Measuring the Effects of Agricultural Supply News Shocks

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Abstract

We study the impact of agricultural supply news shocks, which reflect changes in anticipated U.S. field crop production, on both the domestic agricultural sector and the broader economy. To identify these shocks, we employ a recently-developed approach that exploits the exogeneity of high-frequency USDA harvest news. Our results indicate that these news shocks have a statistically and economically significant impact on U.S. agriculture and even portions of the domestic and global macroeconomy. Specifically, we observe that a poor harvest news shock generates an immediate increase in the production-weighted real price of U.S. field crop commodities, and eventual reductions in U.S. industrial production, corn exports, the price of dry bulk shipping services, and the quantity of food-at-home purchases, while raising domestic livestock prices, real ethanol prices, and the price Americans pay for food-at-home. Weaker statistical evidence indicates that a negative agricultural news shock may also raise domestic unemployment, fertilizer prices, and financial uncertainty, while reducing soybean and rice exports and activity in the domestic supply chain, as well as ethanol production and consumption.

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The United States Department of Agriculture (USDA) publishes a variety of reports that contain valuable information for agricultural stakeholders, providing—among other things—updated information about the existing level of stocks, and expectations for planted acreage, harvest yield, crop production, exports, imports, and marketing-year ending stocks. USDA news about crops is primarily focused on the supply of agricultural commodities, which are frequently affected by weather, pest, and policy shocks; this is intuitive, since changes in food commodity demand occur more slowly, based on the growth in population and income. As new information is digested by traders, they adjust commodity prices to reflect updated expectations about fundamentals—assuming that markets are efficient (Adjemian, 2012). Ultimately, accurate USDA news can facilitate better resource allocation decisions by market participants (Gouel, 2020).

A growing body of research has examined the reaction of commodity futures prices to USDA news (Sumner and Mueller, 1989; Fortenbery and Sumner, 1993; Isengildina-Massa et al., 2008; Adjemian, 2012; Dorfman and Karali, 2015; Adjemian and Irwin, 2018, 2020; Ying et al., 2019; Karali et al., 2020; Huang et al., 2021; Cao and Robe, 2022). Indeed, Karali et al. (2020) use an identification through censoring (ITC) approach to document that 78% of the return variance for daily corn futures is explained by changes in supply-side fundamentals, as represented by production surprises. While these and related studies document that USDA news regularly moves commodity futures prices, few researchers have explored the wider impact of USDA supply news. Cao et al. (2023) provide a notable exception, investigating how the release of USDA reports can affect the equity prices of publicly-listed food companies using the Capital Asset Pricing Model.

In this article, we are concerned with measuring agricultural supply news shocks (that correlate to USDA news about existing stocks or anticipated changes to U.S. field crop production) and their impact on elements of the agricultural sector and the broader domestic and global economy. To do so, we employ a novel approach proposed by Känzig (2021) that exploits the exogeneity of the news in important USDA publications, and uses it as an external instrument in a VAR model. We measure news as the high-frequency changes in U.S. field crop futures prices around USDA supply announcements, and include in the analysis key field crops in the United States: corn, oats, rice, soybeans, and wheat, weighted by their annual share of domestic production. The supply-related announcements we consider are USDA's monthly World Agricultural Supply and Demand Estimates (WASDE), its quarterly Grain Stocks, and its annual Prospective Plantings and Acreage reports. These reports are closely monitored by market participants involved in supply management and speculative decision-making (Goyal and Adjemian, 2021).

Our analysis establishes a set of empirical findings on the effects of a poor agricultural news shock both within and beyond U.S. agriculture. Such a shock generates an immediate rise in the (production-weighted) real price of domestic field crop commodities, and also a reduction in U.S. industrial production that is consistent with food processing's share. It likewise initially reduces the producer price index for livestock, although that price recovers in time; this observation aligns with the idea that livestock producers trim the size of their herd when they anticipate increases in the cost of feed (Schulz, 2022). Poor agricultural news also reduces the quantity of commodities available for export (for corn, soybeans, and rice); this implies that the shock likewise reduces the demand for dry bulk shipping services, all else equal, and we find that indeed the Baltic Dry Index (BDI) level falls. Domestic freight volumes and expenditures also fall following the shock. Poor commodity news increases real U.S. ethanol prices, (although the effect is only statistically significant at a single standard deviation), which is consistent with corn being a primary component in the production of ethanol; it also reduces ethanol production and consumption. The shock generates an increase in food-at-home prices and a slight decrease in the quantity of food Americans consume at home. Less robust statistical evidence suggests that these shocks also increase unemployment, fertilizer prices, and financial uncertainty, while decreasing soybean and rice exports, activity in the domestic supply chain, and ethanol production and consumption.

We also perform historical decompositions to explore how agricultural supply news shocks contributed to U.S. field crop commodity prices, and also the price Americans pay for food consumed at home. While field crop prices are strongly influenced by agricultural commodity supply news shocks, retail-level food prices are not. This is unsurprising, given that in-store prices are dominated by processing, packaging, transportation, and marketing costs (USDA, 2022).

Moreover, the agricultural supply news shock that we estimate can itself be used in future work as an economic shock uncorrelated to other exogenous shocks identified in the literature, e.g., those for oil supply news or monetary policy. For example, Adjemian et al. (2023) 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 contribution to food price inflation. The remainder of the paper is structured as follows. First, we present the methodology section, including the construction of USDA surprise series and diagnostic tests. Next, we provide an overview of the empirical approach to estimate the impacts of agricultural supply news shock and provide an outline of the data used. We then present our results. Finally, we discuss the implications of our findings and conclude the paper.

Methodology

To quantify a structural agricultural supply news shock, we construct a series of high-frequency surprises around the release of USDA crop production reports. These reports provide a wide range of field crop production and stock information, which enables market participants to discover market prices. By examining the price reaction of U.S. field crop futures following the release of USDA supply news, we obtain a reliable measure of the impact of agricultural supply news.

In our analysis, we take into account various agricultural supply news sources, including key reports published by USDA such as the monthly World Agricultural Supply and Demand Estimates (WASDE), quarterly Grain stocks report, and annual Prospective Plantings and Acreage reports. These reports play a crucial role in providing comprehensive information about market conditions for major agricultural commodities at both domestic and global levels. The monthly WASDE report serves as a valuable source of data on production, consumption, trade, and price forecasts for agricultural commodities. It contains estimates and annual forecasts for domestic and global commodity production, consumption, trade, and prices. The Grain Stocks report, published quarterly, provides information on the current levels of grain stocks, including major crops like corn, soybeans, wheat, and other grains produced in the United States. This data helps to assess the availability and inventory of grains in the United States. The Prospective Plantings report, released annually in March, provides insights into farmers' intended plantings for the upcoming growing season and includes data on the previous year's crop harvest. This information also helps in understanding farmers' planting decisions and estimating future crop production. Similarly, the Acreage report, published annually in June, offers data on the actual planted acreage of major crops. This report is valuable for assessing the size and distribution of crop production across different regions. These USDA reports are highly anticipated by market participants and stakeholders as they offer critical information for analyzing crop supply and demand dynamics, helping traders, policymakers, and analysts make informed decisions and assess market conditions. In the subsequent sections, we provide a detailed explanation of our approach to constructing the USDA supply surprise series.

Constructing USDA surprise series

We employ the U.S. filed crop commodity futures prices traded at the Chicago Board of Trade (CBOT) to construct the USDA surprise series for the period of 1990-2022. These futures prices are highly regarded as effective indicators that reflect commodity price expectations in the market, i.e., the commodity futures market effectively captures the information about price expectations provided by USDA announcements.

In this section, our main focus is on measuring the changes in field crop commodity futures prices within a one-day window around the USDA announcement. To construct our benchmark surprise series, we collected a total of 592 USDA crop supply reports spanning from 1990 to 2022. Out of these reports, 394 reports came from the WASDE reports, 132 reports came from the Grain Stocks reports, 33 reports are obtained from Prospective Plantings reports, and another 33 reports were derived from the Acreage reports. However, it is worth noting that there were specific instances where multiple reports were consistently released on the same day. Specifically, 33 reports from both the WASDE and Grain Stocks reports were consistently released together in January. Similarly, another 33 reports from Grain Stocks and Prospective Plantings were released simultaneously in March, and yet another 33 reports from Grain Stocks and Acreage reports were published together in June each year.

Following Känzig (2021), we construct the USDA supply surprise series by measuring the daily returns on U.S. field crop futures prices (relative to their share of domestic production) around the announcement of USDA crop production reports.[1] We calculate surprises as price changes for each commodity across the first five maturities nearest expiration, and then aggregate the individual commodity surprises up into a single surprise series according to their production weights. The price change is calculated as the natural log difference between the daily futures price before and after USDA report publication:

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

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.[2,3]

Standard asset pricing theory holds that

[1] The delivery months for U.S. commodity futures traded on the Chicago Board of Trade (CBOT) vary across commodities. The futures contracts months are Mar., May, July, Sep., and Dec. for corn; Mar., May, July, Sep., and Dec. for oats; Mar., May, July, Sep., Nov., and Jan. for rice; Jan., Mar., May, July, Aug., Sep., and Nov. for soybeans; Mar., May, July, Sep., and Dec. for wheat.

[2] In May 1994, USDA shifted the release time of major crop reports from 3 pm to 8:30 am Eastern time; it made a similar change for the Grain Stocks report in September 1994 (USDA, 1994). Because 3 pm occurred after the close of domestic futures market trading, to accurately measure the market reaction to USDA announcements, we difference closing prices on the announcement day and the following trading day prior to the release time change. After that, we difference prices from the trading day before and the day of the announcement date.

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

$$F_{t,d,i}^{h} \; = \; \mathrm{E}_{t,d,i}[P_{t+h}] \; - \; RP_{t,d,i}^{h}, \tag{2}$$

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

$$USDA\ Surprise_{t,d,i}^{h} \; = \; \mathrm{E}_{t,d,i}[P_{t+h}] - \; \mathrm{E}_{t,d-1,i}[P_{t+h}] \tag{3}$$

Next, we aggregate the surprise series for each field crop into a single USDA surprise series, weighting by its share of domestic production in metric tons for that marketing year.[4] As in equation (4), we calculate and apply production weights to the change in each individual commodity's futures price around USDA announcements, and then sum them up. The resulting weighted average of field crop commodity futures prices serves as an overall measure of USDA supply news for field crops.

The USDA supply surprise series implies that

$$USDA\ Surprise_{t,d}^{h} \; = \; \sum_i USDA\ Surprise_{t,d,i}^{h} \; \times S_{y,i} \tag{4}$$

where $S_{y,i}$ represents the production (weight-based) share of commodity i in year y.

We acknowledge that selecting the event window size involves a trade-off between capturing the complete response to the USDA announcement and filtering out background noise that could be caused by other news events (Nakamura and Steinsson, 2018*a*). In our study, we choose a one-day window in equation (1) because a shorter window may not adequately capture the entire impact of the agricultural supply news on commodity futures prices; a one-day window allows us to capture the relevant price movements associated with the news while minimizing the influence of unrelated noise in the market.

Like Känzig (2021), we also calculate a composite measure that captures USDA supply news spanning the first five deliveries in the futures term structure for each commodity. That is, we use the first principal component of the USDA surprises derived from changes in U.S. field crop commodity futures prices to generate the individual commodity series in equation (1), and then aggregate those principal component series up into an overall supply news series in equation (4).

