but increases with a stronger confidence level over the longer term; this reversal is in line with the regularity that expected feed cost increases prompt producers to bring more animals to slaughter in the short term, increasing immediate meat supplies but reducing herd sizes until feed costs stabilize (Schulz, 2022).

The next three panels focus on the energy market. We find that real ethanol prices decrease in the short run following poor field crop supply news; this effect may be tied to the slowdown in real GDP. Real oil prices follow a similar path, although its impulse response is insignificant. Yet, poor agricultural supply news reduces global oil production by 0.28 percent, about six months later. This finding aligns with D&P (2016), where global oil production also declines with a lag at a similar magnitude. In the final two panels, the agricultural supply news shock leads to a reduction in the quantity of food-at-home consumed by Americans, by around 0.19 percent about one year later, and an increase in food-at-home prices of about the same magnitude. Both responses are statistically significant at the 90 percent confidence level, and both make intuitive sense. Moreover, the food price effect is consistent with a 0.18 percent back-of-the-envelope calculation implied by the direct impact of the immediate 2.6% rise in field crop commodity prices, given that the farm production share of food and beverages in food-at-home was around 7.1% from 1993-2022 (USDA, 2023b).

(Figure 3. Volatility-adjusted impulse response functions to a normalized agricultural supply news shock)

Quantitative importance of agricultural supply news shocks

While impulse response functions illustrate the transmission mechanism of an exogenous shock, they do not explain the portion of historical fluctuations in commodity markets and macroeconomic indicators attributable to these shocks or evaluate their average significance (Baumeister & Peersman, 2013). In this section, we conduct relevant historical decompositions and forecast error variance decompositions to provide a comprehensive understanding of agricultural supply news shocks.

Historical decompositions

Figures 4 illustrate the cumulative historical contribution of USDA's agricultural supply news to the real domestic weighted-average field crop commodity spot prices, with a one standard deviation confidence bands, generated from 10,000 bootstrap replications from 1993 to 2023.[16] The explained lines in these figures represent percent deviations from the mean, while the other series represents the contribution of USDA's agricultural supply news to historical realizations. The differences between the series in the chart represent the contribution that other factors made to historical observations.

Clearly, the figure shows that the two series are highly correlated over time; often they nearly overlap and are statistically significant at a single standard deviation. Supply news shocks identified with USDA surprises are important determinants of field crop commodity prices; they regularly account for a significant share of realized price changes—but they are clearly not the only source of news about crop fundamentals. For instance, in June 1996, GS and AR reports indicated that corn and soybean stocks were 1.72 billion bushels (50 percent) and 623 million bushels (21 percent) lower than pre-report estimates, respectively (Good, 1996), prompting a spike in crop prices; we estimate that the shock series explains 14 percentage points of that month’s 38 percent deviation of crop prices from their long-run average. Conversely, larger corn production prospects in the August 2006 WASDE report led to a sharp decline in prices (Good, 2006); USDA news shocks explained more than half of that month’s realized price. By August 2011, the WASDE report forecasted a significant reduction in corn and sorghum production for the 2011/12 crop year—556 million bushels lower than the previous year—driving up prices (USDA, 2011). Finally, the January 2022 GS report revealed a reduction in all wheat stocks, 18 percent lower than the previous year and 43 percent lower than the previous month, contributing to a spike in field crop prices (USDA, 2022).

At other times, deviations between the series in the figure suggest that outside factors are substantially more important contributors to field crop commodity price changes. For instance, between the late 1990s and early 2000s, decreases in food commodity prices were largely driven by weaker demand. The Asian financial crisis (1997-99) led to a slowdown in economic growth across Asia, reducing global demand (Peters, Langley, & Westcott, 2009). Because they are not based on U.S. domestic production, these shocks would not be picked up by our identification approach. Similarly, the 2001 Dot-com bubble bust (April to November 2001), caused by a sharp decline in the equity value of internet companies, also dampened invest demand (Bernanke, 2005). External factors also likely explain the divergence between the mustard and green series beginning in 2020 in the figure. The historical decompositions for food-at-home prices, domestic GDP, and the S&P 500 index are presented in Appendix D.

(Figure 4. Historical decomposition: USDA’s agricultural supply news contributions to U.S. real field crop commodity prices)

Forecast error variance decomposition

The results from the earlier impulse responses and historical decomposition confirm the significant impact of agricultural supply news shock on various economic variables. However, to quantify how much of the historical variation in variables of interest can be explained by agricultural supply news shocks, we apply forecast error variance decompositions to our baseline model. The latter measure how much of the error in predicting the baseline model variables at future steps is caused by the exogenous agricultural supply news shocks over time (Montiel Olea, Stock, & Watson, 2021).

Table 2 presents the contributions that agricultural supply news makes to monthly forecast error variance decompositions of the baseline variables. They account for 43 percent of the impact month's variance in U.S. real field crop commodity prices, although this contribution declines to 29 percent in the long run, indicating that other economic shocks account for a dominant share of field crop price volatility (Peersman, 2022); this is consistent with the historical decomposition in figure 5. In contrast, agricultural supply news shocks explain a relatively small portion of the short-run forecast error variance of the macroeconomic variables we include, although their persistent effects emerge over time, as their explanatory power increases. In the long run they account for 15 percent, 7 percent, 5 percent, 7 percent, and 11 percent of the 4-year ahead forecast error variation in the U.S. real GDP, industrial production, equity prices, the VIX, and the Baltic Dry Index. This regularity may be due to the fact that the actual harvest occurs at a lag to the news shock; in the case of the Baltic Dry Index, negative news about the upcoming harvest affects freight transportation demand over time, since transportation demand is derived from supply and demand dynamics (Denicoff, Prater, & Bahizi, 2014). The explanatory power of the agricultural supply news shock for the variance of food price and quantity consumed errors likewise rises over time.

(Table 2. Forecast error variance decomposition)

Propagation mechanism of agricultural supply news shocks

Our impulse response results confirm that agricultural supply news shocks affect the agricultural sector, the supply chain, financial markets, and the broader macroeconomy through changes in expectations for domestic and global commodity production and trade flows. In this section, we explore the additional effects of these shocks beyond our baseline variables. Following Känzig (2021), we estimate the next set of impulse responses by adding a single variable at a time to the baseline proxy SVAR. Sources and definitions of the variables used are provided in Appendix C.

Pass-through of agricultural supply news shocks to consumer prices

We found that agricultural supply news shocks that raise field crop commodity prices also have a significant impact on food prices. News shocks also influence other components through multiple channels, such as direct changes in food prices, potential shifts in energy prices due to the use of grains in biofuel production, and higher production costs for firms, leading to price increases for non-energy goods (see De Winne & Peersman, 2016, p.241).

Figure 5 shows the impact of agricultural supply news shocks on the main components of consumer prices, except for food, which we avoid including given its place in the baseline model through the PCE index. In the figure, an agricultural supply news shock leads to an immediate rise in core CPI, but these impulse responses quickly dissipate. The energy component begins to rise two months later and continues increasing for a year, although these responses are statistically insignificant—following a similar path to our ethanol IRF in the baseline model, although the magnitudes are smaller. D&P (2016) argue that the insignificant impact may be misleading, as the impulse responses do not consider time variation, especially given that biofuels have only recently become a significant energy source. However, our sample period begins in 1992, before the widespread adoption of biofuels. Demand for field crops expanded significantly with the government-mandated surge in biofuel demand starting in the mid-2000s, contributing to the spike in field crop prices (Carter, Rausser, & Smith, 2011; 2017). In contrast, the pass-through for durable goods takes longer. At the mean, durables prices decrease in the short run but begin to rise after a time, eventually peaking at 0.28 percent in the after about four years in response to the shock.

(Figure 5. Impacts on consumer prices)

Pass-through of agricultural supply news shocks to consumer expenditures

Because food consumption is unavoidable, rising food prices in response to agricultural news shocks decrease consumers' discretionary income, all else equal, reducing expenditures not only for food and energy but also for other categories. Figure 6 shows the impulse responses of different consumer expenditure categories. As expected, a negative crop supply news shock lowers expenditures on nondurable goods (food and beverages purchased for off-premises consumption make up around 40 percent of this category). This same trend is also observed for other sorts of expenditures, including both services and energy goods and services. However, we do not find that the effects on expenditures for durable goods are statistically significant at the 32 percent level and cannot conclude that agricultural news shocks reduce consumer expenditures on durable items.

(Figure 6. Impacts on consumer expenditures)

Pass-through of agricultural supply news shocks to economic activity and monetary policy

Figure 7 shows that a poor harvest shock reduces global economic activity and affects both the domestic labor market and monetary policy. Just as the U.S. GDP and domestic industrial production decrease in response to poor harvest news, global industrial production falls as well—although the impact trough is about half the magnitude and estimated less precisely. In response to the shock, domestic labor market tightness, measured by the ratio of job openings to unemployment, increases at first, but then falls substantially, eventually reaching a trough decline of 5.3 percent (and coinciding with our projection of the slowdown in the GDP). Like D&P (2016), we find that a poor harvest shock also affects U.S. monetary policy: our normalized news shock raises the federal funds rate by 7 basis points after a year, with the elevated rate persisting for over two years, before eventually reversing. As D&P (2016) argue, a 10-basis point increase in the federal funds rate typically reduces real GDP by 0.05 percent to 0.1 percent (e.g., Christiano, Eichenbaum, & Evans, 1999; Bernanke & Mihov, 1998). Using this guideline, the monetary policy reaction to a negative harvest news shock could account for nearly one-quarter of the overall impact we measure that it has on economic output, given that the (maximum) impulse response of the real GDP to the shock is around a 0.28 percent decline in our baseline model.

(Figure 7. Impacts on economic activity and monetary policy)

Sensitivity of the results

In this section, we re-estimate the baseline model with different model specifications to assess the robustness of our findings. These include testing different models, variables, instruments, sample periods, and scales of instruments.

Alternative models

Like Känzig (2021), we also employ a heteroskedasticity-based approach to estimate the baseline model, which clears away the effects of outside shocks that may confound our instrument during the daily event window. This approach takes into account the potential presence of background noise. As shown in Appendix figure E.1, the impulse responses derived from this approach are quite similar to those recovered through the use of an external instrument. The point estimates are quite close to each other, and although the estimates from the heteroskedasticity-based approach are less precise, they are still significant at the level of a single standard deviation. This offers robustness to our findings and suggests that any potential bias caused by background noise is likely to be negligible.

Our construction of impulse responses using the VAR approach relies on the assumption that the model accurately represents the dynamic relationships of all variables included in the model. However, this assumption does not hold for the external instruments approach, as the contemporaneous responses of many variables in a model may be close to zero. As a result, a substantial portion of the long-term dynamics may be derived from the structure imposed by our approach, as noted by Nakamura and Steinsson (2018b). To relax that, we use a local projection framework that similarly instruments the USDA supply news series as an alternative method for estimating impulse responses to an agricultural supply shock. Appendix figure E.2 shows that the point estimates from the two approaches are quite similar in the short run, but the impulse responses from local projections become more volatile and less precise over time. Overall, both sets of results imply the same general effects of poor field crop supply news on the modeled variables.

Alternative field crop commodity price variable

Our baseline model uses a composite U.S. field crop commodity price measure, weighted by each commodity's production share, to identify the impact of agricultural supply news. Specifically, we include the major field crops produced in the United States—corn, soybeans, wheat, rice, and oats. Yet, corn and soybeans together account for around 84 percent of total production. For robustness, we re-estimate the baseline model using an alternative price variable that only combines prices for these latter two commodities, weighted by their production shares. This alternative yields results consistent with the baseline model but with stronger instrument strength, as shown in Appendix figure E.3.

Alternative instrumental variable

We also test the sensitivity of the baseline model using an alternative instrument. Following Roberts and Schlenker (2013), we aggregate each field crop's USDA news series into a single news series using calorie weights instead of production shares. To do this, we use conversion factors proposed by Lucille and Paul Williamson (1942). The results in Appendix figure E.4 indicate that using calorie-weighted USDA news series as an alternative external instrument produces consistent results and slightly improves the strength of the instrument.

Alternate sample periods

The COVID-19 pandemic is a historical outlier in many ways, including the progress of its associated business cycle—the recession it caused as well as the subsequent expansion was faster than any other in U.S. history (Bennett & Walstrum, 2022). So, we re-estimate our baseline model using data only from the pre-COVID-19 pandemic period (1992M01 to 2019M12), which represents relatively stable economic conditions. The results show that the impulse responses during the pre-pandemic period are similar, although a handful are somewhat different and are less precisely estimated, as depicted in Appendix figure E.5.

Non-volatility-adjusted impulse response functions

In our analysis, to address the potential impact of pre-existing macroeconomic conditions on price volatility, we scale our proxy to the long-run conditional volatility of U.S. real agricultural commodity prices, using the component GARCH model developed by Engle and Lee (1999). Finally, we test our baseline impulse response functions without this scaling. As shown in Appendix figure E.6, the impulse responses from the non-volatility-adjusted model remain consistent with the baseline model, though the strength of the instrument declines to about two-thirds of that in the baseline model.

Conclusions

We identify agricultural supply news shocks that are correlated with USDA announcements about existing stocks or anticipated changes to field crop production in the United States and assess their effects on the agricultural and food sectors, as well as the broader domestic and global economy through multiple channels. We follow a recently-developed approach by Känzig (2021), exploiting the exogeneity of the news contained in important USDA publications. Specifically, we use the USDA supply news series—measured as high-frequency changes in the production-weighted average U.S. field crop price—as an external instrument within a VAR model.

De Winne and Peersman (2016), in an article closest to our own, study how global harvest disruptions affect the U.S. macroeconomy using a VAR model and a narrative approach. They employ a series of global food commodity production indices derived from FAO annual crop production data for 192 countries to capture unanticipated changes in aggregate crop production. Their findings indicate that a negative global harvest shock increases real food commodity prices and the U.S. CPI, while depressing food commodity production, the volume of seeds for planting, global economic activity, U.S. GDP, and the S&P 500 index. Our findings, produced at a higher frequency using U.S. crop data and a different approach that is less exposed to endogeneity issues (since, e.g., prices include forecasts about global planting decisions), are generally in the same direction and of similar magnitude. Our volatility-adjusted impulse responses indicate that, on average, a poor agricultural news shock increases the real price of domestic field crop commodities but reduces domestic real GDP and industrial production (consistent with food processing's share), as well as global oil production. The shock also leads to a temporary increase in core CPI. However, in contrast with D&P, our results also indicate that bad harvest news impacts the S&P 500 index (pressuring it down) and implied volatility (increasing it). We further show that the shock immediately reduces the producer price index for U.S. livestock before later raising it (possibly through the herd management channel), but increases grain exports before later reducing them (as importers seek supplies ahead of the poor harvest that lowers supplies of grain); it traces out a similar effect on global bulk shipping prices (likely through the derived demand for shipping services). Bad harvest news raises food-at-home prices (comparable to the direct impact of field crop prices on retail products, given their 7.1% share in production) and slightly reduces the quantity of food consumed at home.

Our historical decompositions assess the contributions of agricultural supply news shocks to the evolution of U.S. field crop commodity prices, food prices, U.S. GDP, and the

S&P 500 index (see Appendix D for the results on food-at-home prices, U.S. GDP, and the S&P 500 index). We show that, while they explain a significant portion of the evolution in crop prices, harvest shocks contribute less to food-at-home prices (since farm inputs represent a relatively small component of retail food products), domestic GDP, and the equity prices. And our decompositions of forecast errors for the baseline model variables confirm that domestic agricultural supply news significantly contribute to the fluctuations in all the variables we model, but especially U.S. real field crop commodity prices, domestic real GDP, core CPI, grain exports, the BDI, and global oil production. Finally, we demonstrate that these shocks may also have broader economic consequences: they reduce global economic activity. In the domestic market, they affect labor market tightness and the federal funds rate, while contributing to an increase in the CPI for durable goods; they also lead to declines in expenditures for nondurable goods, for energy goods and services, and for services overall.

We anticipate that the agricultural supply news shock series we identify will provide valuable insights into related inquiries into the agricultural sector and even the macroeconomy. Our empirical results reveal that it is uncorrelated to other news shocks, like those for oil supply and monetary policy, and so offers a unique source of exogeneity that researchers can exploit. For example, Adjemian, Li, and Jo (2024), in their decomposition of food price inflation into supply- and demand-driven innovations, show that poor agricultural supply news raises the contribution that the supply side of the market makes to food price inflation.