[4] For instance, in the 2022 marketing year the share of field crop production in metric tons for corn, soybeans, wheat, rice, and oats was 0.671, 0.225, 0.092, 0.01, and 0.002, respectively.

To aggregate the daily agricultural supply news series, denoted as $USDA\ Surprise_{t,d}^{h}$, into a monthly series, denoted as $USDA\ Surprise_{t}^{h}$, we use the following approach: if there is only one USDA announcement within a given month, we assign the monthly surprises as equal to that daily surprise. However, when there are multiple USDA announcements within a month, such as March, June, and September, we sum the daily surprises to obtain the monthly surprise. Furthermore, in cases where there is no USDA announcement during a particular month (as in October 2013 and January 2019 due to the U.S. federal government shutdown), we assign a value of zero to the monthly USDA surprise.

Assessment of USDA Surprise Series

In this section, we conduct a set of diagnostic tests to evaluate the validity and reliability of the USDA surprise series. These tests include a narrative evaluation, a placebo test that measures the level of noise in the series, and other tests such as autocorrelation, predictability, and correlation with other shocks.

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. commodity markets. Figure 1 displays the surprise series, estimated as the first principal component of the changes in the production-weighted average of the five nearest-to-deliver U.S. field crop commodity futures prices around USDA situation and outlook reports.[5] Although these reports provide information about both the supply and demand side of commodity markets, USDA's supply news—gathered based on detailed field-level and supply chain participants—are the key news to the market. According to the figure, USDA's news routinely surprises the markets, generating field crop commodity price changes around and sometimes over 5%. These significant 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 and Young, 2004); afterwards, farmers could more efficiently respond to market signals and make production choices based on factors such as profitability, consumer demand, and environmental considerations, and not be as heavily influenced by subsidy programs. June reports often feature prominently in the surprise series, because June includes USDA's annual Acreage report that identifies how American producers allocated their cropland (versus how they

[5] Our analysis is focused on the main field crops in the United States: corn, oats, rice, soybeans, and wheat; situation and outlook reports we consider include the monthly World Agricultural Supply and Demand Estimates (WASDE), quarterly Grain Stocks, and annual Prospective Plantings and Acreage issues.

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).[6] 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, 2009*a*).[7] In June of the same year, the June 1 Grain Stocks and Acreage 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 Prospective Plantings report (USDA, 2009*b*).[8] The following year's June WASDE report instead caused a spike in corn prices, because the higher 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).[9] Finally, the June, 2021 Grain Stocks report revealed a significant reduction in corn and soybeans 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).[10]

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[6] 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

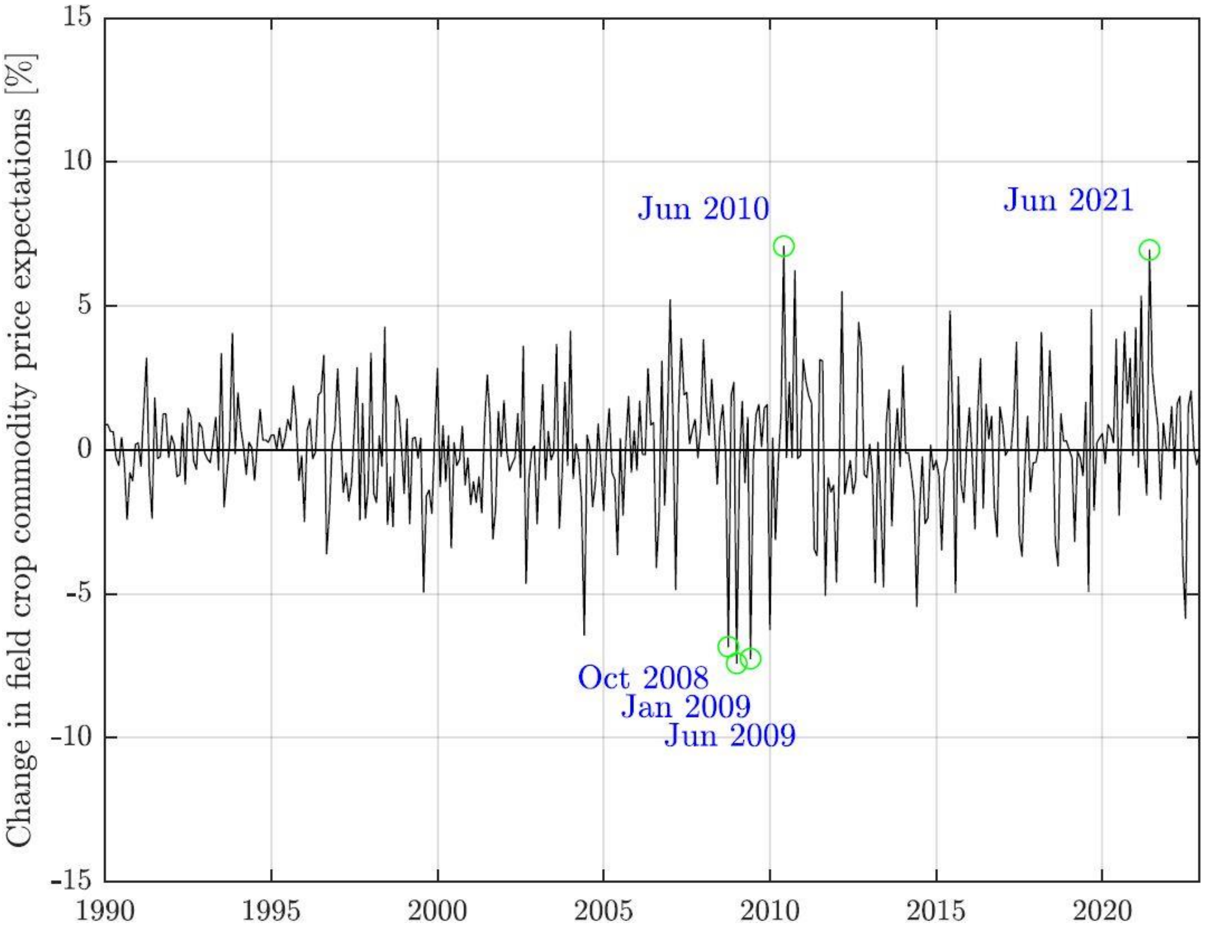
[7] See the WASDE report published on January 9, 2009. This report can be accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/t148fh48x/79407x60h/wasde-01-12-2009.pdf

[8] See the Grain Stocks 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

[9] 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

[10] See the Grain Stocks 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

Figure 1. Historical series of USDA supply surprises, 1990-2022



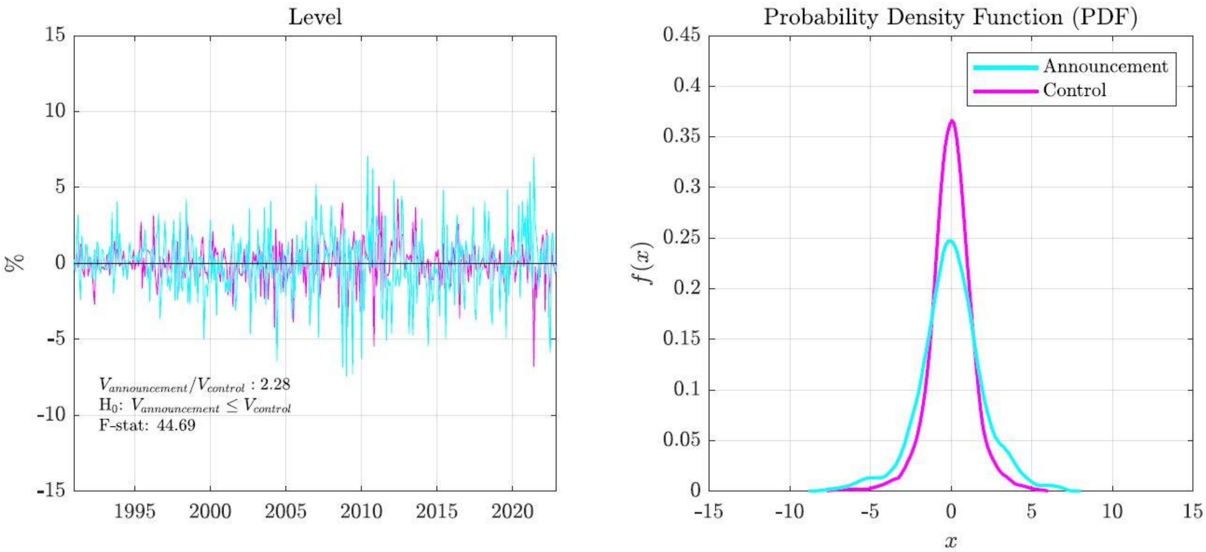
Notes: The monthly USDA surprise series represents the first principal component derived from changes in the U.S. field crop commodity futures prices (relative to their share of domestic production), specifically those for corn, oats, rice, soybeans, and wheat, around the publication of USDA supply news reports (see Appendix A for the series for each commodity). For each commodity, we include futures prices from the nearby to the fourth deferred contracts.

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 and 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 USDA report release. 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 holidays, the trading days are delayed by one business day.

Figure 2 compares the changes in U.S. field crop commodity futures prices around USDA announcements with those on control days. In the figure, 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.[11] 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.

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 announcement 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.

Additional diagnostic tests on the USDA surprise series

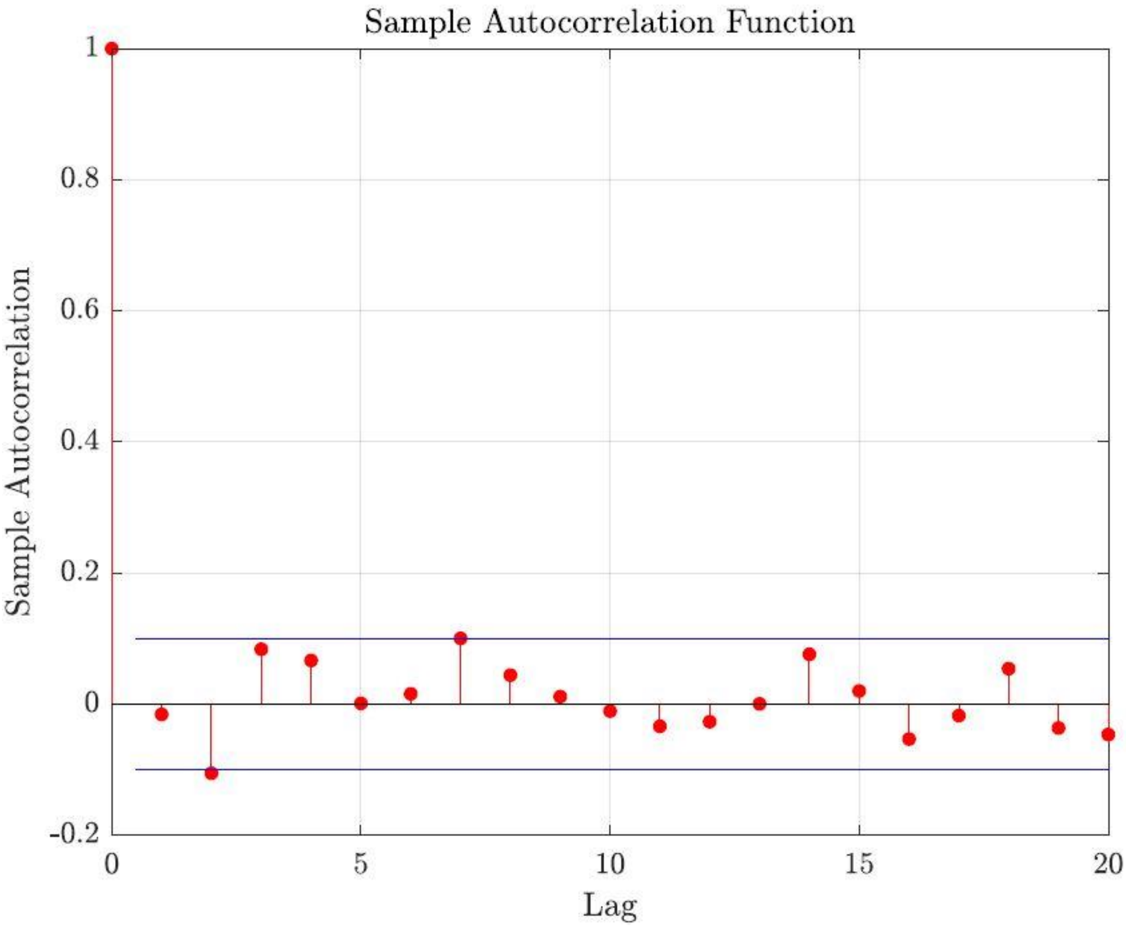
To ensure the validity of the series, we conduct additional diagnostic tests as recommended by Ramey (2016). Specifically, we test the series' autocorrelation, forecastability, and correlation with other shocks. Figure 3 displays the results of the autocorrelation function of the series. That plot offers little evidence that the USDA news series is serially correlated, indicating that the series is unlikely to be influenced by past shocks or trends. The Granger causality test results presented in Table 1 show no