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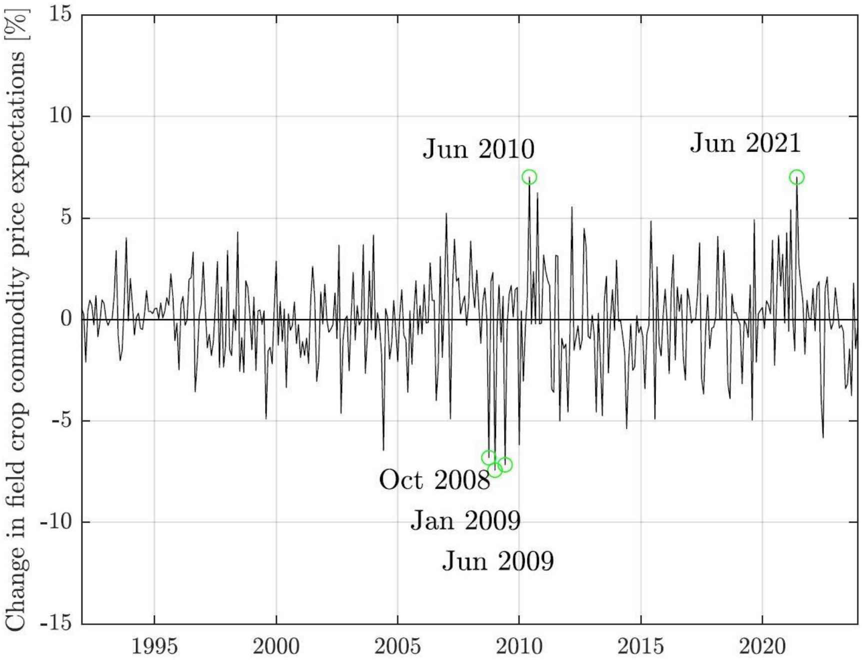
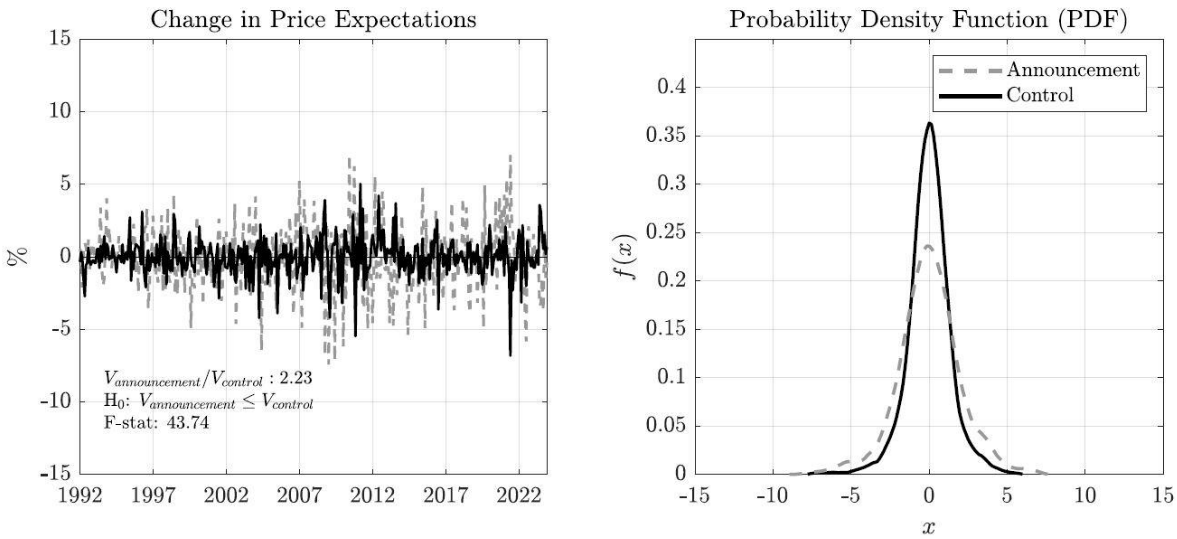
Figures and Tables

Figure 1. Historical series of USDA supply surprises, 1992-2023



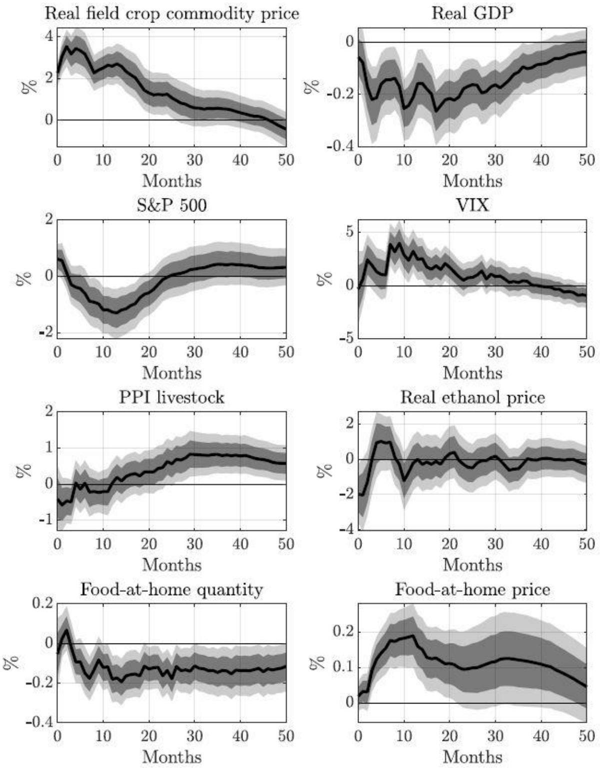
Notes: The monthly USDA surprise series represents the first principal component derived from changes in U.S. field crop commodity futures prices (relative to their share of domestic production), specifically those for corn, oats, rice, soybeans, and wheat, around the publication of USDA supply news reports (see Appendix A.2 for individual commodity series and the volatility-adjusted USDA supply surprises).

Figure 2. Comparing the USDA announcement to control days



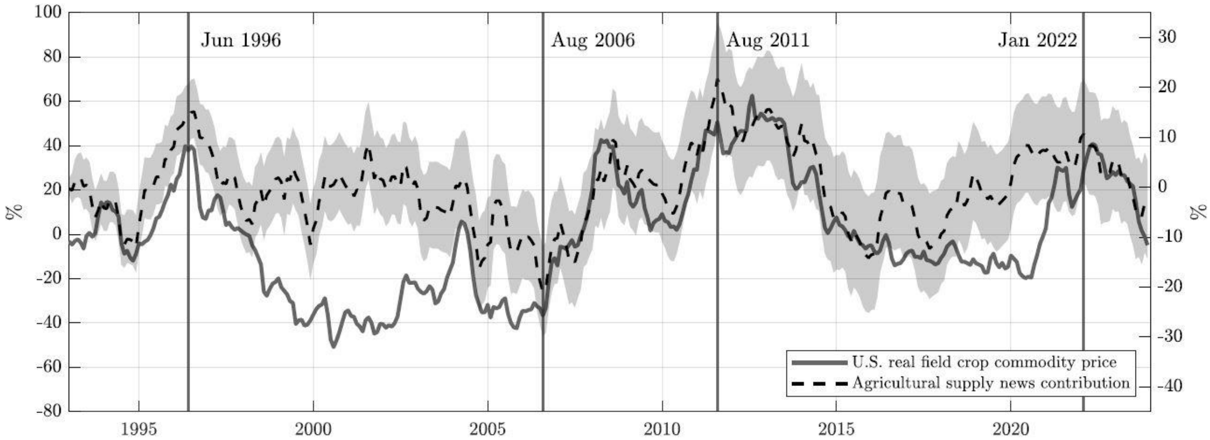
Notes: The two figures represent changes in the weighted average of U.S. field crop commodity price (daily) on USDA announcements compared to control days. The figure on the left displays changes in daily prices made to the monthly time series, while the figure on the right illustrates an empirical probability density function (PDF), plotted using an Epanechnikov kernel over the left panel data.

Figure 3. Volatility-adjusted impulse response functions to a normalized agricultural supply news shock



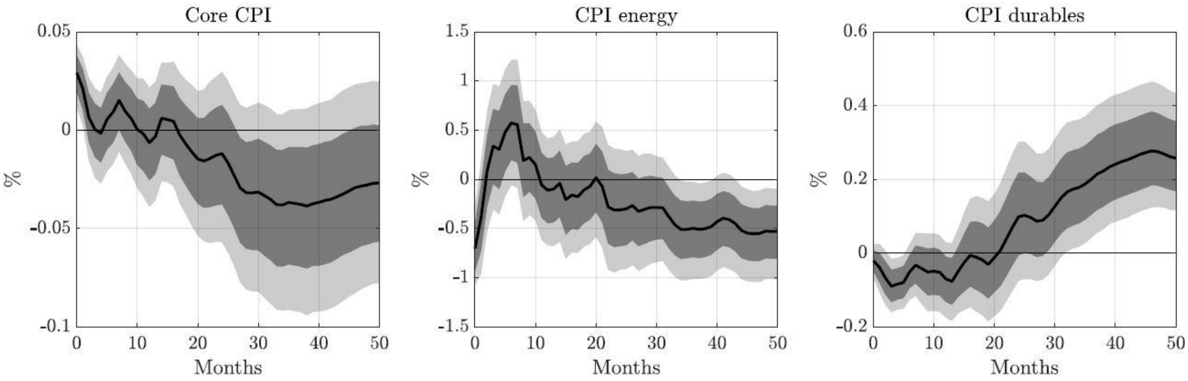
Notes: The solid black line represents the point estimate. The dark gray region indicates the 68 percent confidence band, while the light gray region represents the 90 percent confidence band for the impulse responses.

Figure 4. Historical decomposition: USDA's agricultural supply news contributions to U.S. real field crop commodity prices



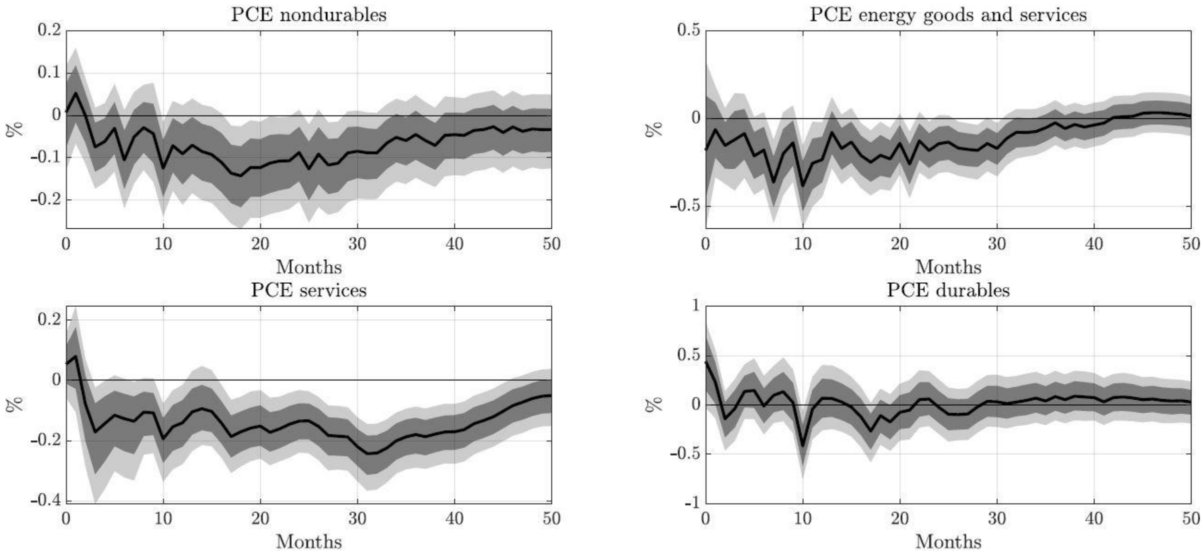
Notes: The figure depicts the cumulative historical contribution of USDA supply news to the U.S. real field crop commodity prices, in deviations from their mean, from 1993 to 2023 at the monthly frequency. The gray solid line represents the weighted-average U.S. real field crop commodity price, expressed as percentage deviations from its mean. The black dashed line is the agricultural supply news contribution. The left axis corresponds to the field crop commodity price, and the right axis to the supply news contribution. The light gray shading represents a 68 percent confidence interval. Vertical bars highlight key historical USDA supply news episodes.

Figure 5. Impacts on consumer prices



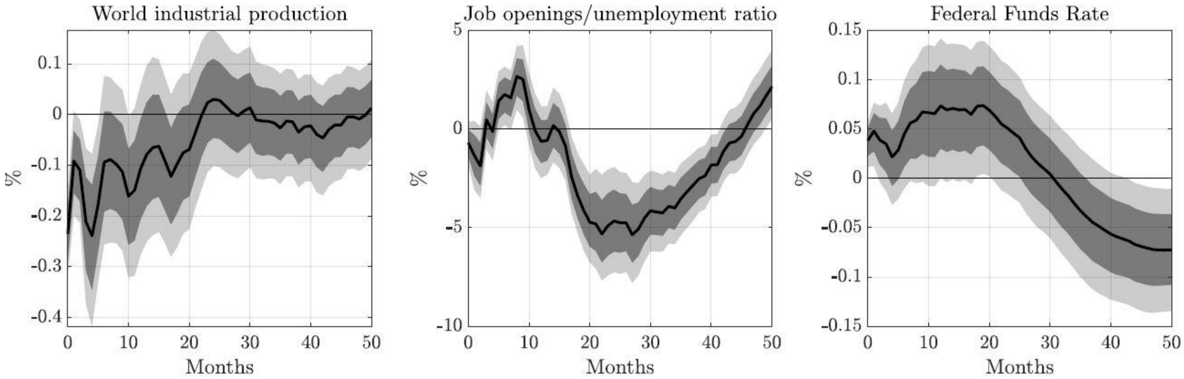
Notes: The solid pink line represents the point estimate. The light and dark shadings represent 68 percent and 90 percent confidence intervals, respectively.

Figure 6. Impacts on consumer expenditures



Notes: The solid pink line represents the point estimate. The light and dark shadings represent 68 percent and 90 percent confidence intervals, respectively Each variable is deflated by its respective chain-type price index.

Figure 7. Impacts on economic activity and monetary policy



Notes: The solid pink line represents the point estimate. The light and dark shadings represent 68 percent and 90 percent confidence intervals, respectively.

Table 1. F-test results in the first stage of the VAR

	Front	First def.	Second def.	Third def.	Fourth def.	Comp.
F-statistic	16.14	16.46	16.52	17.75	16.59	16.93
Robust F-statistic	17.67	18.77	18.74	19.30	17.40	18.70

Table 2. Forecast error variance decomposition

Month	Real field crop price	Real GDP	U.S. industrial production	Core CPI	S&P 500
0	0.43	0.01	0.01	0.14	0.04
	[0.18, 0.67]	[0.00, 0.07]	[0.00, 0.10]	[0.01, 0.38]	[0.00, 0.24]
12	0.53	0.11	0.06	0.02	0.05
	[0.24, 0.71]	[0.03, 0.29]	[0.01, 0.23]	[0.00, 0.09]	[0.01, 0.19]
24	0.39	0.15	0.07	0.01	0.05
	[0.17, 0.59]	[0.04, 0.38]	[0.02, 0.28]	[0.00, 0.03]	[0.01, 0.16]
36	0.33	0.16	0.07	0.00	0.05
	[0.14, 0.53]	[0.05, 0.40]	[0.02, 0.24]	[0.00, 0.02]	[0.01, 0.13]
48	0.29	0.15	0.07	0.00	0.05
	[0.13, 0.48]	[0.05, 0.37]	[0.02, 0.22]	[0.00, 0.01]	[0.01, 0.12]

Month	VIX	Grain exports	Baltic Dry Index	PPI livestock	Real ethanol price
0	0.00	0.15	0.04	0.01	0.06
	[0.00, 0.00]	[0.02, 0.35]	[0.00, 0.23]	[0.00, 0.09]	[0.00, 0.34]
12	0.07	0.08	0.05	0.01	0.02
	[0.03, 0.18]	[0.03, 0.19]	[0.02, 0.15]	[0.00, 0.04]	[0.01, 0.07]
24	0.09	0.10	0.06	0.02	0.02
	[0.04, 0.19]	[0.04, 0.23]	[0.02, 0.14]	[0.01, 0.05]	[0.01, 0.04]
36	0.08	0.10	0.07	0.05	0.02
	[0.04, 0.17]	[0.04, 0.21]	[0.03, 0.15]	[0.01, 0.12]	[0.01, 0.04]
48	0.07	0.09	0.11	0.07	0.02
	[0.04, 0.15]	[0.04, 0.20]	[0.05, 0.22]	[0.02, 0.17]	[0.01, 0.03]

Month	Real oil price	Oil production	Food-at-home quantity	Food-at-home price
0	0.00	0.06	0.00	0.01
	[0.00, 0.02]	[0.00, 0.24]	[0.00, 0.03]	[0.00, 0.06]
12	0.01	0.10	0.05	0.18
	[0.00, 0.03]	[0.02, 0.31]	[0.02, 0.12]	[0.03, 0.41]
24	0.01	0.10	0.08	0.11
	[0.00, 0.02]	[0.03, 0.28]	[0.03, 0.20]	[0.02, 0.31]
36	0.01	0.10	0.08	0.08
	[0.00, 0.03]	[0.03, 0.25]	[0.03, 0.22]	[0.02, 0.22]
48	0.02	0.09	0.09	0.07
	[0.01, 0.05]	[0.03, 0.22]	[0.03, 0.22]	[0.02, 0.21]

Notes: The table above shows the forecast error variance decompositions of the baseline variables caused by exogenous agricultural supply news shocks, with 0, 12, 24, 36, and 48 month horizons. The 90 percent confidence bands for these values are presented within brackets. Descriptions and sources of these variables are available in Appendix C.