[11] 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 and Forsythe, 1974).

evidence of Granger causality among the variables in our model at the 5 percent significance level. This indicates that the variables are unable to predict changes in the time series.

Furthermore, we examine whether the USDA supply news series is correlated with other structural shocks in the literature, such as oil supply news shocks, oil supply shocks, oil consumption demand shocks, economic activity shocks, and monetary shocks. The results, presented in Table 2, indicate no significant correlation between the news series and other structural shocks, indicating that the series we are measuring is orthogonal to other news and policy events.

Figure 3. 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 blue line indicates the 95 percent confidence band.

Table 1. Granger causality test results

Variable	p-value
USDA supply news series	0.4087
U.S. real field crop commodity price	0.7062
U.S. industrial production	0.8096
U.S. PPI for livestock	0.3066
U.S. corn exports	0.1844
Baltic Dry Index	0.2518
U.S. real ethanol price	0.0935
U.S. food-at-home quantity	0.1852
U.S. food-at-home price	0.9792
Joint hypothesis	0.2090

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 2. Correlation with different shocks

Variable	Correlation	P-value	Observations	Sample period
Oil supply news shocks	0.02	0.71	396	1990M01 - 2022M12
Oil supply shocks	-0.05	0.36	396	1990M01 - 2022M12
Oil consumption demand shocks	-0.05	0.36	396	1990M01 - 2022M12
Economic activity shocks	-0.02	0.63	396	1990M01 - 2022M12
Monetary shocks	-0.02	0.70	396	1990M01 - 2022M12

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, and economic activity shocks from Baumeister and Hamilton (2019). In addition, monetary 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.

Empirical Approach

One challenge with USDA surprise series that are measured directly as a shock is that they may only capture a portion of the true shock and may contain measurement errors (Stock and Watson, 2018). Rather than treat the USDA surprise series as a direct shock, we instead exploit it as an instrument for the shock in this study. Specifically, we employ the USDA surprise series as an external instrument in a VAR model of the agricultural commodity market to identify a structural agricultural supply news shock following the method developed by Stock and Watson (2012) and Mertens and Ravn (2013).[12]

[12] 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 and Watson, 2018).

An external instrument must satisfy two conditions: first, it should be correlated only with the shock of interest (relevance); second, it should be uncorrelated with other structural shocks (contemporaneous exogeneity).

In addition to our main identification method, we also present alternative approaches for identifying the impacts of agricultural supply news shocks. First, we use a heteroskedasticity-based identification that accounts for background noise in USDA supply surprises caused by other shocks during the event window (Rigobon, 2003; Rigobon and Sack, 2004; Nakamura and Steinsson, 2018*a*; Känzig, 2021). This approach allows us to filter out background noise by comparing the movements in U.S. field crop commodity futures prices during event windows around USDA announcements to other equally long and otherwise similar event windows that do not include a USDA announcement.

Next, we employ Jordà's (2005) local projection method 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 and Steinsson, 2018*a*). Furthermore, the surprise series explains only a small portion of field crop commodity prices, and it is intuitive that the outcome variables for extended periods in the future are influenced by a wide range of other shocks, resulting in a low signal-to-noise ratio in the analysis. Consequently, it becomes challenging 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 assessment of the effects of agricultural supply news shocks.

Conceptual model

Once again following Känzig (2021), we specify the reduced-form VAR (p) model

$$y_t = b + B_1 y_{t-1} + \cdots + B_p y_{t-p} + u_t, \tag{5}$$

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 $Var(u_t) = \sum$, b is a $n \times 1$ vector of constants, and $B_1, \ldots, B_p$ are $n \times n$ coefficient matrices.

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

$$u_t = S\varepsilon_t, \tag{6}$$

where S 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

$$\Sigma = S\Omega S'. \tag{7}$$

Without loss of generality, we order the agricultural supply news shock as the first shock in the VAR model (i.e., $\varepsilon_{1,t}$). In this section, our objective is to identify the structural vector of interest, s_1, which corresponds to the initial column of S.[13]

Identification with external instruments

We identify the structural vector of interest using external instruments, also known as proxies, assuming that the background noise in the USDA surprise series is marginal. Suppose we possess an external instrument, which in this study is the USDA supply surprise series denoted as z_t. To ensure the validity of z_t, it is necessary to satisfy the following conditions:

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

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

where $\varepsilon_{1,t}$ represents the agricultural supply news shock and $\varepsilon_{2:n,t}$ represents a $(n-1) \times 1$ vector of the other structural shocks. The identity in (8) is referred to as the relevance condition, while (9) is known as contemporaneous exogeneity. Under the relevance and the contemporaneous exogeneity conditions, we can identify s_1 up to sign and scale:

$$\tilde{s}_{2:n,1} \equiv s_{2:n,1}/s_{1,1} = \mathbb{E}[z_t u_{2:n,t}]/\mathbb{E}[z_t u_{1,t}], \tag{10}$$

given that $\mathbb{E}[z_t u_{2:n,t}] \neq 0$. The estimate of $s_{2:n,1}/s_{1,1}$ can be the IV estimator of $u_{2:n,t}$ on $u_{1,t}$ using z_t as an instrumental variable. The structural vector of interest is represented as $s_1 = (s_{1,1}, \tilde{s}'_{2,1} s_{1,1})'$, where $s_{1,1}$ is the first element of s_1 and $\tilde{s}'_{2,1}$ is a $(n-1) \times 1$ vector of coefficients capturing the contemporaneous responses of the other $n-1$ endogenous variables to a one-unit shock to the first variable. Then, the scale s_1 can be obtained by rescaling the output response to normalize the effect on $y_{1,t}$ subject to $\Sigma = S\Omega S'$. When we set $\Omega = diag(\sigma^2_{\varepsilon_1}, \ldots, \sigma^2_{\varepsilon_n})$ and $s_{1,1} = x$, this suggests that a

[13] 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 and Ricco, 2023).

unit increase in $\varepsilon_{1,t}$ has a positive impact of magnitude x on $y_{1,t}$. In this context, we normalized the USDA supply news shock so that it represents an immediate five percent rise in the U.S. field crop commodity price.

Identification through heteroskedasticity approach

The heteroskedasticity-based estimation approach uses a weaker identifying assumption that allows for background noise in USDA news surprise series caused by other shocks during a one-day window. Like Känzig (2021), we suppose that the movements in the U.S. field crop commodity futures, z_t, are influenced by both agricultural supply news and other shocks as follows.

$$z_t = \varepsilon_{1,t} + \sum_{j\neq 1} \varepsilon_{j,t} + \omega_t,$$

where $\varepsilon_{j,t}$ represents other shocks that impact U.S. field crop commodity futures and $\omega_t \sim iidN(0, \sigma_\omega^2)$, representing measurement error such as microstructure noise. As z_t is influenced by other shocks, it no longer remains a valid external instrument. Nevertheless, we can still identify the structural impact vector by leveraging the presence of heteroskedasticity in the data. The identifying assumption is based on the notion that the variance of USDA crop supply news shocks rises during USDA announcements, while the variance of all other shocks remains unchanged. We define R1 as a sample of USDA announcement dates, representing the treatment group, and R2 as a sample of trading days without any USDA announcements but comparable in other aspects, serving as the control group. The assumptions are expressed as follows:

$$\begin{aligned} &\sigma^2_{\varepsilon_1,R1} > \sigma^2_{\varepsilon_1,R2} \\ &\sigma^2_{\varepsilon_j,R1} = \sigma^2_{\varepsilon_j,R2}, \quad \text{for } j = 2,\ldots,n. \\ &\sigma^2_{\omega,R1} = \sigma^2_{\omega,R2}. \end{aligned} \tag{11}$$

Under these assumptions, the structural impact vector can be expressed as follows:

$$s_1 = \frac{\mathbb{E}_{R1}[z_t u_t] - \mathbb{E}_{R2}[z_t u_t]}{\mathbb{E}_{R1}[z_t^2] - \mathbb{E}_{R2}[z_t^2]} \tag{12}$$

An alternative way to obtain this estimator is by using an instrumental variable approach, as suggested by Rigobon and Sack (2004). In this approach, we employ $\tilde{z} = (z'_{R1}, -z'_{R2})'$ as an instrument in a regression model where the reduced-form innovations are regressed on $z = (z'_{R1}, z'_{R2})'$. Our findings demonstrate that the impulse responses from the heteroskedasticity-based estimator are comparable to those from external instruments approach, thus providing further support for the validity of the external instruments approach.

Local projections approach

When estimating impulse responses using a Vector Autoregressive (VAR) model, it is necessary to meet several restrictive properties, including symmetry, shape invariance, history independence, and multi-dimensionality (see Jordà, 2005). In order to assess the level of restrictiveness imposed by the VAR model, we estimate impulse responses to the identified agricultural supply news shock using local projections, as proposed by Jordà (2005).

$$y_{j,t+h} = \beta_0^j + \delta_h^j AgriculturalNewsShock_t + \beta_h^{j\prime} x_{t-1} + \xi_{j,t,h}, \qquad (13)$$

where $y_{j,t+h}$ represents the outcome variables, $AgriculturalNewsShock_t (= \hat{\varepsilon}_{1,t})$ represents the agricultural supply news shock identified through the external instruments approach, x_{t-1} represents a vector of control variables, and the error term, $\xi_{j,t,h}$, is serially correlated. δ_h^j represents impulse responses to the agricultural supply news shock of variable j at horizon h. We employ a simulation (or a parametric bootstrap technique), similar to that used by Stock and Watson (2018), to calculate confidence intervals for the estimated impulse response function. Instead of relying on the USDA supply surprise, we employ the agricultural news shock because the shock increases the statistical power by spanning all periods of the sample. By comparing the impulse responses from both the VAR and local projections approaches, we find that they yield similar results, as shown in the Results section.