Endnotes

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[*] Michael K. Adjemian is a Professor in the Department of Agricultural and Applied Economics at the University of Georgia, and a consultant to the Commodity Futures Trading Commission. No Commission resources were used in this work and its findings do not necessarily represent its views. Jungkeon Jo is a Ph.D. candidate in the same academic department.

[1] Although USDA's ending stocks estimates incorporate demand-side information, by construction, those projections are based on publicly-available data, so don't represent news surprises. Supply information, on the other hand, is confidential until published (see, e.g., Adjemian, 2012b).

[2] Specifically, we estimate the news content of USDA's monthly World Agricultural Supply and Demand Estimates (WASDE), which provides a balance sheet of production, consumption, and trade data, as well as price forecasts for major agricultural commodities; its quarterly Grain Stocks (GS) report, detailing current and historical grain stock levels for both major (like corn, soybeans, wheat) and minor crops; as well as its annual Prospective Plantings (PP) and Acreage reports (AR), which respectively document farmers' planting intentions for the upcoming growing season, and actual planted acreage. See Appendix A for more detail on the reports we include.

[3] Specifically, we study corn, oats, rice, soybeans, and wheat, weighted by their annual share of domestic production. Our weighting is quite literal, since the commodities data are denominated in millions of metric tons (MMT).

[4] Expiration months for Chicago Board of Trade (CBOT) futures vary by commodity: March, May, July, September, and December (corn, oats, and wheat); January, March, May, July, August, September, and November (soybeans); March, May, July, September, November, and January (rice).

[5] The maturities of futures contracts for US field crop commodities used in this study range from the nearby to the fourth deferred contract maturities.

[6] For instance, in 2023 the share of field crop production in MMT for corn, soybeans, wheat, rice, and oats was 0.696, 0.202, 0.088, 0.012, and 0.001, respectively.

[7] From 1992 to 2023, USDA supply news generated >= 5 percent daily changes in (weighted) field crop price on 14 occasions. Six of these involved price increases, while the remaining eight involved price decreases.

[8] See the WASDE report published on October 10, 2008. This report can be accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/bc386j52m/zc77sq44s/wasde-10-10-2008.pdf

[9] See the WASDE report published on January 9, 2009. This report can be accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/t148fh48x/79407x60h/wasde-01-12-2009.pdf

[10] See the GS report published on June 30, 2009. This report can be accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/xg94hp534/5m60qt78h/8910jw560/GraiStoc-06-30-2009.pdf; See the Acreage report published on June 30, 2009. This report can be accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/j098zb09z/n296x138b/7h149r817/Acre-06-30-2009.pdf

[11] See the WASDE report published on June 10, 2010. This report can be accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/j098zb41q/b8515n719/wasde-06-10-2010.pdf

[12] See the GS report published on June 30, 2021. This report can be accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/xg94hp534/pz50ht47k/0g355c356/grst0621.pdf

[13] A Brown-Forsythe test is a statistical test that is used to estimate the equality of variances across groups using deviations from the median (Brown & Forsythe, 1974).

[14] An external instrument is an instrument that is not included in a model, but rather a variable obtained from outside the model that is used to help identify the dynamic causal effects of the shock in the VAR model (Stock & Watson, 2018).

[15] In VAR models, invertibility is a critical assumption which implies that the VAR model includes all relevant information necessary to recover the underlying structural shocks (Känzig, 2021). Non-invertibility arises when the model fails to capture all relevant information, leading some endogenous variation to be misclassified as exogenous. An external instrument approach requires weaker assumptions: only the shock of interest should be invertible and the instrumental variable should satisfy a limited lead-lag exogeneity (Miranda-Agrippino & Ricco, 2023).

[16] We note that the decompositions we perform do not measure the total contribution of agricultural supply news, however, only the part that correlates with our instrument.

Agricultural Supply News as Exogenous Shocks to the Macroeconomy

Online Appendix

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Appendix A: USDA reports and historical series of USDA news

A.1. USDA announcement schedule

Table A.1. outlines the USDA crop report schedule. We consider 574 USDA reports over the period of study, including 382 WASDE reports, 128 GS reports, 32 PP reports, and 32 AR reports. Some reports are released on the same day, at the same time: 32 pairs of WASDE and GS reports are published in January, 32 pairs of GS and PP reports in March, and 32 pairs of GS and AR reports in June. Table A.2 lists USDA report publication dates and control dates over the sample period (1992-2023). The release dates are listed on the USDA Economics, Statistics and Market Information System (ESMIS).

[1] During the sample period, USDA shifted the release time of major crop reports: In May 1994, the release time moved from 3 p.m. to 8:30 a.m. EDT, and in January 2013, from 8.30 a.m. to 12 p.m. EDT. Before 1994, USDA reports were released outside of futures market trading hours, so the following trading day is used to measure the USDA news surprise in those cases. For control days, we use the same weekday one week (7 days) after the monthly WASDE report, unless it falls on a holiday; in that case, the trading day is delayed by one business day. The daily series are also aggregated into monthly series: if there is only one USDA announcement in a month, the monthly surprises equal that daily surprise. For months with multiple announcements (e.g., March, June, and September), we sum up the daily surprises.

For months without any USDA announcements (as in October 2013 and January 2019, due to the U.S. federal government shutdown), a value of zero is assigned to the monthly USDA surprise.

(Table A.1. USDA reports schedule)

(Table A.2. USDA announcements, 1992-2023)

A.2 Historical series of USDA supply surprises for individual field crop commodities and volatility-adjusted series of USDA supply surprises

(Figure A.1 Historical series of USDA supply surprises for corn)

(Figure A.2 Historical series of USDA supply surprises for oats)

(Figure A.3 Historical series of USDA supply surprises for rice)

(Figure A.4 Historical series of USDA supply surprises for soybeans)

(Figure A.5 Historical series of USDA supply surprises for wheat)

(Figure A.6 Volatility-adjusted historical series of USDA supply surprises)

Appendix B: Diagnostic tests

B.1. USDA news series

To ensure the validity of the series, we conduct a set of diagnostic tests as recommended by Ramey (2016), including tests for autocorrelation, forecastability, and correlation with other shocks. Figure B.1 presents the autocorrelation function of the series, showing little evidence of serial correlation. In addition, the Granger causality test results, provided in Table B.1, show no evidence of Granger causality at the 5 percent significance level, suggesting that the USDA news series is not predicted by past economic variables in the baseline model.

We also investigate whether the USDA supply news series is correlated with other structural shocks identified in the literature, such as oil supply news shocks, oil supply shocks, oil consumption demand shocks, economic activity shocks, and monetary policy shocks. As shown in table B.2, the results indicate no significant correlation between the USDA news series and these other structural shocks, confirming that our series is orthogonal to other news and policy events.

(Figure B.1 Autocorrelation test of USDA supply surprise series)

(Table B.1 Granger causality test results)

(Table B.2. Correlation with different shocks)

B.2. A comparison of USDA announcement versus control days for individual field crops

(**Figure B.2. Comparing the USDA announcement to control days for corn)**

(Figure B.3. Comparing the USDA announcement to control days for oats)

(Figure B.4. Comparing the USDA announcement to control days for rice)

(Figure B.5. Comparing the USDA announcement to control days for soybeans)

(Figure B.6. Comparing the USDA announcement to control days for wheat)

(Figure B.7. Comparing the USDA announcement to control days (volatility-adjusted))

Appendix C: Data description and source

Instrumental variable

- Corn futures price (USd/bu.) : Generic 1st ‘C’ Future, Generic 2nd ‘C’ Future, Generic 3rd ‘C’ Future, Generic 4th ‘C’ Future, and Generic 5th ‘C’ Future, collected from Bloomberg terminal.
- Oats futures price (USd/bu.): Generic 1st ‘O’ Future, Generic 2nd ‘O’ Future, Generic 3rd ‘O’ Future, Generic 4th ‘O’ Future, and Generic 5th ‘O’ Future from Bloomberg terminal, collected from Bloomberg terminal.

- Rice futures price (USd/cwt.): Generic 1st ‘RR’ Future, Generic 2nd ‘RR’ Future, Generic 3rd ‘RR’ Future, Generic 4th ‘RR’ Future, and Generic 5th ‘RR’ Future, collected from Bloomberg terminal.
- Soybean futures price (USd/bu.): Generic 1st ‘S’ Future, Generic 2nd ‘S’ Future, Generic 3rd ‘S’ Future, Generic 4th ‘S’ Future, and Generic 5th ‘S’ Future, collected from Bloomberg terminal.
- Wheat futures price (USd/bu.): Generic 1st ‘W’ Future, Generic 2nd ‘W’ Future, Generic 3rd ‘W’ Future, Generic 4th ‘W’ Future, and Generic 5th ‘W’ Future, collected from Bloomberg terminal.

Baseline variables

- Real price of U.S. field crop commodities: U.S. field crop commodity price (production-weighted; cents per bushel) deflated by U.S. consumer price index (CPI). The spot prices for these field crop commodities are collected from USDA National Agricultural Statistics Service Information (NASS).
- U.S. real GDP: An indicator of the U.S. real aggregate output, conceptually aligned with the real Gross Domestic Product (GDP) as defined in National Income and Product Accounts (NIPA). This data are available from S&P Global Market Intelligence.
- U.S. Industrial production: The real output of manufacturing, mining, and electric and gas utilities in the United States, with data sourced from Federal Reserve Economic Data (FRED).
- Core CPI: U.S. CPI for all urban consumers: all items less food and energy, which are available from FRED.

- Baltic Dry Index (BDI): A financial index that measures the expenses associated with shipping various raw materials, such as iron ore, coal, grain, and other bulk commodities, via maritime routes. The data are collected from Bloomberg terminal.
- S&P 500 index: A stock market index that tracks the performance of 500 of the largest companies listed on U.S. stock exchanges, available via Bloomberg terminal (SPX index). The daily price levels are aggregated to compute the monthly average price.
- VIX volatility index: A measure of financial uncertainty, as represented by the CBOE Volatility index. We use the closing prices on the last day of each month, with data available from Yahoo Finance.
- U.S. producer price index (PPI) for livestock: The Producer Price Index for livestock in the United States. This data are collected from FRED.
- U.S. grain exports: Exports of U.S. grains and feeds (metric tons) to countries worldwide, with data available from USDA Foreign Agricultural Service's Global Agricultural Trade System.
- Real ethanol price: The U.S. ethanol price (cents per gallon) deflated by CPI. The ethanol price data is collected from USDA Economic Research Service. U.S. Bioenergy tables. Table 14. Monthly prices for corn (dollars per bushel), fuel ethanol (dollars per gallon), and gasoline (dollars per gallon).
- Real oil price: The spot price of West Texas Intermediate (WTI) crude oil (dollars per barrel), deflated by CPI. The data are sourced from FRED.
- Global oil production: World crude oil including condensate production (1,000 barrel per day). The data are sourced from Bloomberg terminal.

- U.S. quantity purchased of food-at-home: Real PCE for food (chain-type quantity index). The data are sourced from U.S. Bureau of Labor Statistics (BLS).
- U.S. price of food-at-home: PCE for food (chain-type price index). The data are sourced from BLS.

Additional variables

- CPI for energy: U.S. CPI for all urban consumers: energy in U.S. city average. Source: BLS
- CPI for durables: U.S. CPI for all urban consumers: durables in U.S. city average. Source: BLS
- PCE for nondurables: PCE: nondurable goods, deflated by PCE for nondurable goods (chain-type price index). Source: BLS
- PCE for energy goods and services: PCE: energy goods and services, deflated by PCE for energy goods and services (chain-type price index). Source: BLS
- PCE for services: PCE: services, deflated by PCE for services (chain-type price index). Source: BLS
- PCE for durables: PCE: durable goods, deflated by PCE for durable goods (chain-type price index). Source: BLS
- World industrial production: Industrial production of OECD countries along with six major non-member countries—Brazil, China, India, Indonesia, Russian Federation and South Africa—based on data from Baumeister and Hamilton (2019) Source: Dr. Baumeister's webpage
- U.S. job openings to unemployment ratio: This ratio is calculated by dividing job openings (total nonfarm) by the total unemployment level in the United States. Job

openings data are sourced from the Job Openings and Labor Turnover Survey (JOLTS), and unemployment levels are also obtained from BLS.

- Federal Funds Rate: The interest rate at which banks trade money to each other overnight. The rate is guided by the federal funds rate target set by the Federal Open Market Committee (FOMC). Source: Board of Governors of the Federal Reserve System (US)

Appendix D: Historical decompositions of agricultural supply news for other variables

Figures D.1-3 display the cumulative historical contribution of USDA's agricultural supply news to the detrended U.S. food-at-home price index, detrended U.S. real GDP, and detrended S&P 500 index. These variables form the core of our baseline model (see Appendix C for data description and sources).

Agricultural supply shocks also contribute to the evolution of food-at-home prices, domestic GDP, and stock market price, though to a lesser degree.[2] Figure D.1 illustrates the cumulative contribution of agricultural supply news to the (detrended) domestic food-at-home price index (dark red solid line), highlighting two major historical food price events (gray shaded areas). During the 2007-08 global food crisis (Wright & Bobenrieth, 2009), agricultural supply news accounted for 6.1 percentage points of the 6.3 percent peak surge in U.S. food-at-home prices, particularly in November 2008. In 2011, the shock contributed around 4.4 percentage points of the 4.6 percent peak increase in domestic food prices as the economy recovered from the Great Recession. However, during the most recent inflationary period (2021-2023), our shock series explained only about 1.8 percentage points of 6.8 percent rise in food prices.

(Figure D.1. Historical decomposition: USDA's agricultural supply news contributions to U.S. food-at-home price index)

Figure D.2 illustrates the historical contribution of agricultural supply news (green dotted line) to U.S. industrial production (orange solid line), alongside the National Bureau of Economic Research (NBER)'s recession indicators (gray shades). During the Great Recession, USDA's agricultural supply news accounted for 18 percentage points of the trough 1.4 percent decline in domestic real GDP. In contrast, during the 2001 Dot-com recession, agricultural supply news only contributed 1 percentage points to the 2 percent deviation in GDP from the mean in November of that year. During the early period of COVID-19 pandemic, the contribution of news to GDP was also relatively modest. In April 2020, it accounted for only 1 percentage points of the 15 percent fall in GDP.

(Figure D.2. Historical decomposition: USDA's agricultural supply news contributions to U.S. real GDP)

The USDA's crop supply news also contributed somewhat to changes in overall stock prices as represented by the S&P 500 index. Figure D.3 displays the cumulative contribution of the supply news on the S&P 500 index. Stock prices continued to fall following the 2001 Dot-com bubble bust, reaching their lowest point in February 2003. Agricultural supply news accounted for 3.7 percentage point of the 19 percent drop in prices. In March 2009, agricultural supply news contributed roughly 3.5 percentage points to the 67.6 percent reduction in the S&P 500 index during the Great Recession. In contrast, during the recent recession COVID-19, particularly in March 2020, the shock contributed 8.1 percentage points to the 11 percent fall in the S&P 500. This finding contrasts with the results of Cao et al. (2024), who concluded that USDA news does not significantly affect the overall U.S. stock market. However, our study covers a broader time period (1992 – 2023) than Cao et al. (2024), which uses shorter data span from 2009 to 2019 and employs a different identification technique. They use the Capital Asset

Pricing Model to test the five hypotheses about how USDA supply news regarding major field crops (e.g., corn, soybean, and wheat) influences the U.S. stock market.