Results

First-stage regression fit

The external instruments approach we use relies on two key assumptions: (1) that the instrumental variable is correlated with the structural shocks of interest (“relevance”) and (2) that it is uncorrelated with the other structural shocks (“contemporaneous exogeneity”). If the correlation between the instrument and the shocks of interest is weak, the results may be biased. We generate a series of related USDA supply news instruments by 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 3. Note that the “comp.” column represents a composite model that spans the expirations over the first calendar year of the term structure. According to Stock et al. (2002), the first stage F-statistic should ideally be above a threshold value of 10. Additionally, table 3 also reports a robust F-statistic that allows for heteroskedasticity. According to the table, the first-stage F-statistics for our instruments hover around 16, although their strength tends to weaken as the futures contract's maturity lengthens. For individual commodities, the first-stage F-statistics for corn and soybeans are relatively robust, whereas those for oats, rice, and wheat are relatively weaker (see Appendix C for details).

The F-test analysis in table 3 indicates that the robust first-stage F-statistic for the instrument based on the composite instrument is 16.41, and the instrumental variable accounts for approximately 4 percent of the residual of (production-weighted) real prices of U.S. field crop commodities. These results support our external instrument approach.

Table 3. F-test results in the first stage of the VAR

	Front	First def.	Second def.	Third def.	Fourth def.	Comp.
Coefficient	0.281	0.295	0.284	0.298	0.300	0.293
F-statistic	17.80	19.15	16.60	16.54	14.50	17.15
Robust F-statistic	16.30	17.95	16.24	16.06	13.84	16.41
R^2	4.45	4.77	4.16	4.15	3.66	4.30
Adjusted R^2	4.20	4.52	3.91	3.90	3.40	4.05
Observations	384	384	384	384	384	384

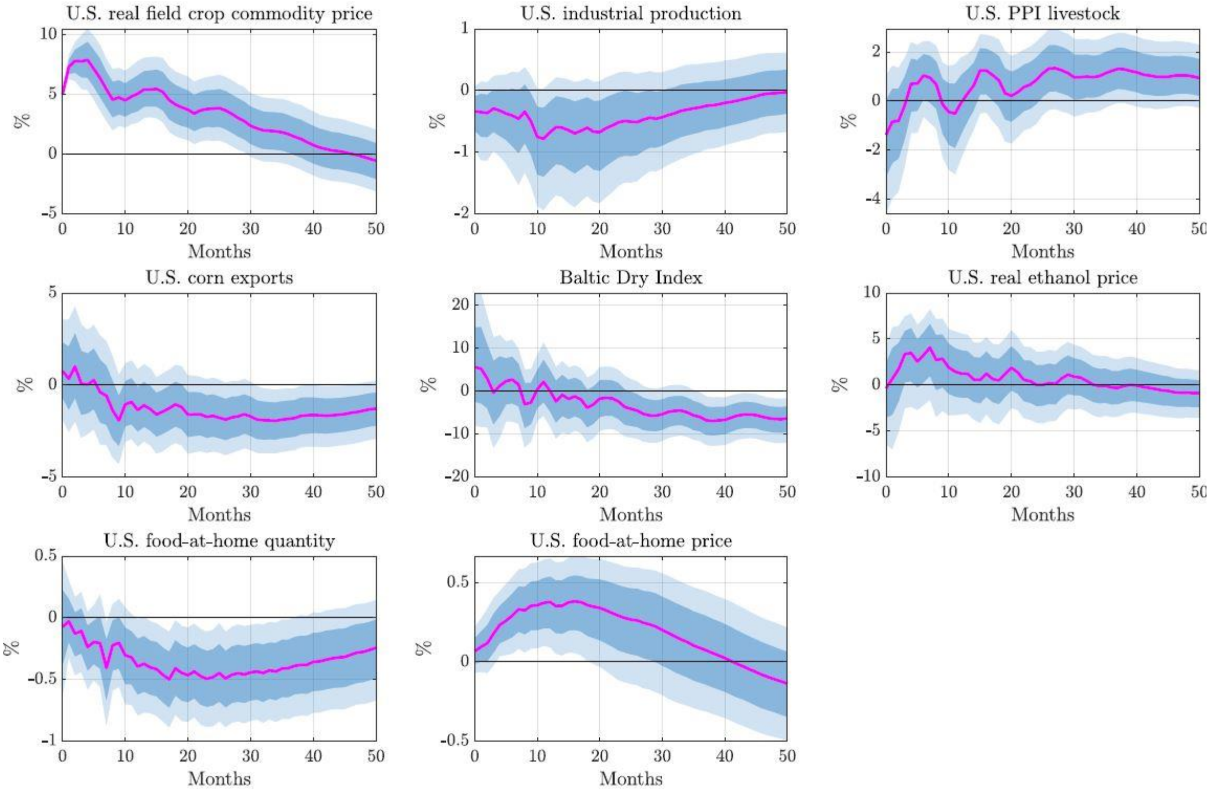
Baseline model results

In this section, we analyze the impacts of an agricultural supply news shock on the baseline model using an external instruments approach. Eight variables make up the baseline model: the real price of U.S. field crop commodities (weighted by their share of domestic production), U.S. industrial production, the U.S. Producer Price index (PPI) for livestock, U.S. corn exports, the Baltic Dry Index, the U.S. real ethanol price, the quantity of food-at-home that Americans consume, and the U.S. food-at-home price index (see Appendix D for the data description, sources, and periods for these variables). We use the USDA news series that we estimate as an instrumental variable to identify the effect of agricultural supply news shocks on this set of baseline variables. Figure 4 displays our estimates of the dynamic response of the baseline variables to an agricultural supply news shock normalized to increase the weighted average U.S. real field crop commodity price by five percent; this can be thought of as 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. Impulse response functions in the figure are plotted for a fifty-month horizon and are presented with accompanying 68 and 90 percent confidence bands, which were generated using 10,000 bootstrap replications.

Impulse response functions in figure 4 generally align with our expectations. In response to the shock, the first panel shows that U.S. real field crop commodity price immediately rises by five percent, as expected given our normalization, and the dynamics indicate that the field crop price remains elevated for a period of about two years. The shock also marginally lowers industrial production in the United States (at the 68 percent confidence level); at the mean, the decrease is smaller than one percent. This is anticipated because U.S. food manufacturing comprised approximately 10-13 percent of domestic industrial production over the period of interest, as displayed in figure 5. At the mean, the livestock price decreases in the short-run, but increases over the longer term; this is in line with the expectation that a rise in expected feed costs induces livestock operations to slaughter more and increase meat supplies in the near term, and trimming herd size until feed costs ease (Schulz, 2022). Similarly, the next two panels in figure 4 indicate that a poor field crop supply news shock decreases the amount of U.S. corn available for export and therefore the demand-side pressure on the price of dry bulk shipping, which we represent with the Baltic Dry Index. Additionally, the poor field crop supply news shock raises U.S. real ethanol prices at nearly the same scale as the shock's effect on commodity prices, which is consistent with corn being the primary component of the ethanol production, although the effect is only statistically significant at a single standard deviation. The final two panels in figure 4 show that an agricultural supply news shock normalized to raise commodity prices by five percent increases food-at-home-prices by around 0.4 percent at its peak (which occurs about one year later), and reduces the quantity of food-at-home that Americans consume by around 0.5 percent at the trough (about one and a half years after that). Both responses are statistically significant at the 90 percent level. This result is in line with the USDA's Food Dollar Series analysis, which indicates that the farm product share of the average dollar that Americans spent on food-at-home was 14.5 percent in 2021 (USDA, 2022).[14] Therefore, a 5 percent increase in commodity prices would imply a food price of about the size we measure, at the mean.

[14] Farm share of the food dollar is calculated as the average compensation that farmers receive for each dollar spent on food, representing their portion of the raw food dollar commodities (Canning, 2011).

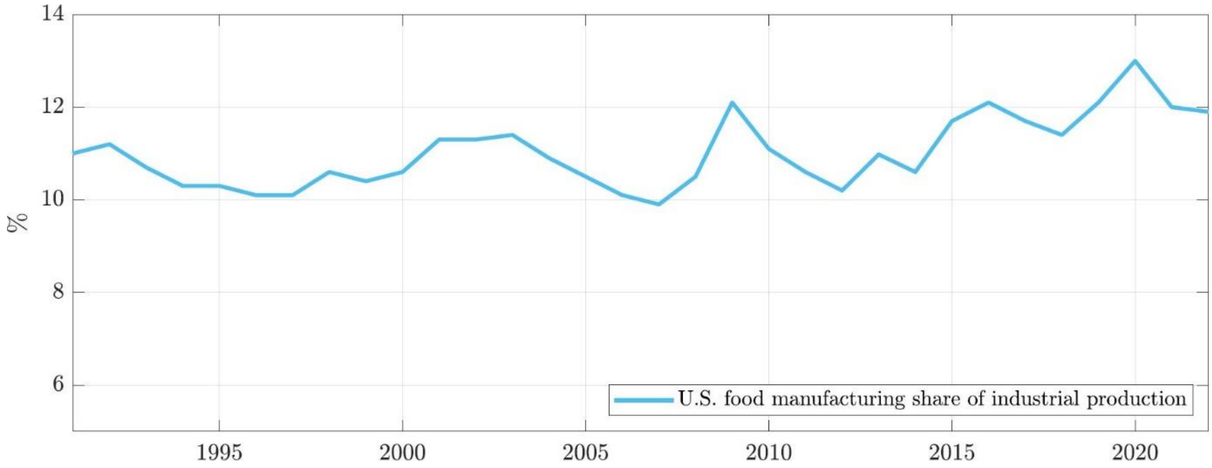
Figure 4. Impulse response functions to an agricultural supply news shock using external instruments approach



First stage results: F-statistic: 17.15, Robust F-statistic: 16.41, R^2: 4.30%, Adjusted R^2: 4.05%

Notes: The impulse responses in the figure are estimated using an external instruments approach. The shock is normalized to a 5 percent increase in the weighted-average U.S. real field crop commodity price. The solid pink line represents the point estimate. The dark blue region indicates the 68 percent confidence band, while the light blue region represents the 90 percent confidence band for the impulse responses.

Figure 5. U.S. food manufacturing share of industrial production, 1990-2022

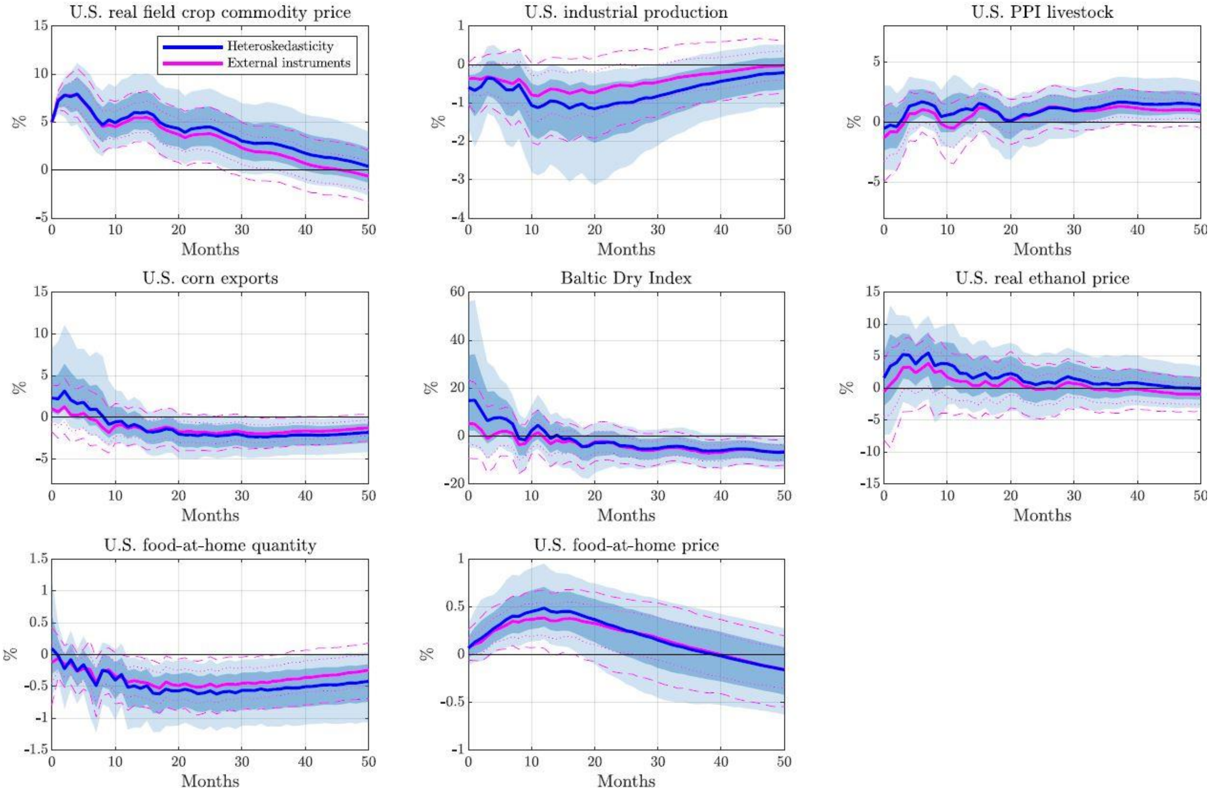


Source: Board of Governors of the Federal Reserve System

Notes: The solid blue line in the figure illustrates the percentage ratio of food manufacturing share to industrial production in the United States from 1990 to 2022. The food manufacturing share represents the annual proportion of food, beverage, and tobacco products manufacturing, which is obtained from the 'Annual Proportions in Industrial Production, Market and Industry Group Summary' table in the Federal Reserve's Industrial Production and Capacity Utilization release.

Like Känzig (2021), we also employ a heteroskedasticity-based approach to estimate the baseline model, which helps us to clear away any other shocks that may confound the instrument during the daily event window. This approach takes into account the potential presence of background noise. As shown in figure 6, the impulse response results from the heteroskedasticity-based approach are similar to those from the external instruments approach: point estimates are quite close to each other. Although the estimates from the heteroskedasticity-based approach are less precise, they are still significant at the level of a single standard deviation. This provides some assurance about the robustness of our findings, and suggests that any potential bias caused by background noise is likely to be negligible.

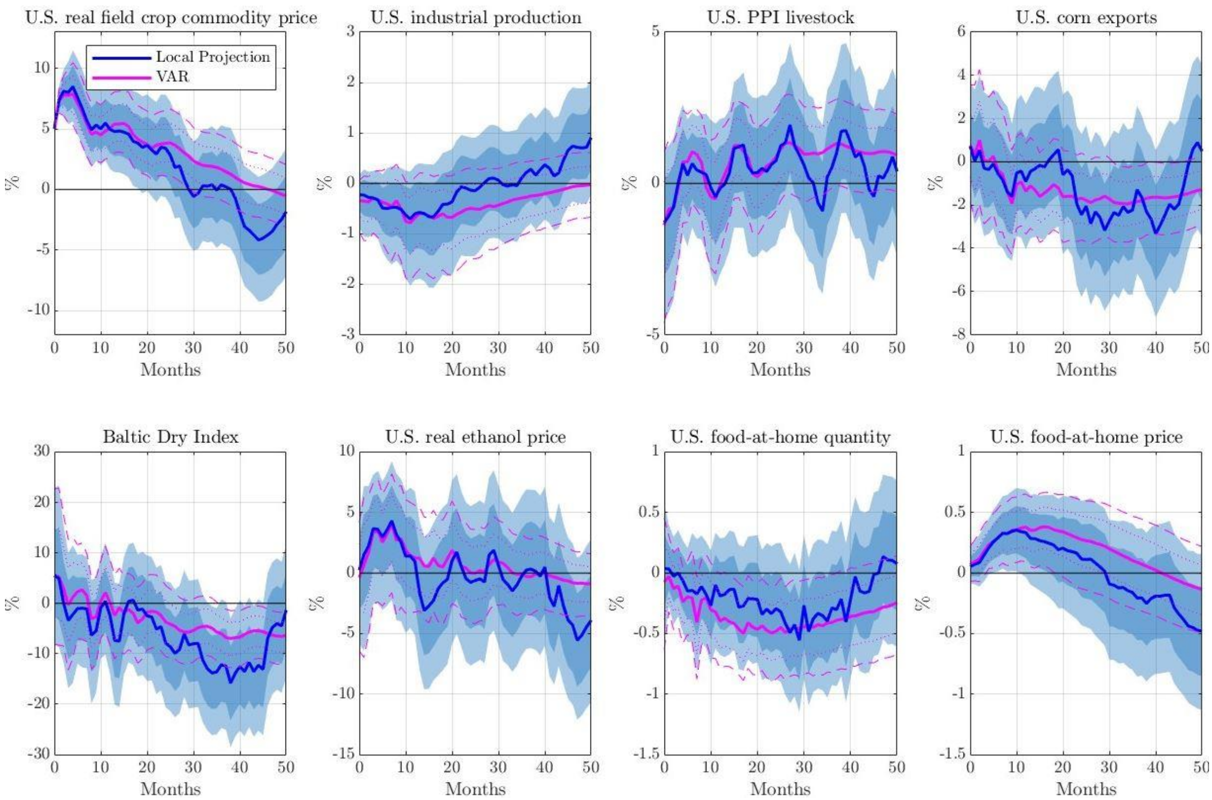
Figure 6. Impulse response functions to an agricultural supply news shock using a heteroskedasticity-based approach



Notes: The impulse responses in the figure are estimated using the heteroskedasticity-based and external instruments approaches. The shock is normalized to a 5 percent increase in the weighted-average U.S. real field crop commodity price. The solid blue line represents the point estimate of the heteroskedasticity-based approach, while the solid pink line represents the point estimate of the external instruments approach. The dark blue region indicates the 68 percent confidence band, while the light blue region represents the 90 percent confidence band for the impulse responses.

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 (2018*b*). 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. Figure 7 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.

Figure 7. 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 used in the analysis is normalized to a 5 percent increase in the weighted-average U.S. real field crop commodity price. The solid blue line represents the point estimate of the local projections approach, while the solid pink line represents the point estimate from the VAR approach. The dark blue region indicates the 68 percent confidence band and the light blue region represents the 90 percent confidence band for the impulse responses.

Historical decomposition of U.S. field crop commodity price

In this section, we assess how the agricultural supply news shocks we measure contributed to observed U.S. field crop commodity and food prices.[15] Figure 8 illustrates the historical decomposition of the domestic weighted-average field real crop commodity prices from 1991 to 2022, along with the role that agricultural supply expectations played in explaining the series. Both series are plotted in deviations from the mean; the green series represents the contribution that agricultural supply news shocks made to field crop futures prices. Differences between the series in the chart represent the contribution that other factors made to observed commodity prices.

Figure 8 shows how important USDA's agricultural supply news is to explaining field crop commodity prices in the United States. Clearly, the two series are highly correlated over time; often they nearly overlap, highlighting the importance of USDA's supply news. For instance, positive agricultural supply news on October 2008 led to a substantial decline in U.S. real field crop commodity prices (Good, 2008). Subsequently, the June 2009 USDA raised its corn stocks estimates, lowering price expectations (Good, 2009). By the following June, USDA estimated a sharp reduction in U.S. corn stocks due to the low test weight crop of 2009, which was attributed to its poor quality (Good, 2010).[16] This caused U.S. real field crop commodity price to rebound. As a final example, the June 2021 Grain Stocks report revealed a significant reduction in corn and soybean stocks, leading agricultural commodity prices to rise (USDA, 2021).

At other times, deviations between the series in figure 8 show that outside factors also play an important role in field crop commodity price changes. During the 2012-2013 period, as a severe drought impacted over 80 percent of farmland in the United States, any additional agricultural supply news shocks during this timeframe had limited influence on the already-elevated crop commodity prices (USDA, 2015). Another example is the recent steep drop and sharp run-up in commodity prices following the outbreak of the pandemic in early 2020, and later magnified by the Russian invasion of Ukraine; these prices cannot be attributed solely to our series of agricultural supply news shocks. Events outside of harvest news—like supply chain disruptions combined with the sharp recession and then rapidly increased aggregate demand since late-2020 (in part stimulated by domestic fiscal and monetary policy)—likely explains why in figure 8 the yellow series diverges from the green series and

[15] 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.

[16] During the 2009 corn harvest season in Indiana, there were more reports of corn grain with low test weight than good or above-average test weights (Nielsen, 2021).

its confidence intervals beginning in 2020. While the two series remain correlated, the news shocks we extract cannot fully explain recently-observed U.S. field crop commodity prices.

As a comparison, figure 9 presents the contribution the news shocks made to food prices in the United States from 1991-2022; clearly the relationship is much weaker than the one in figure 8.[17] Many times, domestic food prices and agricultural supply new shocks are inversely correlated—like in the 1999-2003 period, and again since 2015. However, overall, while the news shock series does not change significantly, food prices exhibit more pronounced movements; we interpret this to mean that field crop commodity news shocks account for only a relatively small portion of food prices.