(Figure D.3. Historical decomposition: USDA's agricultural supply news contributions to S&P 500 index)

Appendix E: Sensitivity and robustness of the results

E.1. Alternative VAR approach

(Figure E.1. Impulse response functions to an agricultural supply news shock using a heteroskedasticity-based approach)

E.2. Alternative method to estimate impulse responses

(Figure E.2. Impulse response functions to an agricultural supply news shock using local projections)

E.3. Alternative variable: just corn and soybeans

(Figure E.3. Volatility-adjusted impulse response functions with alternative field crop commodity price variable)

E.3. Alternative external IV: calorie-weighted production

(Figure E.4. Volatility-adjusted impulse response functions with alternative instrumental variable)

E.4. Alternate sample period

(Figure E.5. Volatility-adjusted impulse response functions for the pre-COVID period (1992-2019))

E.5. Non-volatility-adjusted impulse response functions

(Figure E.6. Non-volatility-adjusted impulse response functions to a normalized agricultural supply news shock)

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Figures and tables

Figure A.1. Historical series of USDA supply surprises for corn

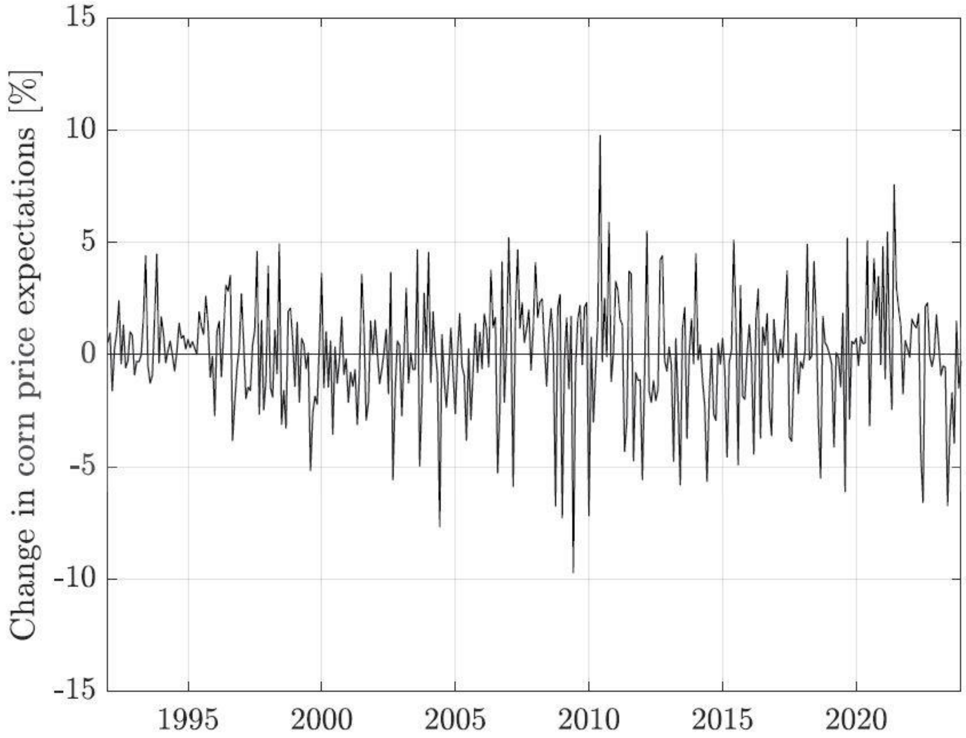


Figure A.2. Historical series of USDA supply surprises for oats

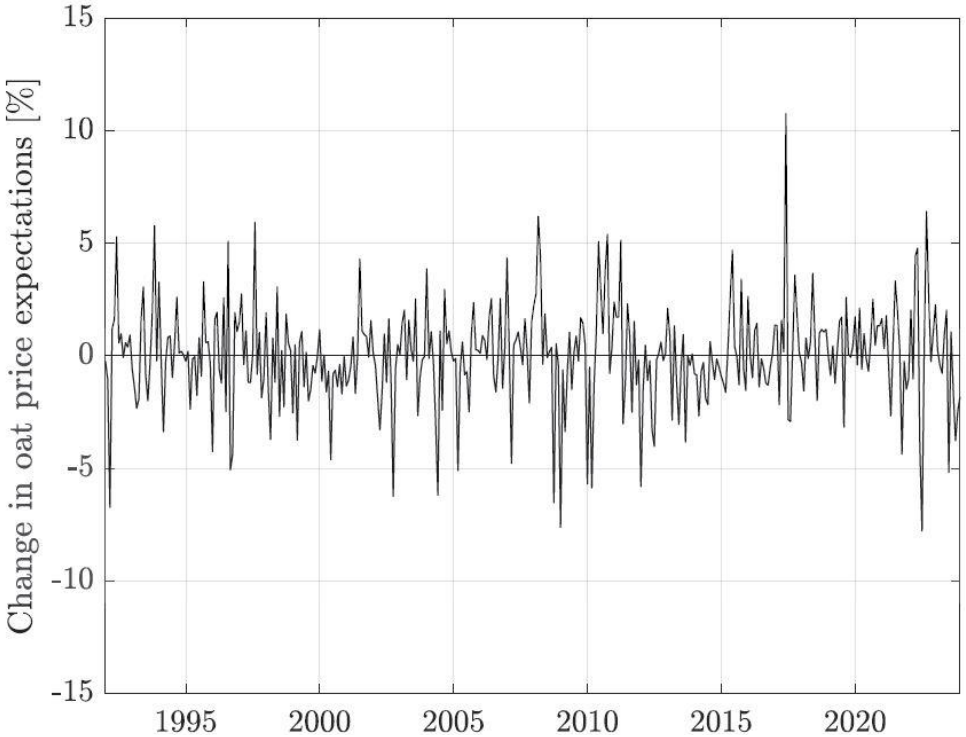


Figure A.3. Historical series of USDA supply surprises for rice

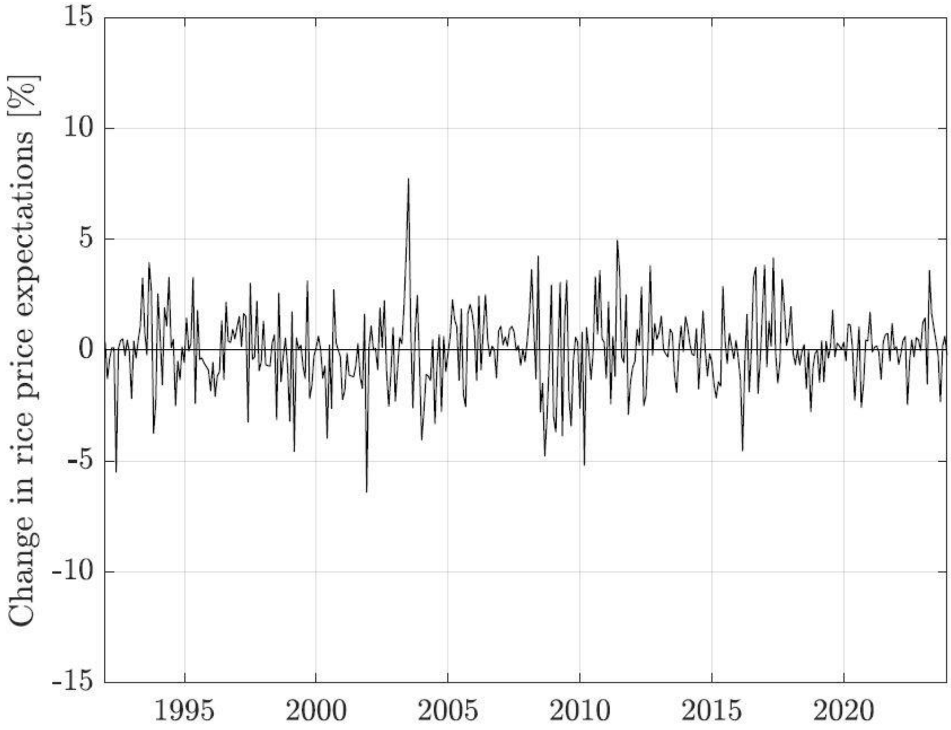


Figure A.4. Historical series of USDA supply surprises for soybeans

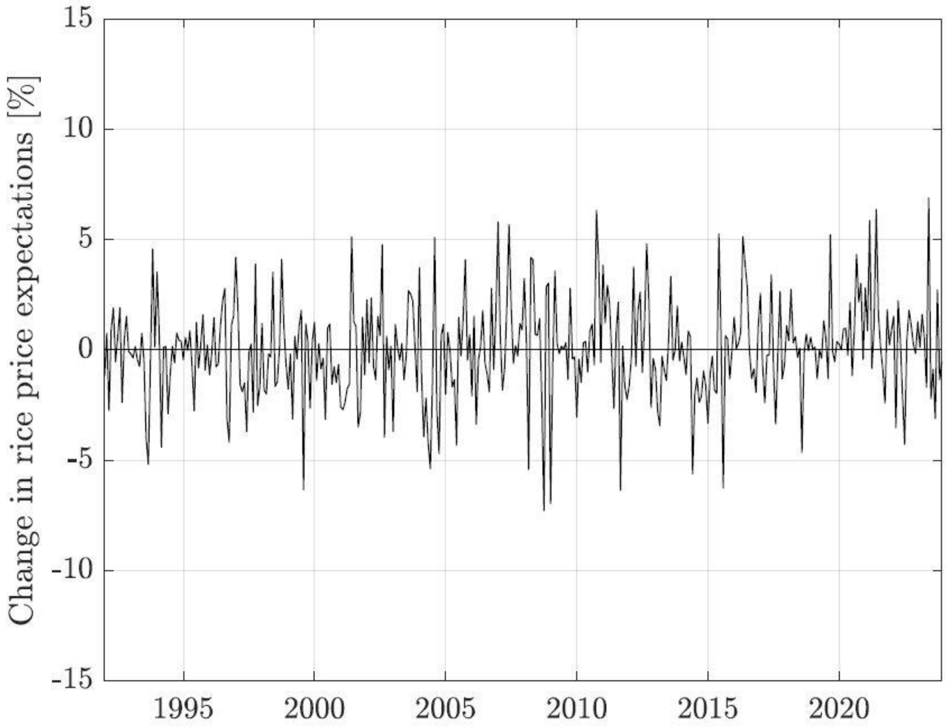


Figure A.5. Historical series of USDA supply surprises for wheat

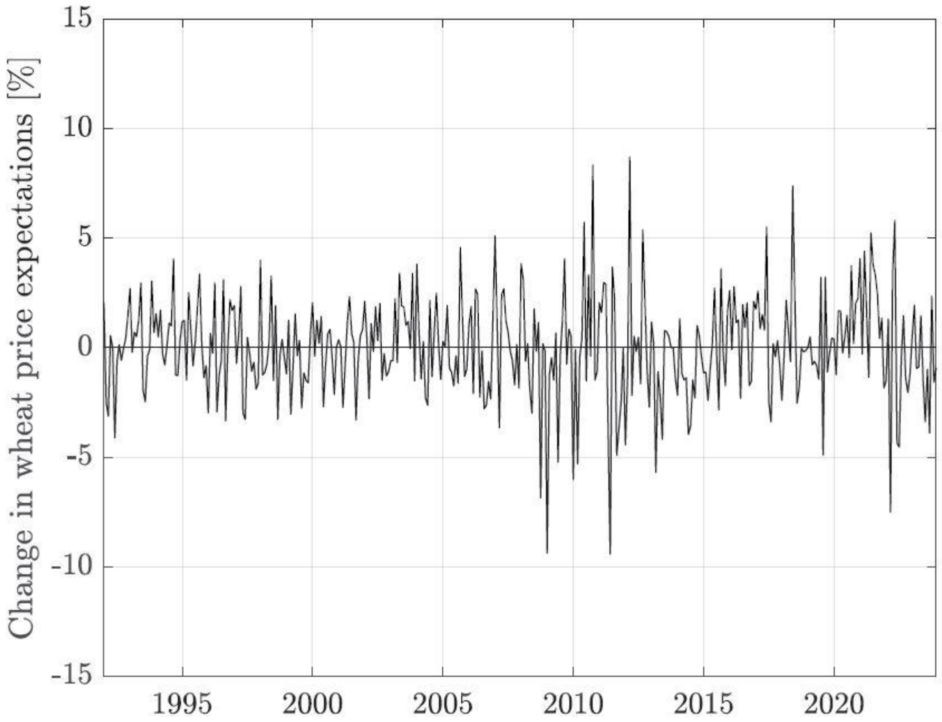


Figure A.6. Volatility-adjusted historical series of USDA supply surprises

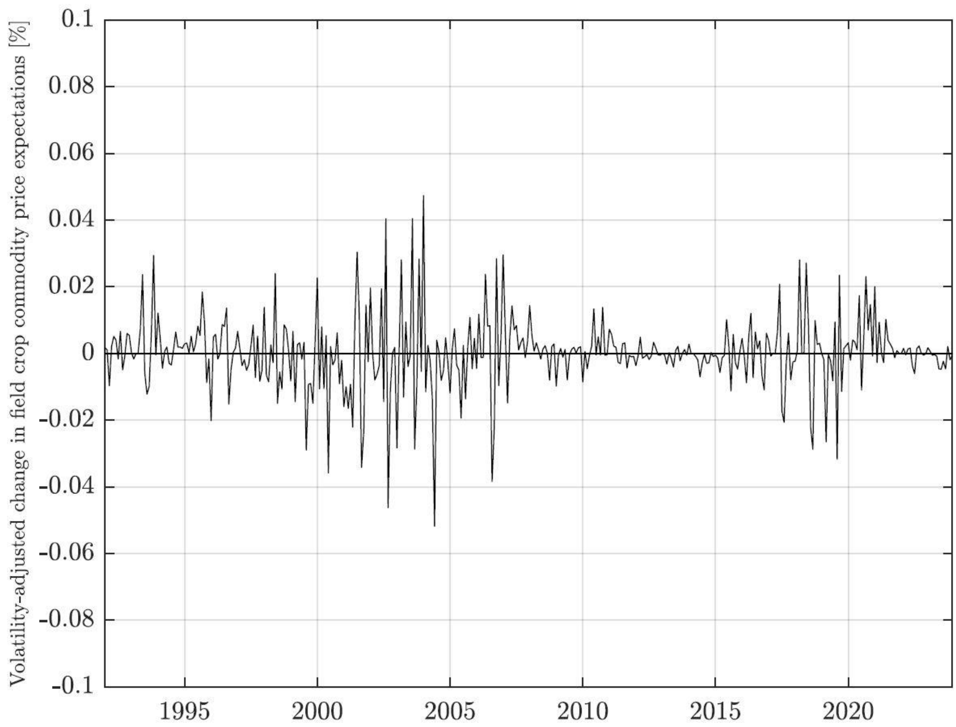
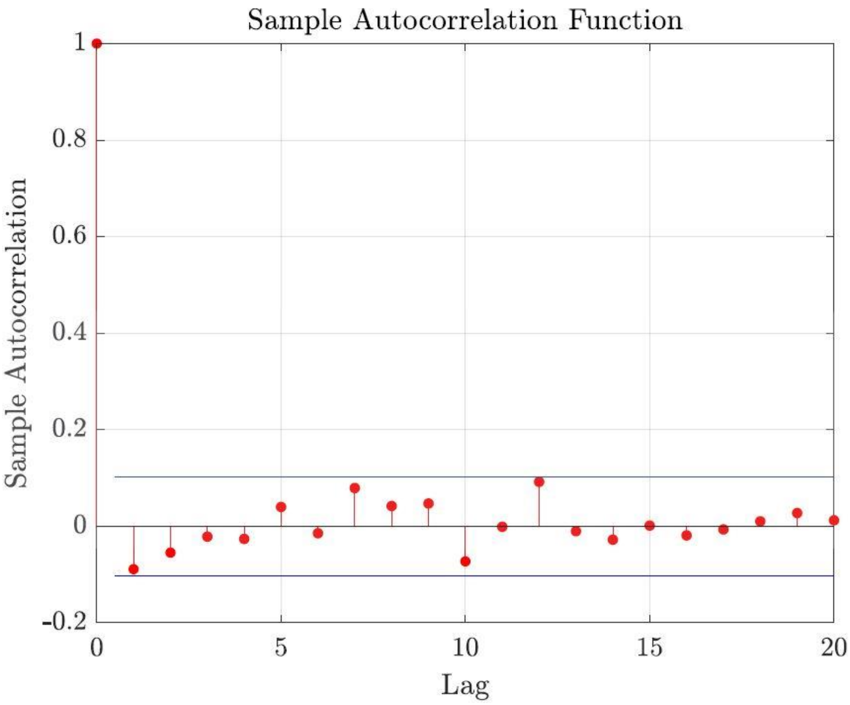


Figure B.1. Autocorrelation test of USDA supply surprise series



Notes: The figure shows the sample autocorrelation function (ACF) of the USDA surprise series. The ACF measures the correlation between the values of a time series at different lags, providing insights into the degree of dependence of the series on its past values. The horizontal lines indicate the 95 percent confidence bands.

Figure B.2. Comparing the USDA announcement to control days for corn

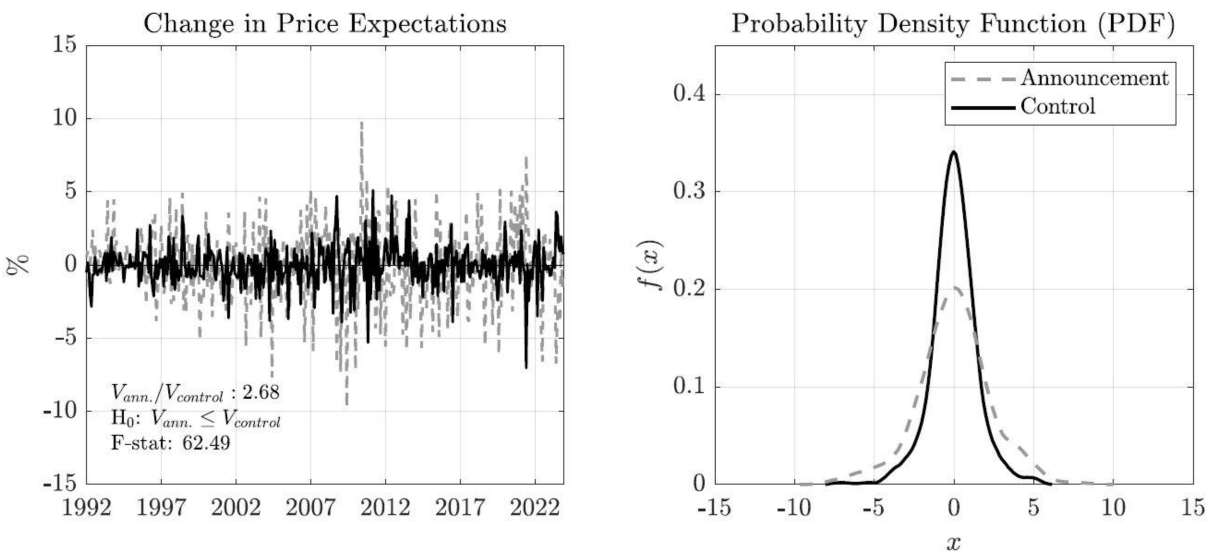


Figure B.3. Comparing the USDA announcement to control days for oats

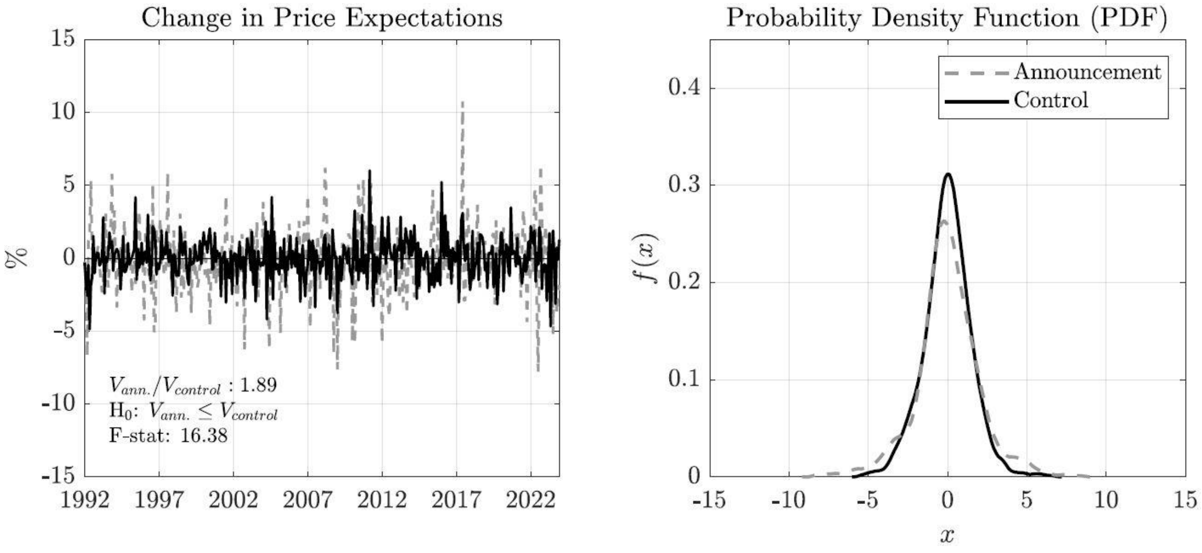


Figure B.4. Comparing the USDA announcement to control days for rice

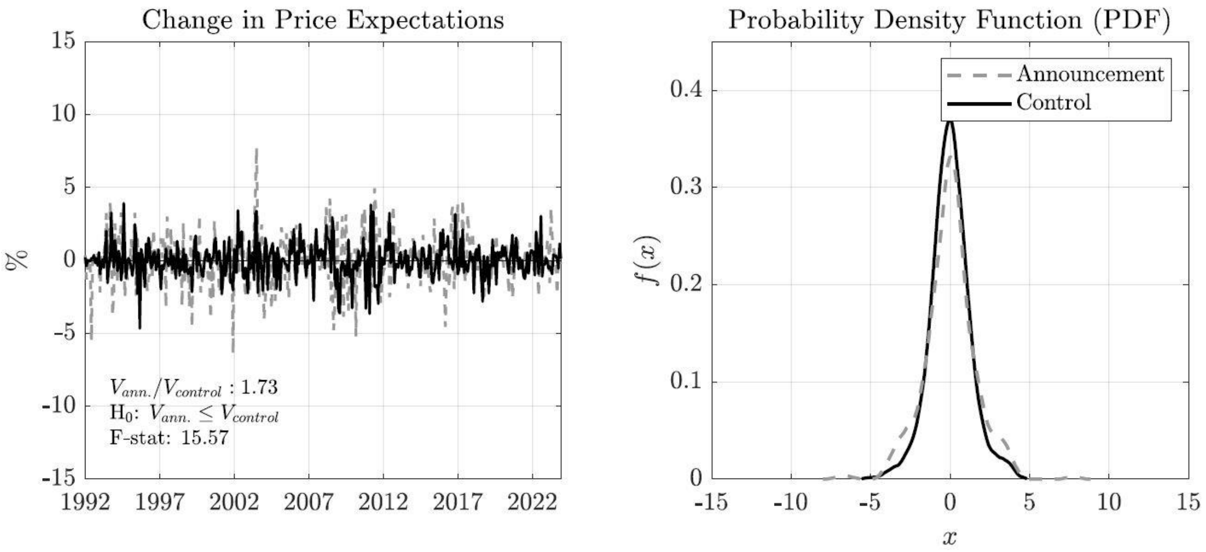


Figure B.5. Comparing the USDA announcement to control days for soybeans

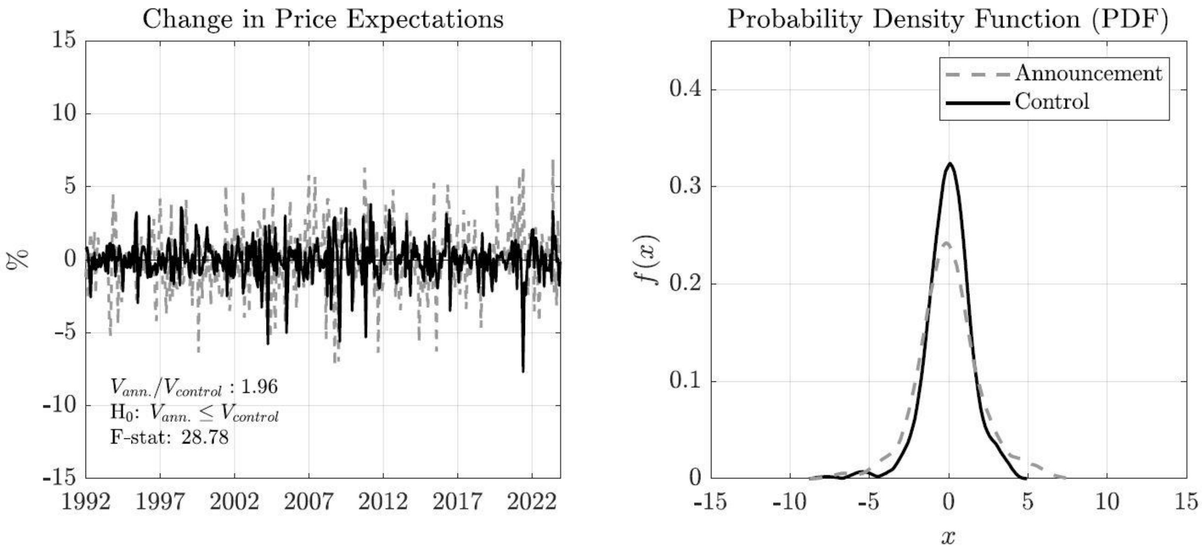


Figure B.6. Comparing the USDA announcement to control days for wheat

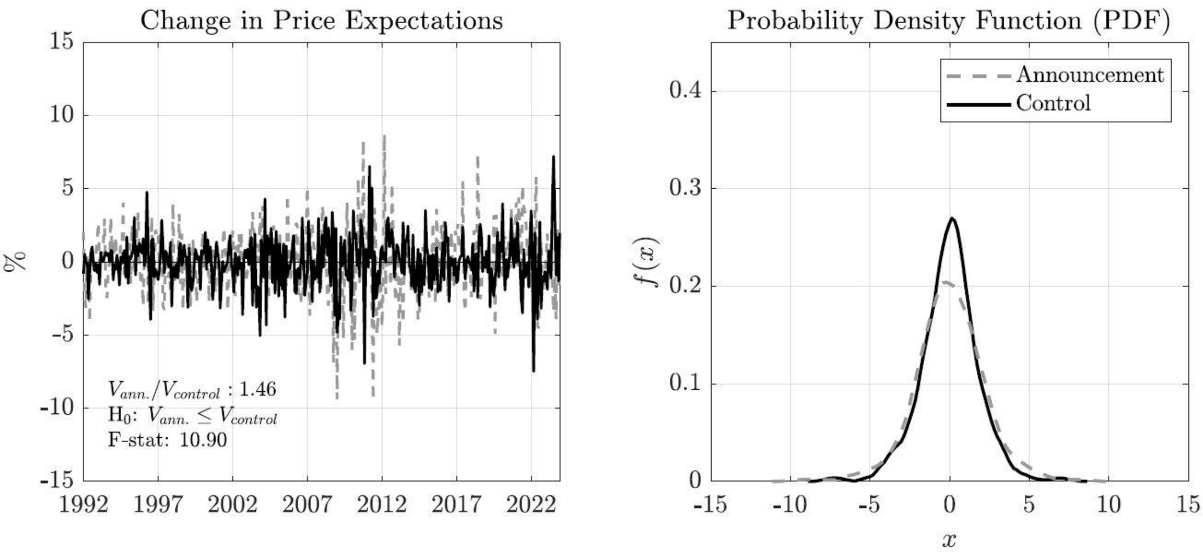


Figure B.7. Comparing the USDA announcement to control days (volatility-adjusted)

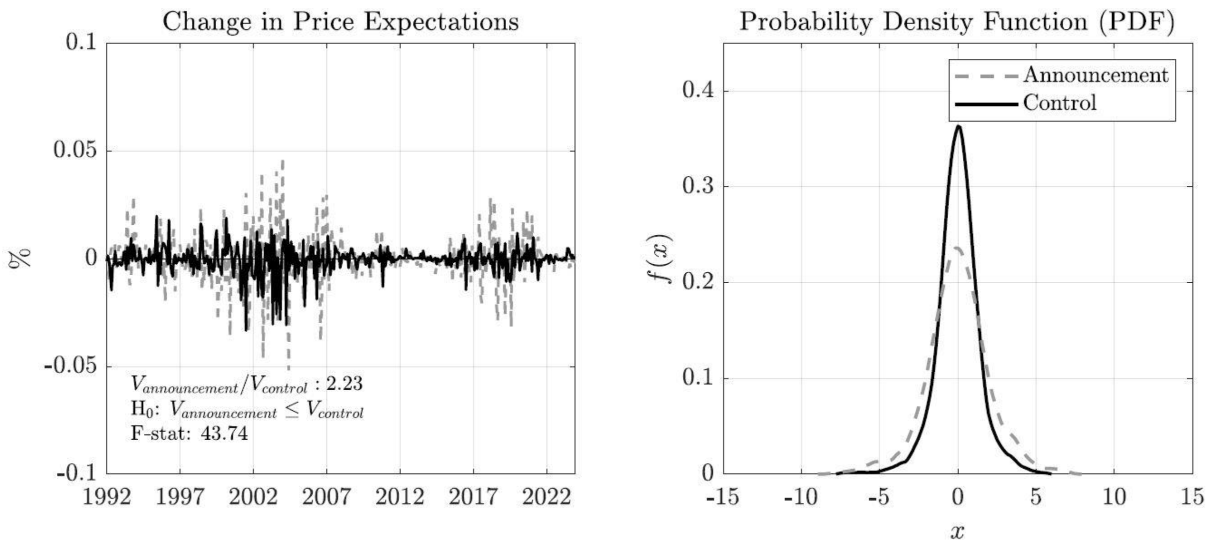
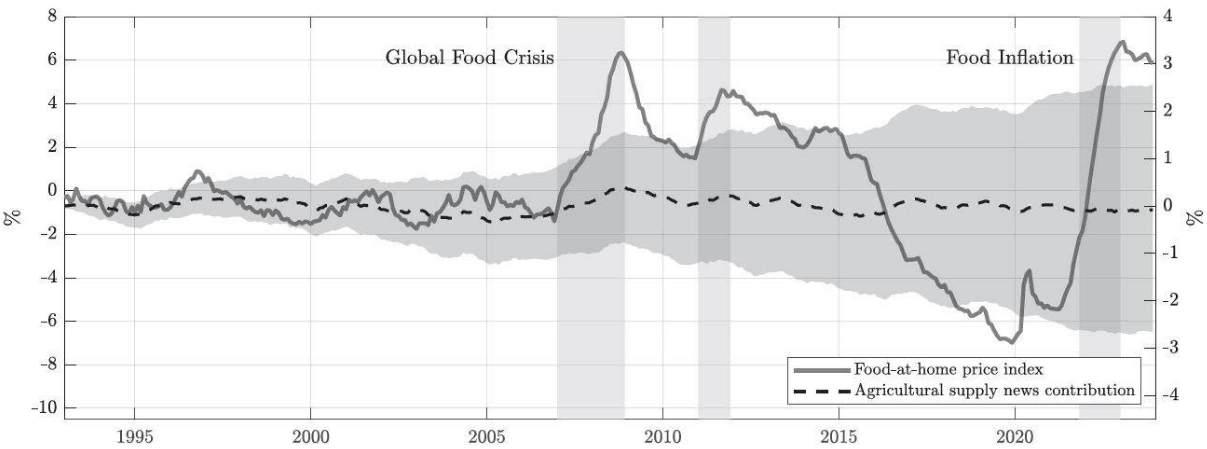
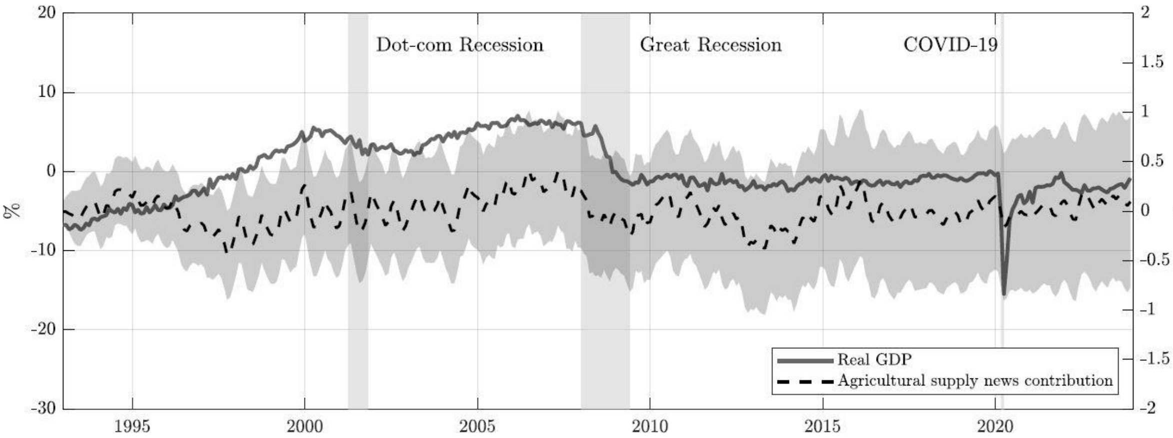


Figure D.1. Historical decomposition: USDA's agricultural supply news contributions to U.S. food-at-home price index



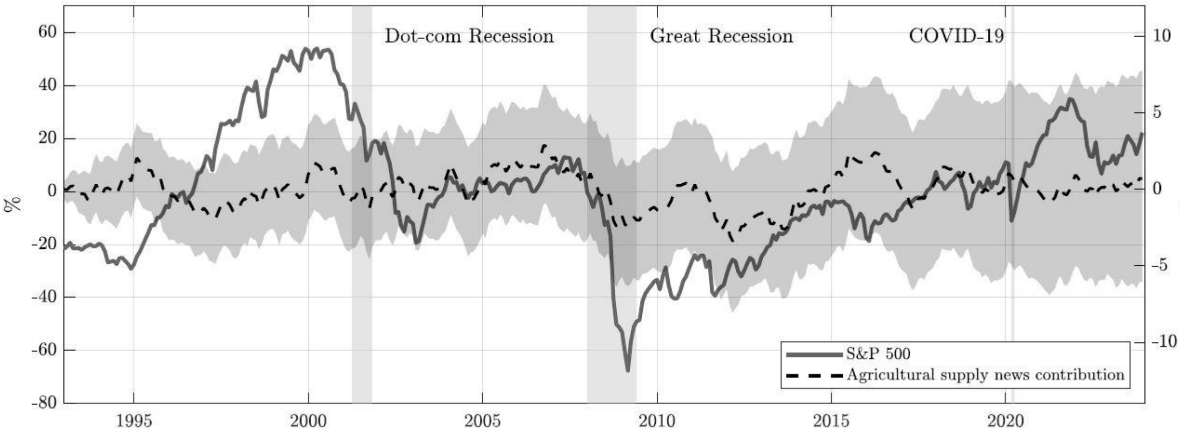
Notes: The figure illustrates the cumulative historical contribution of agricultural supply news to food at home prices from 1993 to 2023 at the monthly frequency. The gray solid line represents the (detrended) U.S. food-at-home price index (PCE for food price index), plotted in deviations from its mean. This food price index, which is indexed to a value of 100 in 2017, has been seasonally adjusted and detrended. The black dashed line is the agricultural supply news contribution. The left axis corresponds to food prices, and the right axis to the supply news contribution. The light gray shading represents 68 percent confidence interval. The grey shades represent the global food crisis, recovery from the Great Recession, and the recent inflation.