This is primarily due to the fact that the majority of the costs associated with the food we consume in the United States are due to processing, packaging, transport, and marketing. According to the Economic Research Service (ERS) annual food dollar series published by USDA, in 2021, for every dollar spent on food in the United States, services, which combines food retail trade and food services, accounted for 46.3 cents, food processing accounted for 15.2 cents, wholesale trade accounted for 10.7 cents, transportation and packaging accounted for 6.5 cents, energy used for the food supply chain accounted for 3.2 cents, and other costs, including finance, insurance and advertising, and others, accounted for 10.7 cents, while farm production accounted for just 7.4 cents of the food dollar value (2022). [18,19]

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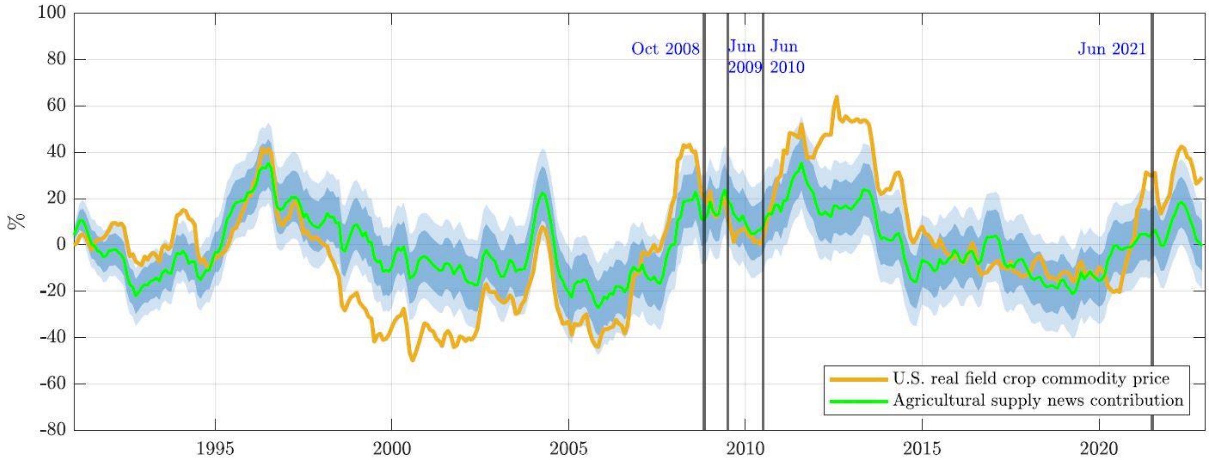
[17] In this study, we define the U.S. food price as the detrended U.S. real personal consumption expenditures price index (PCE) for food. This is achieved through a two-step process. First, the PCE for food, which is a chain-type price index, is adjusted for inflation by deflating it using the Consumer Price Index (CPI) for All Urban Consumers. The CPI reflects price index reflects the average costs of goods and services paid by urban Americans. Following that, the resulting series is detrended to remove any underlying long-term trends (the news shock series does not follow a trend, by construction).

[18] The USDA ERS food dollar series presents annual expenditures on domestically produced by individuals residing in the United States and offers comprehensive insights into the allocation of our food expenditures (Canning, 2011).

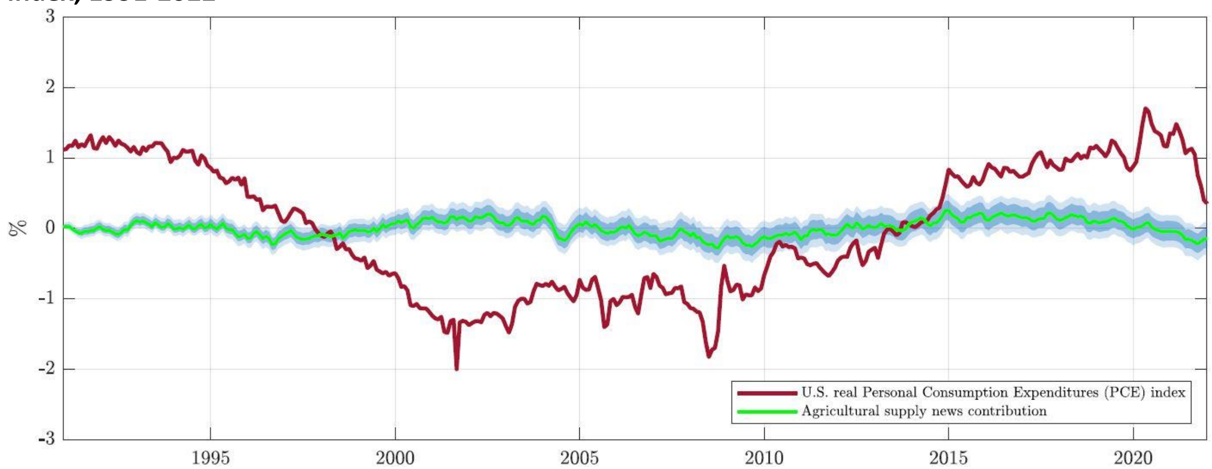
[19] The food dollar values reported here are in nominal dollars.

Figure 8. Historical decomposition of U.S. real field crop commodity prices, 1991-2022



Notes: The figure portrays the cumulative historical contribution of USDA supply news to the U.S. real field crop commodity prices from 1991 to 2022. The mustard solid line represents the weighted-average U.S. real field crop commodity price, expressed as percentage deviations from the mean. The green solid line is the point estimate, and the light and dark shadings represent 68 percent and 90 percent confidence intervals, respectively. The figure also includes historical episodes in USDA supply news reports represented by vertical bars.

Figure 9. Historical decomposition of U.S. real personal consumption expenditures (PCE) price index, 1991-2022



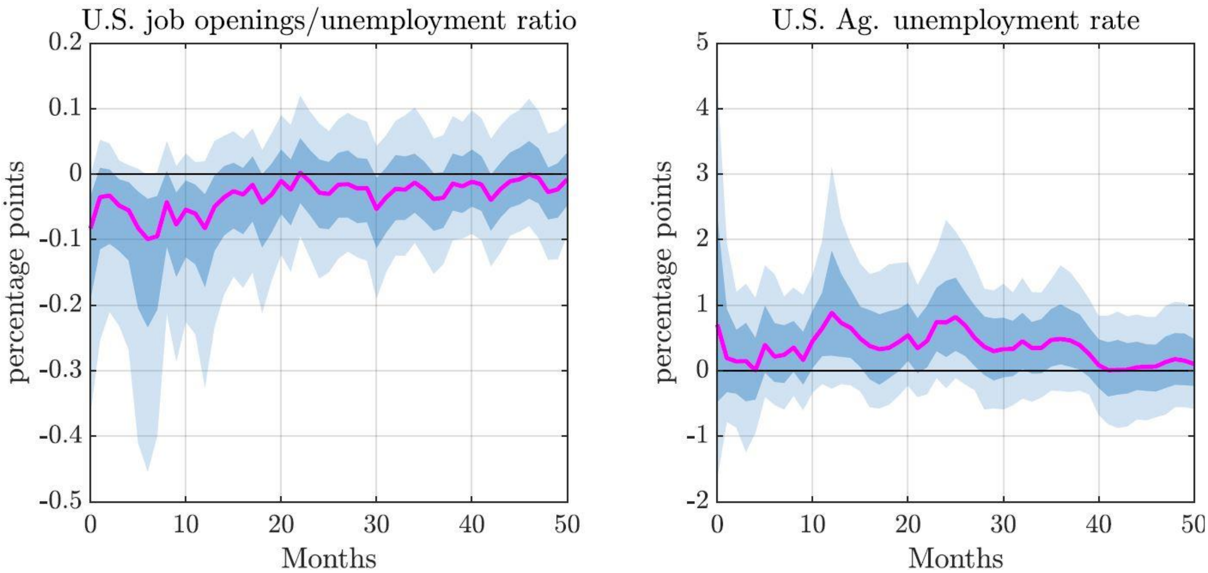
Notes: The figure portrays the cumulative historical contribution of agricultural supply news to the U.S. real personal consumption expenditures price index for the period of 1991-2022. The dark brown solid line represents the de-trended U.S. real personal consumption expenditures (PCE) price index. This PCE index, which is indexed to a value of 100 in 2012, are deflated by the U.S. Consumer Price Index (CPI) for all urban Americans, and then de-trended. The green solid line is the point estimate, and the light and dark shadings represent 68 percent and 90 percent confidence intervals, respectively.

Impacts of agricultural supply news shock on other variables

Our impulse response results above confirm that agricultural supply news shocks affect commodity markets and the agricultural sector. They may also carry wider domestic and global macroeconomy, through changes in expectations for domestic and international commodity production and trade flows. In this section, we explore additional effects of the shocks we extract, beyond our baseline variables. Once again, following Känzig (2021) we estimate the next set of impulse responses by adding a single variable at a time to the baseline VAR.

Figure 10 displays how agricultural supply news shocks affect the domestic labor market: the outcomes for the U.S. job openings to unemployment ratio (left) and unemployment rate in the agriculture sector (right) following the familiar poor-agricultural-supply-news shock that increases commodity prices by five percent. While the number of open jobs for every unemployed person in the United States declines by less than 0.1 percentage point within about six months, the unemployment rate in the agricultural sector increases by just under a full percentage point (at the 68 percent confidence level). Both of these effects are plausible negative consequences of poor news shocks that affect, for example, food production and commodity exports.

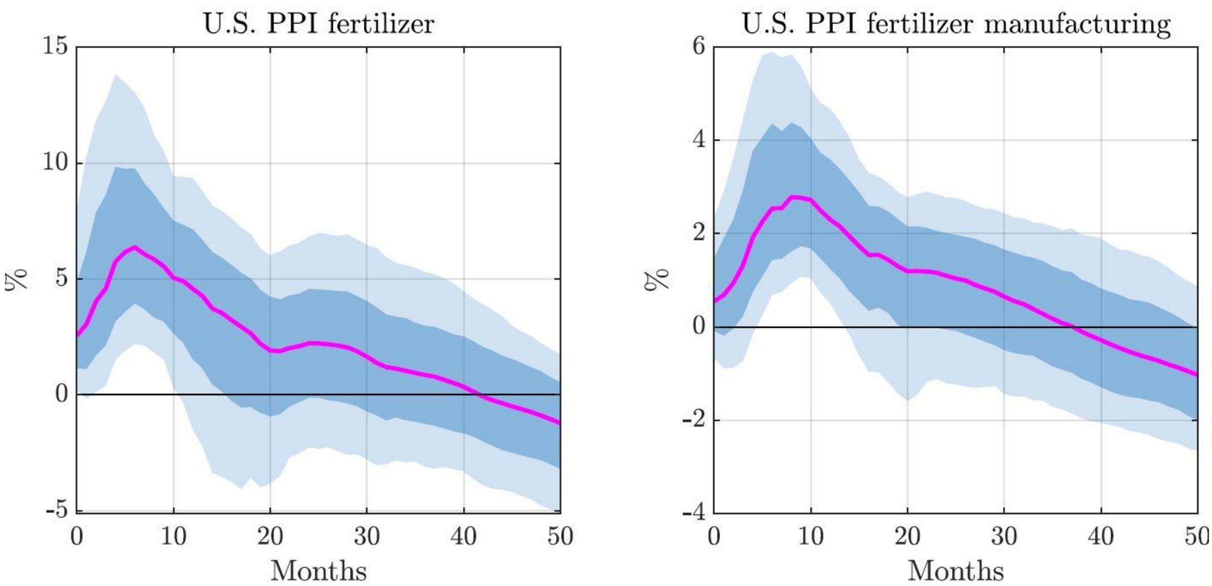
Figure 10. Impacts on the U.S. unemployment



Notes: U.S. job openings/ unemployment ratio in the left panel is calculated by dividing job openings (total nonfarm) by the total unemployment level in the United States. Job openings are obtained from Job Openings and Labor Turnover Survey (JOLTS) for the period of December 2000 to December 2022. The U.S. Ag. unemployment rate on the right panel is measured by the Unemployment Rate for Agricultural and Related Private Wage and Salary Workers obtained from Federal Reserve Economic Data (FRED) for the period of January 2000 to December 2022.