Figure D.2. Historical decomposition: USDA's agricultural supply news contributions to U.S. real GDP



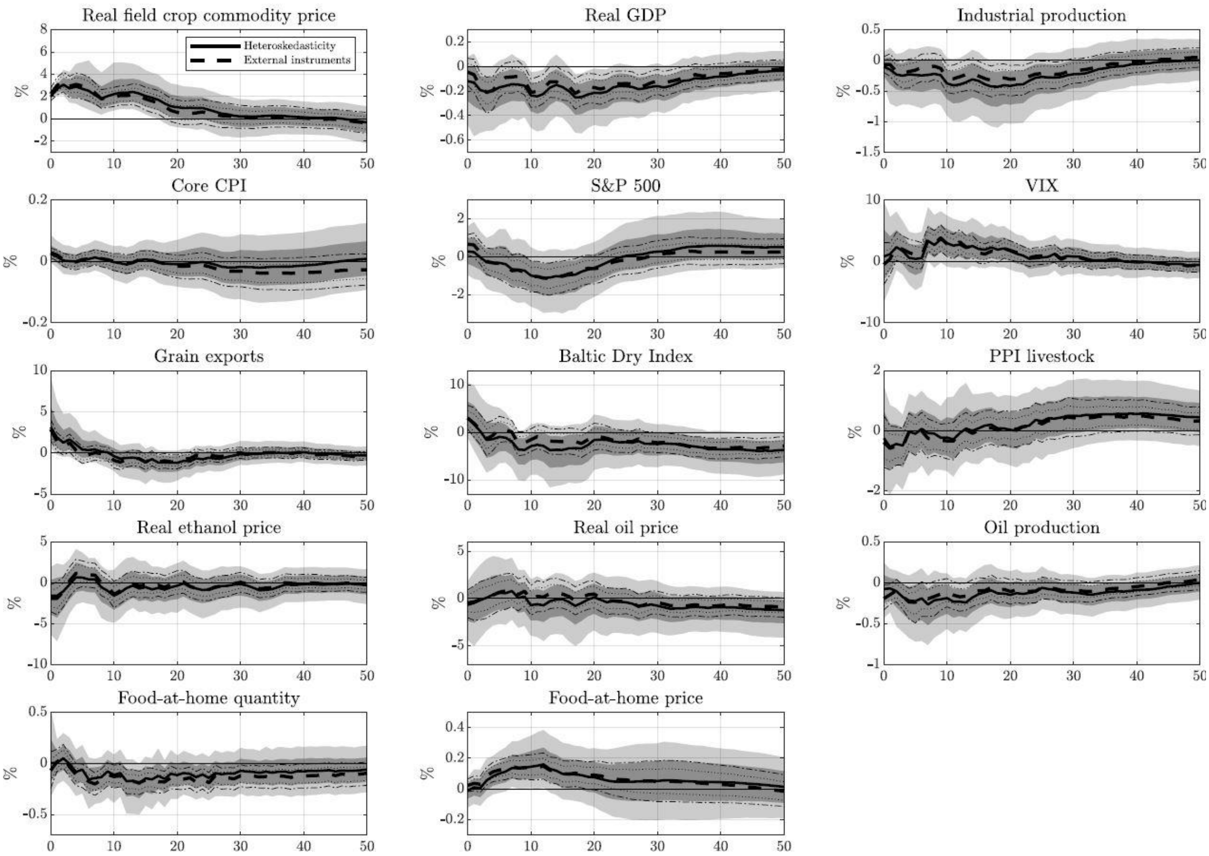
Notes: The figure displays the cumulative historical contribution of agricultural supply news to the U.S. real GDP for the period of 1993-2023 at the monthly frequency. The gray solid line represents the (detrended) U.S. GDP index, plotted in deviations from its mean. This GDP data are sourced from the S&P Global and has been seasonally adjusted and detrended. The black dashed line indicates the agricultural supply news contribution. The left axis corresponds to GDP, and the right axis to the supply news contribution. The light gray shading represents 68 percent confidence interval. Gray shaded areas indicate NBER recessions.

Figure D.3. Historical decomposition: USDA's agricultural supply news contributions to S&P 500 index



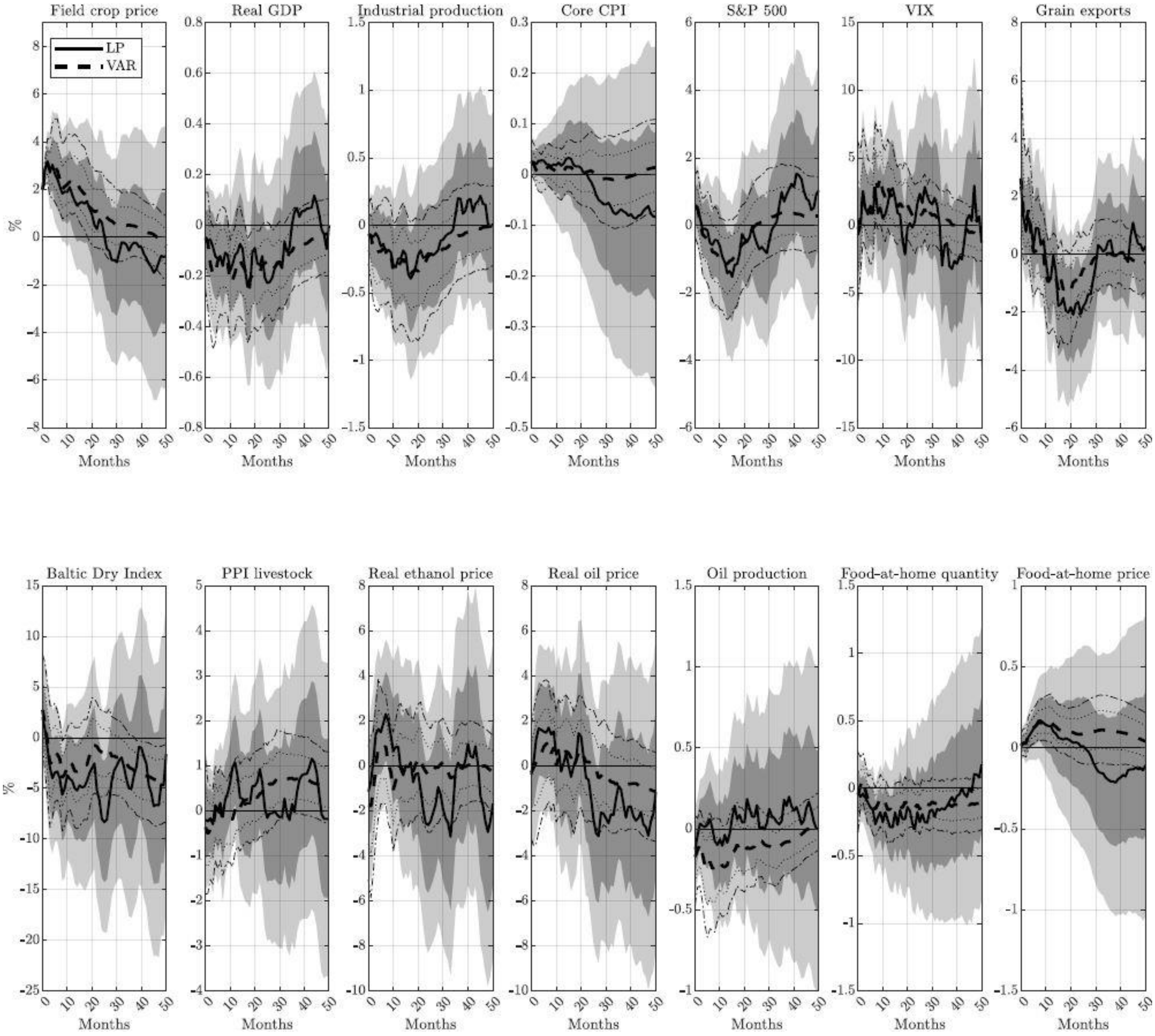
Notes: The figure portrays the cumulative historical contribution of agricultural supply news to the S&P 500 index for the period of 1993-2023 at the monthly frequency. The gray solid line represents the detrended S&P 500 index, which is the average daily close price. This S&P 500 is the average daily closing price provided by Yahoo Finance. These prices have been seasonally adjusted and de-trended. The black dashed line is the agricultural supply news contribution. The left axis corresponds to S&P 500 index, and the right axis to the supply news contribution. The light gray shading represents 68 percent confidence interval. The gray shades represent NBER recessions.

Figure E.1. Impulse response functions to an agricultural supply news shock using a heteroskedasticity-based approach



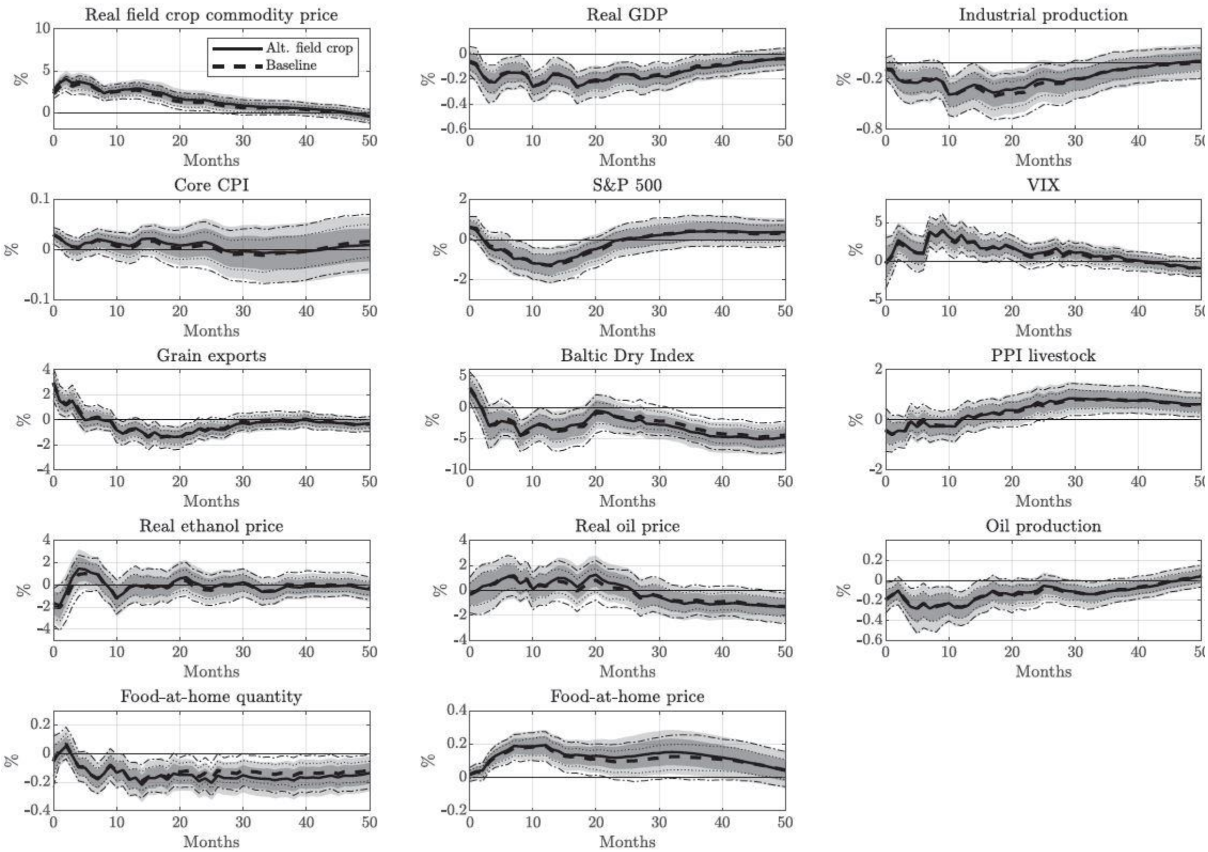
Notes: The impulse responses in the figure are estimated using the heteroskedasticity-based and external instruments approaches. The shock is normalized to a 2 percent increase in the weighted-average U.S. real field crop commodity price. The solid line represents the point estimate of the heteroskedasticity-based approach, while the dashed line represents the point estimate of the external instruments approach. The dark gray and light gray regions indicate the 68 percent and 90 percent confidence bands for the heteroskedasticity-based approach, and the dotted and dash-dotted lines for the external instrument approach. These are generated from 10,000 bootstrap replications.

Figure E.2. Impulse response functions to an agricultural supply news shock using local projections



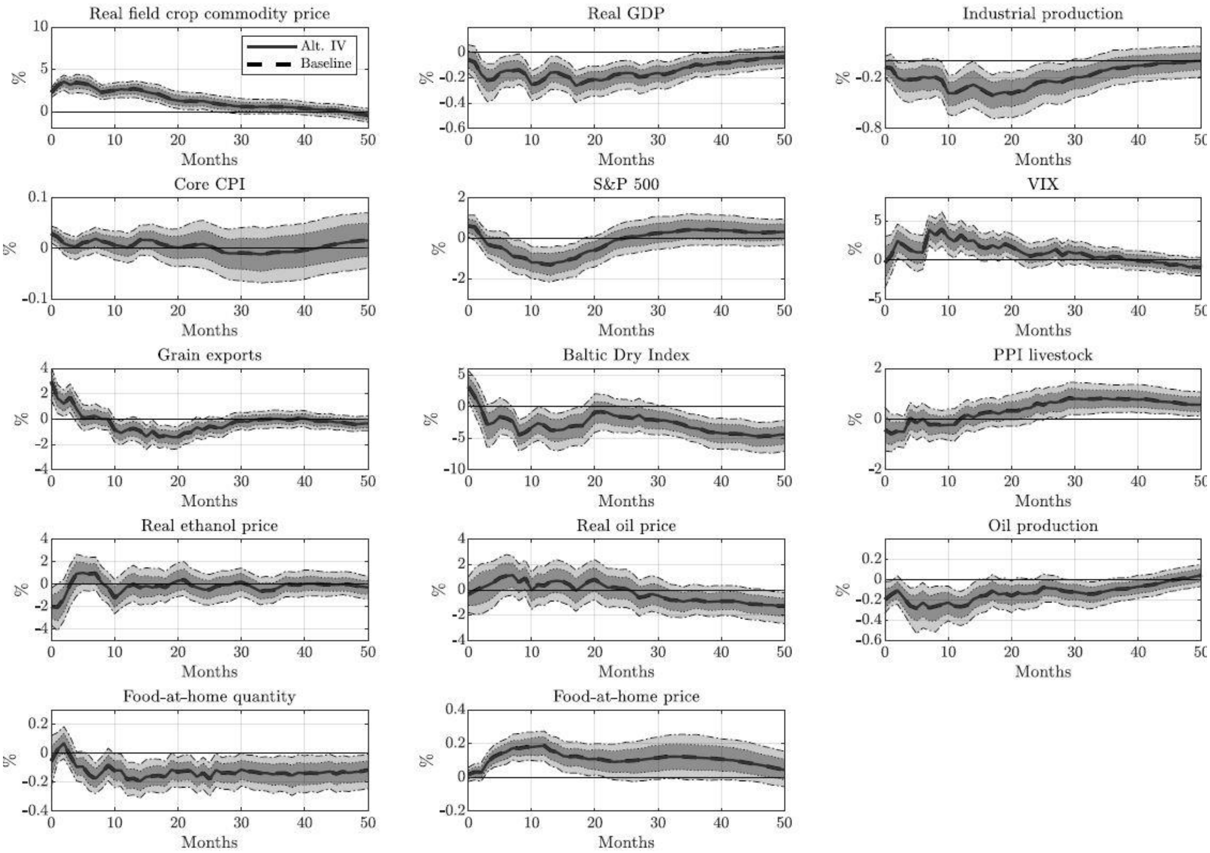
Notes: The figure displays the impulse responses estimated through the local projections and VAR approaches, each instrumenting or agricultural supply news shocks with the USDA news series. The shock is normalized to a 2 percent increase in the weighted-average U.S. real field crop commodity price. The solid line represents the point estimate of the local projections approach, while the dashed line represents the point estimate from the VAR approach. The dark gray region and light gray regions indicate the 68 percent and 90 percent confidence bands for the local projections, and the dotted and dash-dotted lines for the VAR. These are generated from 10,000 bootstrap replications.

Figure E.3. Volatility-adjusted impulse response functions with alternative field crop commodity price variable



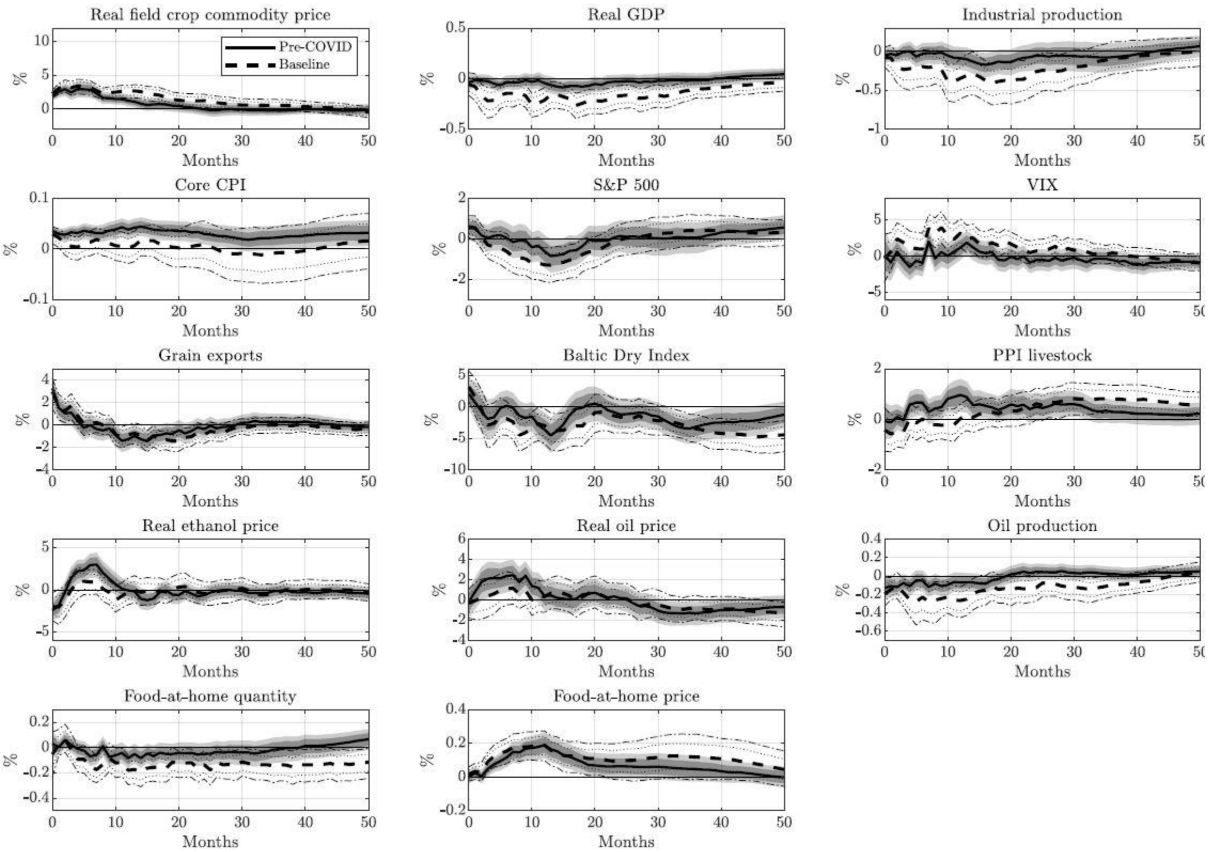
Notes: The shock used in the analysis is normalized to increase the weighted-average U.S. real field crop commodity price by one standard deviation. The solid line represents the point estimate using an alternative field crop commodity variable, including only corn and soybean price, while the dashed line represents the baseline model estimate. The dark and light gray regions indicate the 68 percent and 90 percent confidence bands for the alternative variable model, and the dotted and dash-dotted lines for the baseline model. These are generated from 10,000 bootstrap replications. The first stage F-statistic is 19.47, and robust F-statistic is 20.39.

Figure E.4. Volatility-adjusted impulse response functions with alternative instrumental variable



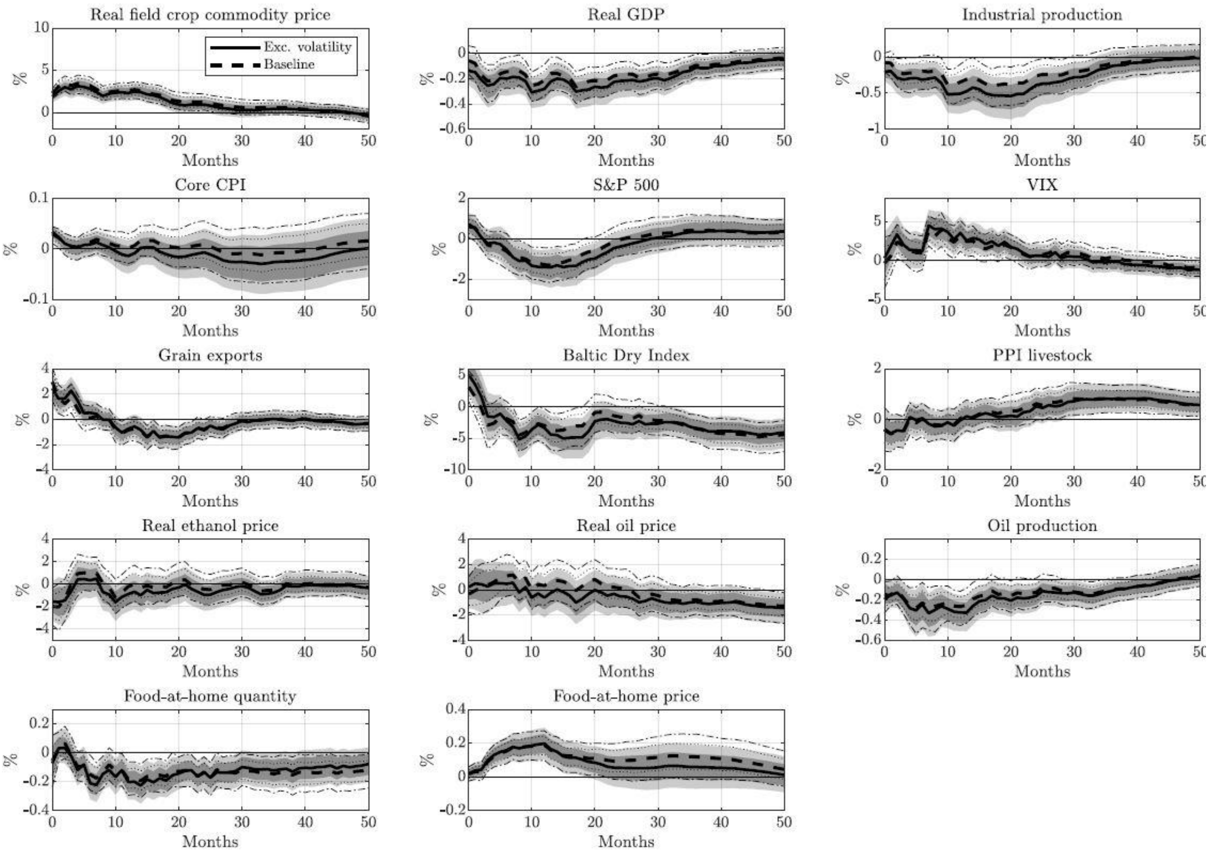
Notes: The shock used in the analysis is normalized to a one standard deviation increase in the weighted-average U.S. real field crop commodity price. The solid line represents the point estimate using an alternative external instrumental variable, specifically the calorie-weighted IV, while the dashed line represents the point estimate of the baseline model. The dark and light gray regions indicate the 68 percent and 90 percent confidence bands for the model with the calorie-weighted IV, and the dotted and dash-dotted ones for the baseline model. These are generated from 10,000 bootstrap replications. The first stage F-statistic is 16.82 and the robust F-statistic is 18.56.

Figure E.5. Volatility-adjusted impulse response functions for the pre-COVID period (1992-2019)



Notes: The shock used in the analysis is normalized to increase the weighted-average U.S. real field crop commodity price by one standard deviation. The solid line represents the point estimate of the model for the pre-COVID period, while the dashed line represents the baseline model estimate (1992-2023). The dark and light gray regions indicate the 68 percent and 90 percent confidence bands for the pre-COVID period model, and the dotted and dash-dotted lines correspond to the baseline model. These are generated from 10,000 bootstrap replications. The first stage F-statistic is 14.18, and the robust F-statistic is 17.39.

Figure E.6. Non-volatility-adjusted impulse response functions to a normalized agricultural supply news shock



Notes: The shock used in the analysis is normalized to increase in the weighted-average U.S. real field crop commodity price by a one standard deviation. The solid line represents the point estimate for the non-volatility adjusted impulse responses, while the solid pink line represents the baseline model estimate (1992-2023). The dark and light gray regions indicate the 68 percent and 90 percent confidence bands for the non-volatility adjusted model, and the dotted and dash-dotted lines correspond to the baseline model. These impulse responses are generated from 10,000 bootstrap replications. The first stage F-statistic is 11.04, and the robust F-statistic is 9.90.

Table A.1. USDA reports schedule

Reports	Frequency	Publication	Overlap
World Agricultural Supply and Demand Estimates (WASDE)	Monthly	Second week of the month	First GS (January)
Grain Stocks (GS)	Quarterly	Second week of January & the end of first-third quarters	First WASDE, PP, & AR
Prospective plantings (PP)	Annual	End of March	Second GS (March)
Acreage (AR)	Annual	End of June	Third GS (June)

Table A.2. USDA announcements, 1992-2023

Period	Publication date	Control date	Notes
1992M01	1/13	1/21	GS & WASDE
1992M02	2/11	2/19	WASDE
1992M03	3/11; 3/31	3/19	3/11 (WASDE); 3/31 (GS & PP)
1992M04	4/10	4/22	WASDE
1992M05	5/11	5/19	WASDE
1992M06	6/10; 6/30	6/18	6/10 (WASDE); 6/30 (AR & GS)
1992M07	7/9	7/17	WASDE
1992M08	8/12	8/20	WASDE
1992M09	9/10; 9/30	9/18	9/10 (WASDE); 9/30 (GS)
1992M10	10/8	10/16	WASDE
1992M11	11/10	11/18	WASDE
1992M12	12/10	12/18	WASDE
1993M01	1/12	1/20	GS & WASDE
1993M02	2/10	2/18	WASDE
1993M03	3/10; 3/31	3/18	3/10 (WASDE); 3/31 (GS & PP)
1993M04	4/12	4/20	WASDE
1993M05	5/11	5/19	WASDE
1993M06	6/10; 6/30	6/18	6/10 (WASDE); 6/30 (AR & GS)
1993M07	7/12	7/20	WASDE
1993M08	8/11	8/19	WASDE
1993M09	9/9; 9/30	9/17	9/9 (WASDE); 9/30 (GS)
1993M10	10/12	10/20	WASDE
1993M11	11/9	11/17	WASDE
1993M12	12/9	12/17	WASDE
1994M01	1/12	1/20	GS & WASDE
1994M02	2/10	2/18	WASDE
1994M03	3/10; 3/31	3/18	3/10 (WASDE); 3/31 (GS & PP)
1994M04	4/12	4/20	WASDE
1994M05	5/10	5/17	WASDE; The release time has been updated to 8:30 a.m. EST.
1994M06	6/9; 6/30	6/16	6/9 (WASDE); 6/30 (GS & AR)
1994M07	7/12	7/19	WASDE
1994M08	8/11	8/18	WASDE
1994M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
1994M10	10/12	10/19	WASDE
1994M11	11/9	11/16	WASDE
1994M12	12/9	12/16	WASDE
1995M01	1/12	1/19	GS & WASDE
1995M02	2/10	2/17	WASDE
1995M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
1995M04	4/11	4/18	WASDE
1995M05	5/11	5/18	WASDE
1995M06	6/12; 6/30	6/19	6/12 (WASDE); 6/30 (AR & GS)
1995M07	7/12	7/19	WASDE
1995M08	8/11	8/18	WASDE
1995M09	9/12; 9/29	9/19	9/12 (WASDE); 9/29 (GS)
1995M10	10/11	10/18	WASDE
1995M11	11/9	11/16	WASDE
1995M12	12/12	12/19	WASDE
1996M01	1/16	1/23	GS & WASDE
1996M02	2/9	2/16	WASDE
1996M03	3/12; 3/29	3/19	3/12 (WASDE); 3/29 (GS & PP)
1996M04	4/11	4/18	WASDE
1996M05	5/10	5/17	WASDE
1996M06	6/12; 6/28	6/19	6/12 (WASDE); 6/28 (AR & GS)
1996M07	7/12	7/19	WASDE
1996M08	8/12	8/19	WASDE
1996M09	9/11; 9/30	9/18	9/11 (WASDE); 9/30 (GS)
1996M10	10/11	10/18	WASDE
1996M11	11/12	11/19	WASDE
1996M12	12/12	12/19	WASDE
1997M01	1/10	1/17	GS & WASDE
1997M02	2/12	2/19	WASDE
1997M03	3/11 & 3/31	3/18	3/11 (WASDE); 3/31 (GS & PP)
1997M04	4/11	4/18	WASDE
1997M05	5/12	5/19	WASDE
1997M06	6/12; 6/30	6/19	6/12 (WASDE); 6/30 (AR & GS)
1997M07	7/11	7/18	WASDE
1997M08	8/12	8/19	WASDE
1997M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
1997M10	10/10	10/17	WASDE

Period	Publication date	Control date	Notes
1997M11	11/10	11/17	WASDE
1997M12	12/11	12/18	WASDE
1998M01	1/13	1/20	GS & WASDE
1998M02	2/11	2/18	WASDE
1998M03	3/12; 3/31	3/19	3/12 (WASDE); 3/31 (GS & PP)
1998M04	4/9	4/16	WASDE
1998M05	5/12	5/19	WASDE
1998M06	6/12; 6/30	6/19	6/10 (WASDE); 6/30 (AR & GS)
1998M07	7/10	7/17	WASDE
1998M08	8/12	8/19	WASDE
1998M09	9/11; 9/30	9/18	9/11 (WASDE); 9/30 (GS)
1998M10	10/9	10/16	WASDE
1998M11	11/10	11/17	WASDE
1998M12	12/11	12/18	WASDE
1999M01	1/12	1/19	GS & WASDE
1999M02	2/10	2/17	WASDE
1999M03	3/11; 3/31	3/18	3/11 (WASDE); 3/31 (GS & PP)
1999M04	4/9	4/16	WASDE
1999M05	5/12	5/19	WASDE
1999M06	6/11; 6/30	6/18	6/11 (WASDE); 6/30 (AR & GS)
1999M07	7/12	7/19	WASDE
1999M08	8/12	8/19	WASDE
1999M09	9/10; 9/30	9/17	9/10 (WASDE); 9/30 (GS)
1999M10	10/8	10/15	WASDE
1999M11	11/10	11/17	WASDE
1999M12	12/10	12/17	WASDE
2000M01	1/12	1/19	GS & WASDE
2000M02	2/11	2/18	WASDE
2000M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
2000M04	4/11	4/18	WASDE
2000M05	5/12	5/19	WASDE
2000M06	6/9; 6/30	6/16	6/9 (WASDE); 6/30 (AR & GS)
2000M07	7/12	7/19	WASDE
2000M08	8/11	8/18	WASDE
2000M09	9/12; 9/29	9/19	9/12 (WASDE); 9/29 (GS)
2000M10	10/12	10/19	WASDE
2000M11	11/9	11/16	WASDE
2000M12	12/12	12/19	WASDE
2001M01	1/11	1/18	GS & WASDE
2001M02	2/8	2/15	WASDE
2001M03	3/8; 3/30	3/15	3/8 (WASDE); 3/30 (GS & PP)
2001M04	4/10	4/17	WASDE
2001M05	5/10	5/17	WASDE
2001M06	6/12; 6/28	6/19	6/12 (WASDE); 6/28 (AR & GS)
2001M07	7/11	7/18	WASDE
2001M08	8/12	8/19	WASDE
2001M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2001M10	10/11	10/18	WASDE
2001M11	11/12	11/19	WASDE
2001M12	12/10	12/17	WASDE
2002M01	1/11	1/18	GS & WASDE
2002M02	2/8	2/15	WASDE
2002M03	3/8; 3/28	3/15	3/8 (WASDE); 3/28 (GS & PP)
2002M04	4/10	4/17	WASDE
2002M05	5/10	5/17	WASDE
2002M06	6/12; 6/28	6/19	6/10 (WASDE); 6/28 (AR & GS)
2002M07	7/11	7/18	WASDE
2002M08	8/12	8/19	WASDE
2002M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2002M10	10/11	10/18	WASDE
2002M11	11/12	11/19	WASDE
2002M12	12/10	12/17	WASDE
2003M01	1/10	1/17	GS & WASDE
2003M02	2/11	2/18	WASDE
2003M03	3/11; 3/31	3/18	3/11 (WASDE); 3/31 (GS & PP)
2003M04	4/10	4/17	WASDE
2003M05	5/12	5/19	WASDE
2003M06	6/11; 6/30	6/18	6/11 (WASDE); 6/30 (AR & GS)
2003M07	7/11	7/18	WASDE
2003M08	8/12	8/19	WASDE
2003M09	9/11; 9/30	9/18	9/11 (WASDE); 9/30 (GS)