An agricultural supply news shock that raises crop prices also leads to an increase in the price of fertilizer, a significant input cost for crop production. As shown in figure 11, the poor harvest expectation shock produces an immediate increase of 6 percent in U.S. fertilizer prices (left) and 3 percent in fertilizer manufacturing prices (right). It may be that poor crop news, possibly due to natural disasters such as floods or droughts, can incentivize producers to enhance their yields in order to compensate for the expected losses. One way they may employ is increasing fertilizer application. The increased demand for fertilizers would pressure fertilizer prices higher. For example, at the beginning of 2021, the Corn Belt region in the United States experienced the impact of strong winds known as derechos, which resulted in crop losses and tighter crop stocks. This led to a higher demand for fertilizers to compensate for reduced yields (Harris, 2022). Additionally, the "La Niña" weather patterns in Brazil cause droughts that affect soybean production, further contributing to the increased demand for fertilizers.

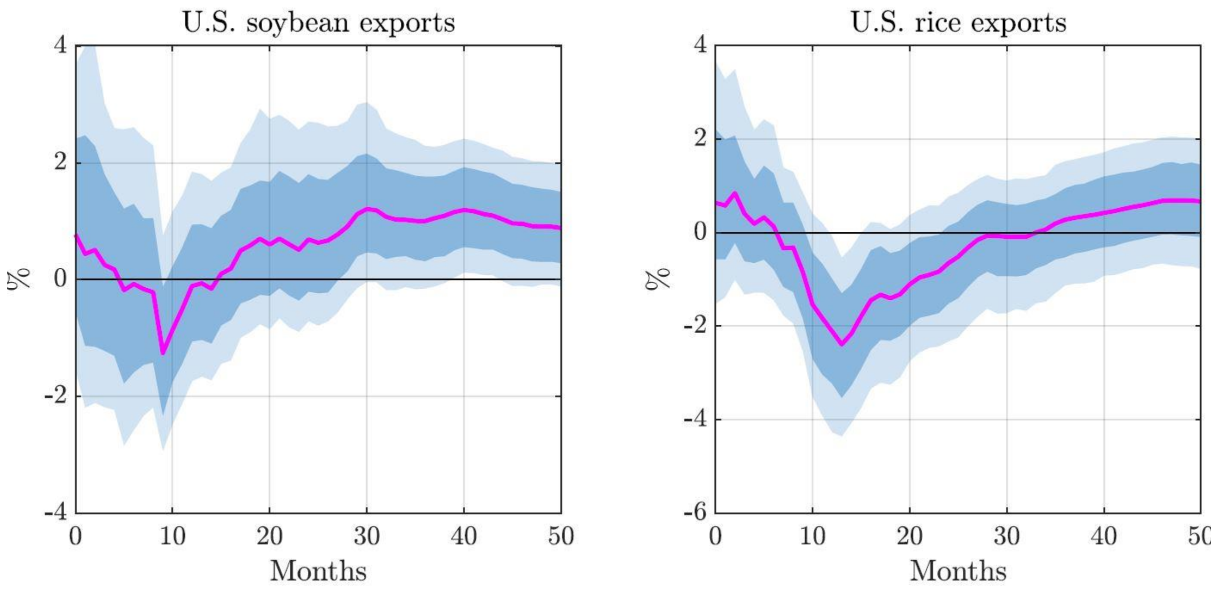
Figure 11. Impacts on U.S. fertilizer prices



Notes: In this figure, the U.S. Producer Price Index (PPI) for fertilizer materials (left panel) is measured using the PPI by Commodity for Fertilizer Materials obtained from Federal Reserve Economic DATA (FRED). The U.S. PPI for fertilizer manufacturing (right panel) is measured by PPI by Commodity for Mixed Fertilizers from the FRED. The data used in our analysis spans from January 1990 to December 2022.

Figure 12 depicts the impulse responses of the exports of U.S. field crop commodities. Poor harvest shocks reduce U.S. crop availability, leading to a decline in exports. However, over the long term the negative agricultural supply shock moderates and exports recover. Interestingly, soybean exports appear to recover relatively rapidly compared to rice exports. This observation aligns with the fact that the U.S. soybeans are considered a demand inelastic product in the global market, primarily due to the strong demand for U.S. soybeans from China (Adjemian et al., 2019

Figure 12. Impacts on U.S. field crop commodity exports



Notes: The left panel of the figure presents U.S. soybean exports ,which are measured based on estimates provided in the monthly World Agricultural Supply and Demand Estimates (WASDE) reports from January 1990 to December 2022. Similarly, the right panel displays U.S. rice exports, also measured using estimates from the monthly WASDE reports during the same period.

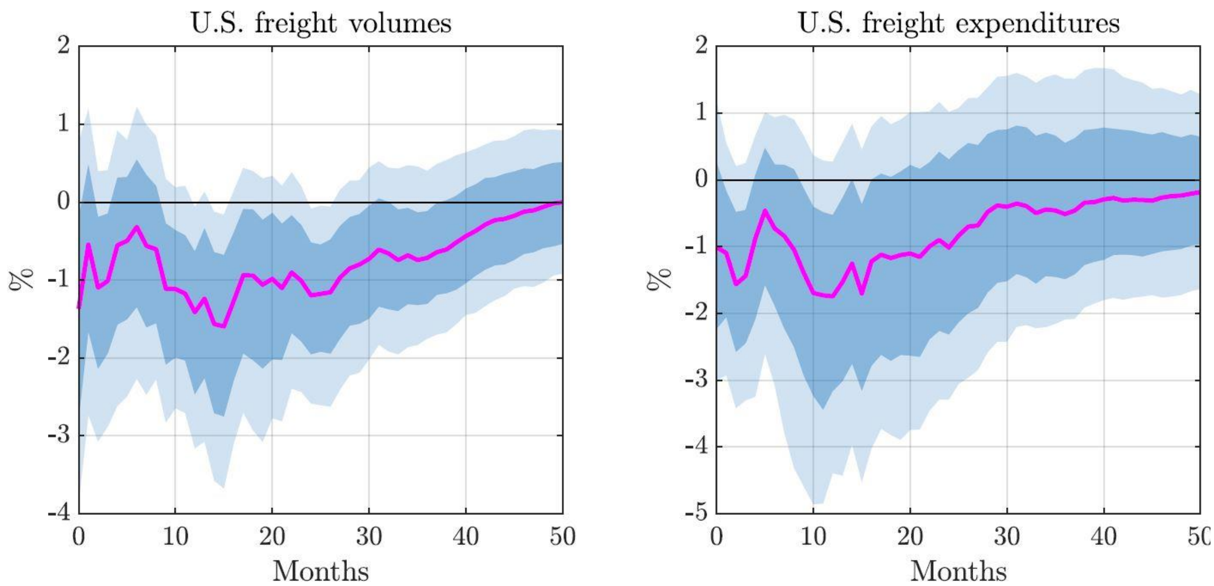
Figure 13 illustrates the impulse responses of freight volumes and expenditures in the United States.[20] The results show that a rise in field crop commodity price leads to a reduction of approximately two percent in both freight volumes and expenditures, although the impact is only statistically significant at a single standard deviation. These findings align with the observed decrease in the BDI we measure in our baseline analysis: a poor harvest news shock diminishes the quantity of U.S. field crops available, consequently leading to decline in freight volume and freight expenditures within the United States.

The agricultural supply news shock does not have a strong influence on U.S. ethanol production and consumption displayed in figure 14. In response to the shock, both variables experience a slight decline about a year after the shock, although the significance of this decline is marginal.[21]

[20] We use the Cass Freight Index to measure freight shipments and expenditures in the United States. This index tracks the number of freight shipments by various transportation modes across North America (Cass Information Systems, 2023).

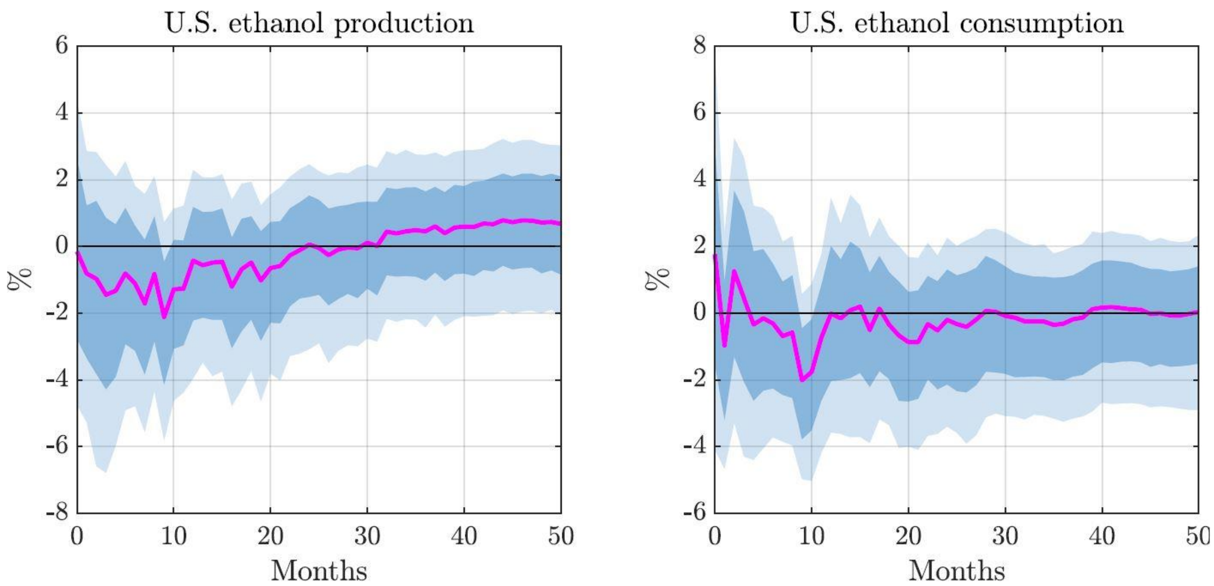
[21] It is important to note that the news shock measured in our study represents a five percent increase in weighted average crop commodity prices. However, if we focus the model only on corn, the effect is stronger, as expected. Specifically, while the shock to (production-weighted) field crops reduces domestic ethanol production by 2.1 percent, the shock specifically on corn leads to a larger reduction of 2.7 percent at the trough. Similarly, concerning ethanol consumption, the model based on the crop news shock leads to a reduction of 2 percent, while the model focusing only on corn generates a more reduction of 2.1 percent at the

Figure 13. Impacts on the domestic supply chain



Notes: In this figure, U.S. freight volumes (left panel) and U.S. freight expenditures (right panel) are measured by the Cass Freight Index. This index tracks the number of freight shipments by various transportation modes in North America. The data used in our analysis spans from January 1990 to December 2022.