Period	Publication date	Control date	Notes
2003M10	10/10	10/17	WASDE
2003M11	11/12	11/19	WASDE
2003M12	12/11	12/18	WASDE
2004M01	1/12	1/20	GS & WASDE
2004M02	2/10	2/17	WASDE
2004M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
2004M04	4/8	4/15	WASDE
2004M05	5/12	5/19	WASDE
2004M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2004M07	7/12	7/19	WASDE
2004M08	8/12	8/19	WASDE
2004M09	9/10; 9/30	9/17	9/10 (WASDE); 9/30 (GS)
2004M10	10/12	10/19	WASDE
2004M11	11/12	11/19	WASDE
2004M12	12/10	12/17	WASDE
2005M01	1/12	1/19	GS & WASDE
2005M02	2/9	2/16	WASDE
2005M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
2005M04	4/8	4/15	WASDE
2005M05	5/12	5/19	WASDE
2005M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2005M07	7/12	7/19	WASDE
2005M08	8/12	8/19	WASDE
2005M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2005M10	10/12	10/19	WASDE
2005M11	11/10	11/17	WASDE
2005M12	12/9	12/16	WASDE
2006M01	1/12	1/19	GS & WASDE
2006M02	2/9	2/16	WASDE
2006M03	3/13; 3/31	3/20	3/13 (WASDE); 3/31 (GS; PP)
2006M04	4/10	4/17	WASDE
2006M05	5/12	5/19	WASDE
2006M06	6/9; 6/30	6/16	6/9 (WASDE); 6/30 (AR; GS)
2006M07	7/12	7/19	WASDE
2006M08	8/11	8/18	WASDE
2006M09	9/12; 9/29	9/19	9/12 (WASDE); 9/29 (GS)
2006M10	10/12	10/19	WASDE
2006M11	11/9	11/16	WASDE
2006M12	12/11	12/18	WASDE
2007M01	1/12	1/19	GS & WASDE
2007M02	2/9	2/16	WASDE
2007M03	3/9; 3/30	3/16	3/9 (WASDE); 3/30 (GS & PP)
2007M04	4/10	4/17	WASDE
2007M05	5/11	5/18	WASDE
2007M06	6/11; 6/29	6/18	6/11 (WASDE); 6/29 (AR & GS)
2007M07	7/12	7/19	WASDE
2007M08	8/10	8/17	WASDE
2007M09	9/12; 9/28	9/19	9/12 (WASDE); 9/28 (GS)
2007M10	10/12	10/19	WASDE
2007M11	11/9	11/16	WASDE
2007M12	12/11	12/18	WASDE
2008M01	1/11	1/18	GS & WASDE
2008M02	2/8	2/15	WASDE
2008M03	3/11; 3/31	3/18	3/11 (WASDE); 3/31 (GS & PP)
2008M04	4/9	4/16	WASDE
2008M05	5/9	5/16	WASDE
2008M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2008M07	7/11	7/18	WASDE
2008M08	8/12	8/19	WASDE
2008M09	9/12; 9/30	9/19	9/10 (WASDE); 9/30 (GS)
2008M10	10/10	10/17	WASDE
2008M11	11/10	11/17	WASDE
2008M12	12/11	12/18	WASDE
2009M01	1/12	1/20	GS & WASDE
2009M02	2/10	2/17	WASDE
2009M03	3/11; 3/31	3/18	3/11 (WASDE); 3/31 (GS & PP)
2009M04	4/9	4/16	WASDE
2009M05	5/12	5/19	WASDE
2009M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2009M07	7/10	7/17	WASDE
2009M08	8/12	8/19	WASDE

Period	Publication date	Control date	Notes
2009M09	9/11; 9/30	9/18	9/11 (WASDE); 9/30 (GS)
2009M10	10/9	10/16	WASDE
2009M11	11/10	11/17	WASDE
2009M12	12/10	12/17	WASDE
2010M01	1/12	1/19	GS & WASDE
2010M02	2/9	2/16	WASDE
2010M03	3/10; 3/31	3/17	3/10(WASDE); 3/31 (GS & PP)
2010M04	4/9	4/16	WASDE
2010M05	5/11	5/18	WASDE
2010M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2010M07	7/9	7/16	WASDE
2010M08	8/12	8/19	WASDE
2010M09	9/10; 9/30	9/17	9/10 (WASDE); 9/30 (GS)
2010M10	10/8	10/15	WASDE
2010M11	11/9	11/16	WASDE
2010M12	12/10	12/17	WASDE
2011M01	1/12	1/19	GS & WASDE
2011M02	2/9	2/16	WASDE
2011M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
2011M04	4/8	4/15	WASDE
2011M05	5/11	5/18	WASDE
2011M06	6/9; 6/30	6/16	6/9 (WASDE); 6/30 (AR & GS)
2011M07	7/12	7/19	WASDE
2011M08	8/11	8/18	WASDE
2011M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2011M10	10/12	10/18	WASDE
2011M11	11/9	11/16	WASDE
2011M12	12/9	12/16	WASDE
2012M01	1/12	1/19	GS & WASDE
2012M02	2/9	2/16	WASDE
2012M03	3/9; 3/30	3/16	3/9 (WASDE); 3/30 (GS & PP)
2012M04	4/10	4/17	WASDE
2012M05	5/10	5/17	WASDE
2012M06	6/12; 6/29	6/19	6/12 (WASDE); 6/29 (AR & GS)
2012M07	7/11	7/18	WASDE
2012M08	8/10	8/17	WASDE
2012M09	9/12; 9/28	9/19	9/12 (WASDE); 9/28 (GS)
2012M10	10/11	10/18	WASDE
2012M11	11/9	11/16	WASDE
2012M12	12/11	12/18	WASDE
2013M01	1/11	1/18	GS & WASDE
2013M02	2/8	2/15	WASDE
2013M03	3/8; 3/28	3/15	3/8 (WASDE); 3/28 (GS & PP)
2013M04	4/10	4/17	WASDE
2013M05	5/10	5/17	WASDE
2013M06	6/12; 6/28	6/19	6/12 (WASDE); 6/28 (AR & GS)
2013M07	7/11	7/18	WASDE
2013M08	8/12	8/19	WASDE
2013M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2013M10		10/18	USDA announcement canceled due to the federal government shutdown.
2013M11	11/8	11/15	WASDE
2013M12	12/10	12/17	WASDE
2014M01	1/10	1/17	GS & WASDE
2014M02	2/10	2/18	WASDE
2014M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
2014M04	4/9	4/16	WASDE
2014M05	5/9	5/16	WASDE
2014M06	6/11; 6/30	6/18	6/11 (WASDE); 6/30 (GS)
2014M07	7/11	7/18	WASDE
2014M08	8/12	8/19	WASDE
2014M09	9/11; 9/30	9/18	9/11 (WASDE); 9/30 (GS)
2014M10	10/10	10/17	WASDE
2014M11	11/10	11/17	WASDE
2014M12	12/10	12/17	WASDE
2015M01	1/12	1/20	GS & WASDE
2015M02	2/10	2/17	WASDE
2015M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
2015M04	4/9	4/16	WASDE
2015M05	5/12	5/19	WASDE
2015M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2015M07	7/10	7/17	WASDE

Period	Publication date	Control date	Notes
2015M08	8/12	8/19	WASDE
2015M09	9/11; 9/30	9/18	9/11 (WASDE); 9/30 (GS)
2015M10	10/9	10/16	WASDE
2015M11	11/10	11/17	WASDE
2015M12	12/9	12/16	WASDE
2016M01	1/12	1/19	GS & WASDE
2016M02	2/9	2/16	WASDE
2016M03	3/9; 3/31	3/16	3/9 (WASDE); 3/31 (GS & PP)
2016M04	4/12	4/19	WASDE
2016M05	5/10	5/17	WASDE
2016M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2016M07	7/12	7/19	WASDE
2016M08	8/12	8/19	WASDE
2016M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2016M10	10/12	10/19	WASDE
2016M11	11/9	11/16	WASDE
2016M12	12/9	12/16	WASDE
2017M01	1/12	1/19	GS & WASDE
2017M02	2/9	2/16	WASDE
2017M03	3/9; 3/31	3/16	3/9 (WASDE); 3/31 (GS & PP)
2017M04	4/11	4/18	WASDE
2017M05	5/10	5/17	WASDE
2017M06	6/9; 6/30	6/16	6/9 (WASDE); 6/30 (AR & GS)
2017M07	7/12	7/19	WASDE
2017M08	8/10	8/17	WASDE
2017M09	9/12; 9/29	9/19	9/12 (WASDE); 9/29 (GS)
2017M10	10/12	10/19	WASDE
2017M11	11/9	11/16	WASDE
2017M12	12/12	12/19	WASDE
2018M01	1/12	1/19	GS & WASDE
2018M02	2/8	2/15	WASDE
2018M03	3/8; 3/29	3/15	3/8 (WASDE); 3/29 (GS & PP)
2018M04	4/10	4/17	WASDE
2018M05	5/10	5/17	WASDE
2018M06	6/12; 6/29	6/19	6/12 (WASDE); 6/29 (AR & GS)
2018M07	7/12	7/19	WASDE
2018M08	8/10	8/17	WASDE
2018M09	9/12; 9/28	9/19	9/12 (WASDE); 9/28 (GS)
2018M10	10/11	10/18	WASDE
2018M11	11/8	11/15	WASDE
2018M12	12/11	12/18	WASDE
2019M01		1/22	USDA announcement canceled due to the federal government shutdown.
2019M02	2/8	2/15	WASDE
2019M03	3/8; 3/29	3/15	3/8 (WASDE); 3/29 (GS & PP)
2019M04	4/9	4/16	WASDE
2019M05	5/10	5/17	WASDE
2019M06	6/11; 6/28	6/18	6/11 (WASDE); 6/28 (AR & PP)
2019M07	7/11	7/18	WASDE
2019M08	8/12	8/19	WASDE
2019M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2019M10	10/10	10/17	WASDE
2019M11	11/8	11/15	WASDE
2019M12	12/10	12/17	WASDE
2020M01	1/10	1/17	GS & WASDE
2020M02	2/11	2/18	WASDE
2020M03	3/10; 3/31	3/17	3/10 (WASDE); 3/31 (GS & PP)
2020M04	4/9	4/16	WASDE
2020M05	5/12	5/19	WASDE
2020M06	6/11; 6/30	6/18	6/11 (WASDE); 6/30 (AR & GS)
2020M07	7/10	7/17	WASDE
2020M08	8/12	8/19	WASDE
2020M09	9/11; 9/30	9/18	9/11 (WASDE); 9/30 (GS)
2020M10	10/9	10/16	WASDE
2020M11	11/10	11/17	WASDE
2020M12	12/10	12/17	WASDE
2021M01	1/12	1/19	GS & WASDE
2021M02	2/9	2/16	WASDE
2021M03	3/9; 3/31	3/16	3/9 (WASDE); 3/31 (GS & PP)
2021M04	4/9	4/16	WASDE
2021M05	5/12	5/19	WASDE
2021M06	6/10; 6/31	6/17	6/10 (WASDE); 6/31 (AR & GS)

Period	Publication date	Control date	Notes
2021M07	7/12	7/19	WASDE
2021M08	8/12	8/19	WASDE
2021M09	9/10; 9/30	9/17	9/10 (WASDE); 9/30 (GS)
2021M10	10/12	10/19	WASDE
2021M11	11/9	11/16	WASDE
2021M12	12/9	12/16	WASDE
2022M01	1/12	1/19	GS & WASDE
2022M02	2/9	2/16	WASDE
2022M03	3/9; 3/31	3/16	3/9 (WASDE); 3/31 (GS & PP)
2022M04	4/8	4/18	WASDE
2022M05	5/12	5/19	WASDE
2022M06	6/10; 6/30	6/17	6/10 (WASDE); 6/30 (AR & GS)
2022M07	7/12	7/19	WASDE
2022M08	8/12	8/19	WASDE
2022M09	9/12; 9/30	9/19	9/12 (WASDE); 9/30 (GS)
2022M10	10/12	10/19	WASDE
2022M11	11/9	11/16	WASDE
2022M12	12/9	12/16	WASDE
2023M01	1/12	1/19	GS & WASDE
2023M02	2/8	2/15	WASDE
2023M03	3/8; 3/31	3/15	3/8 (WASDE); 3/31 (GS; PP)
2023M04	4/11	4/18	WASDE
2023M05	5/12	5/19	WASDE
2023M06	6/9; 6/30	6/16	6/9 (WASDE); 6/30 (AR; GS)
2023M07	7/12	7/19	WASDE
2023M08	8/11	8/18	WASDE
2023M09	9/12; 9/29	9/19	9/12 (WASDE); 9/29 (GS)
2023M10	10/12	10/19	WASDE
2023M11	11/9	11/16	WASDE
2023M12	12/8	12/15	WASDE

Table B.1. Granger causality test results

Variable	p-value
Proxy	0.1393
Real field crop commodity price	0.6531
Real GDP	0.3483
Industrial production	0.6076
Core CPI	0.6904
S&P 500 index	0.1964
VIX volatility index	0.8164
Grain exports	0.3724
Baltic Dry Index	0.9171
PPI livestock	0.4579
Real ethanol price	0.3434
Real oil price	0.4384
Oil production	0.3304
Food-at-home quantity	0.1430
Food-at-home price	0.3774
Joint hypothesis	0.8770

Notes: The table reports the results of the Granger causality tests conducted on the proxy and baseline variables in our model, along with their corresponding p-values. The analysis employs a lag order of 12 and only includes a constant term.

Table B.2. Correlation with different shocks

Variable	Correlation	P-value	Observations	Sample period
Oil supply news shocks	-0.02	0.65	384	1992M01 - 2023M12
Oil supply shocks	-0.03	0.62	384	1992M01 - 2023M12
Oil consumption demand shocks	-0.07	0.17	384	1992M01 - 2023M12
Oil inventory demand shocks	0.07	0.17	384	1992M01 - 2023M12
Economic activity shocks	-0.03	0.50	384	1992M01 - 2023M12
Federal Funds Rate	-0.03	0.50	384	1992M01 - 2023M12
Monetary policy shocks	0.04	0.43	384	1992M01 - 2023M12
BRW's monetary policy shocks	0.08	0.13	357	1994M01 - 2023M09

Notes: The table displays the correlation between the USDA supply news series and various types of shocks, including oil supply news shocks from Känzig (2021), oil supply shocks, oil consumption demand shocks, oil inventory demand shocks, and economic activity shocks from Baumeister and Hamilton (2019). In addition, monetary policy shocks are represented by the spread between 10-year treasury constant maturity and the federal funds rate, which is obtained from the Federal Reserve Bank of St. Louis. BRW's monetary policy shocks represent a unified Fed monetary policy shock measured, estimated by Bu, Rogers, and Wu. (2021).

Endnotes

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[1] ESMIS includes more than 2,100 publications from agencies of USDA (USDA, 2024). See https://usda.library.cornell.edu/.

[2] In this study, we define the U.S. food price as the detrended U.S. personal consumption expenditures price index (PCE) for food (chain-type price index). Food prices and real GDP are detrended to remove any underlying long-term trends (the news shock series does not follow a trend, by construction).