Figure 14. Impacts on U.S. ethanol production and consumption



Notes: The left panel of the figure represents U.S. ethanol production, which is measured using the fuel ethanol supply offered by U.S. Department of Energy. The data spans from January 1990 to December 2022. The right panel displays U.S. ethanol consumption, which is measured using the fuel ethanol disappearance provided by U.S. Department of Energy. This data is also available for the period from January 1990 to December 2022. The data regarding U.S. ethanol production and consumption is obtained from the 'Table 3. Fuel ethanol supply and disappearance (1,000 gallons) and grain crushings for

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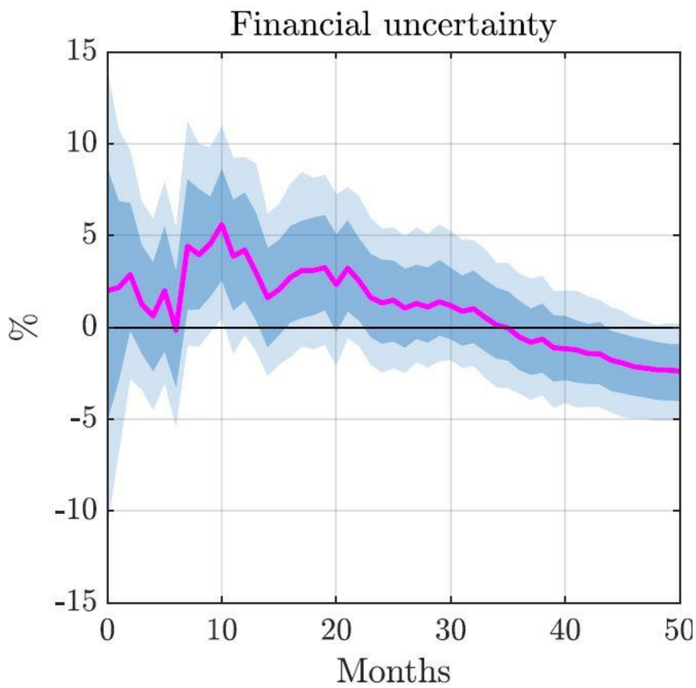
trough (see Appendix E for the figure depicting the impulse responses of ethanol production and consumption to agricultural supply news shock on corn).

fuel alcohol (1,000 bushels) by month' found in the U.S. Bioenergy Tables provided by USDA Economic Research Service (ERS).

Because commodity market news affects output and consumption expectations, poor harvest shocks may also affect uncertainty about macroeconomic conditions. According to Bekaert et al. (2013), the volatility index (VIX) effectively captures both the uncertainty surrounding macroeconomic conditions and the risk aversion.[22,23] The impulse response function we plot in figure 15 indicates that a negative agricultural supply shock calibrated to immediately raise the weighted-average domestic field crop commodity price by five percent likewise increases financial market uncertainty by nearly five percent (at the mean) after about ten months. The effect dissipates over time, as markets adjust.

Figure 15. Impact on financial uncertainty



Notes: The figure represents financial uncertainty, which is measured by the CBOE volatility index. Specifically, we use the closing prices (adjusted for stock splits) on the first day of each month. We then transform the index into its natural logarithm form to estimate the IRFs in log levels. The data covers the period from February 1990 to December 2022 and is obtained from Yahoo Finance.

Conclusion

[22] The CBOE Volatility index is derived from the implied volatilities of options on the S&P 500 equity index (Cboe Global Markets, 2023).

[23] Extant work in agricultural economics, including that of Adjemian et al. (2017) and Cao and Robe (2022), examine how the VIX affects uncertainty about crop commodity prices; our analysis runs searches for crop market effects on the VIX.

We measure agricultural supply news correlated with USDA announcement about existing stocks or anticipated changes to field crop production in the United States, and assess the effects of shocks to the series on both the agricultural sector, and the broader domestic and global economy. 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.

According to our results, poor agricultural news shocks immediately raise the real price of domestic field crop commodities, and eventually reduces domestic industrial production. The average poor news shock also reduces the producer price index for U.S. livestock, possibly through the herd management channel, as livestock producers are sensitive to anticipated higher feed costs (Schulz, 2022), although this price tends to recover over time.

Our results also indicate that poor agricultural supply news lead to a reduction in the quantity of commodities available for export, specifically corn, soybeans, and rice. This is consistent with our findings that the shock reduces the Baltic Dry Index (BDI) level by likely shifting the demand for dry bulk shipments inwards, all else equal. Domestic freight volumes and expenditures likewise fall following the shock. Poor agricultural supply news raises real domestic ethanol prices, but reduces ethanol production and consumption, although the significance of this increase is marginal. This aligns with the fact that corn is a primary component in ethanol production, and corn is only one of the commodities that makes up the production-weighted field crop index. Poor harvest news shocks also lead to an increase in food-at-home prices and a slight decrease in the quantity of food consumers consume at home. Finally, we demonstrate that these shocks may also have broader economic consequences. They contribute (directionally) to an increase in unemployment, fertilizer prices, and financial uncertainty, as measured by the VIX, although the relationships we measure are statistically weaker than our other findings.

We also conduct historical decompositions to examine the contributions of agricultural supply news shocks to U.S. field crop commodity prices and the prices that Americans pay for food consumed at home. We find that while field crop prices are strongly affected by agricultural commodity supply news shocks, retail-level food prices are not. Poor harvest news makes only a very small contribution to retail-level prices. This finding is consistent with the fact that in-store food prices are dominated by processing, packaging, transportation, and marketing costs (USDA, 2022).

We anticipate that the agricultural supply news shock series we extract can provide valuable insights into related inquiries into the agricultural sector and even the macroeconomy. (Indeed, we show that it is uncorrelated to other news shocks, like those for oil supply and monetary policy.) For example, Adjemian et al. (2023) decompose food price inflation into supply- and demand-driven innovations. They show that our poor-agricultural-supply-news shock raises the contribution that the supply side of the market makes to food price inflation.

References

Adjemian, M.K. 2012. “Quantifying the WASDE announcement effect.” *American Journal of Agricultural Economics*, 94(1), pp.238-256. Accessed at: https://onlinelibrary.wiley.com/doi/abs/10.1093/ajae/aar131?casa_token=XFTCoBJmzzkAAAAA:52w64Cy0iRTJ4rfG5l6GmfwqMwY2Brh4DJFpDyfODTHqJn79eZ4RR02BQL1nuNfuXoQHc3ML-_cHI1I

Adjemian, M.K., Bruno, V., Robe, M.A. and Wallen, J. 2017. “What drives volatility expectations in grain and oilseed markets?” *Paper presented at the 2017 Annual Meeting of the Agricultural and Applied Economics Association, July*. Accessed at: https://ageconsearch.umn.edu/record/258452/files/Abstracts_17_05_24_09_18_42_30__199_136_105_95_0.pdf

Adjemian, M.K. and Irwin, S.H. 2018. “USDA announcement effects in real-time.” *American Journal of Agricultural Economics*, 100(4), pp.1151-1171. Accessed at: https://onlinelibrary.wiley.com/doi/abs/10.1093/ajae/aay018?casa_token=kF0d8Gxvbq0AAAAA:9h357MyLCh4gtSUiI0hWtzjDBLxJ1oOz8DIGa2QMwS8dnpt4LCzF_q-U2x95K9EgFxG09aCmpzGaRPs

Adjemian, M.K., Arita, S., Breneman, V., Johansson, R. and Williams, R. 2019. “Tariff Retaliation Weakened the US Soybean Basis.” *Choices*, 34(4), pp.1-9. Accessed at: https://www.jstor.org/stable/27098536?casa_token=Y6Jy5YaMzqQAAAAA%3AG_FXdlFSoaPzdeqF9szKvQjFXw3_CA3XyjvswmNZee-gpaRaHuyUA5Q7lexKl6hHTeqzTxZmjlNi-eMrN-gphSxYWjCl3F2aFceeZT2oLnqMoRAwy_I

Adjemian, M.K. and Irwin, S.H. 2020. “The market response to government crop news under different release regimes.” *Journal of Commodity Markets*, 19, p.100110. Accessed at: https://www.sciencedirect.com/science/article/pii/S2405851319300753?casa_token=Cu50VtqAQfEAAAAA:IlIrF2I_KltykF3fPJW9OIJRHJ96Wo3vnxd3vXwvZqqt-XomjqfkbB39C2ej7nL2J32qlp0MWQ

Adjemian, M. K., Q. Li, and J. Jo. 2023.“Decomposing Food Price Inflation into Supply and Demand Shocks.” Working paper. Accessed at: https://agecon.uga.edu/content/dam/caes-subsite/ag-econ/documents/cvs/Decomposing%20Food%20Price%20Inflation%20into%20Supply%20and%20Demand%20Shocks.pdf

Baumeister, C. and Hamilton, J.D. 2019. "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks." *American Economic Review*, 109(5), pp.1873-1910. Accessed at: https://www.aeaweb.org/articles?id=10.1257/aer.20151569

Bekaert, G., Hoerova, M. and Duca, M.L. 2013. "Risk, uncertainty and monetary policy." *Journal of Monetary Economics*, 60(7), pp.771-788. Accessed at: https://www.sciencedirect.com/science/article/pii/S0304393213000871

Brown, M.B. and Forsythe, A.B. 1974. "Robust tests for the equality of variances." *Journal of the American statistical association*, 69(346), pp.364-367. Accessed at: https://www.tandfonline.com/doi/abs/10.1080/01621459.1974.10482955

Canning, Patrick. *A Revised and Expanded Food Dollar Series: A Better Understanding of Our Food Costs*, ERR-114, U.S. Department of Agriculture, Economic Research Service, February 2011. Accessed at: https://www.ers.usda.gov/publications/pub-details/?pubid=44827

Cao, A.N. and Robe, M.A. 2022. "Market uncertainty and sentiment around USDA announcements." *Journal of Futures Markets*, 42(2), pp.250-275. Accessed at: https://onlinelibrary.wiley.com/doi/full/10.1002/fut.22283

Cao, A.N. and Ionici, Octavian and Robe, Michel A. 2023. "USDA Reports Affect the Stock Market, Too." Available at SSRN: https://ssrn.com/abstract=4391882 or http://dx.doi.org/10.2139/ssrn.4391882

Cass Information Systems, Inc. 2023. The Cass Freight Index: A Measure of North American Activity: Cass Information Systems. Accessed at: https://www.cassinfo.com/freight-audit-payment/cass-transportation-indexes/cass-freight-index

Cboe Global Markets. 2023. Cboe Global Indices: VIX Index Dashboard. Accessed at: https://www.cboe.com/us/indices/dashboard/vix

Dorfman, J.H. and Karali, B. 2015. "A nonparametric search for information effects from USDA reports." *Journal of Agricultural and Resource Economics*, pp.124-143. Accessed at: https://www.jstor.org/stable/44131280?casa_token=YcScBxDJ6joAAAAA:Kdn7H_XUjs67mj9qwtzZ_VEKw_pBUM5H1ulhVqMqXx43XJzSAY9_TKZpFiC4Ut_X3bsAbvVczf_ZMYhNpfuP5Hq0UnNUEyTGvpeuuAOSPDd5_28N7dQ

Fortenbery, T.R. and Sumner, D.A. 1993. “The effects of USDA reports in futures and options markets.” *Journal of Futures Markets*, 13(2), pp.157-173. Accessed at: https://ageconsearch.umn.edu/record/285559/files/confp10-90.pdf

Good, D. 1996. “Change in Weather Drives Corn and Soybean Prices to New Highs.” *farmdoc weekly outlook.* Released Jul. 15th. Accessed at: https://farmdoc.illinois.edu/publications/change-in-weather-drives-corn-and-soybean-prices-to-new-highs

Good, D. 2004. “USDA Crop Reports Provide Many Surprises.” *farmdoc weekly outlook.* Released Jan. 12th. Accessed at: https://farmdoc.illinois.edu/publications/usda-crop-reports-provide-many-surprises

Good, D. 2008. “Where is The Bottom?” *farmdoc weekly outlook.* Released Oct. 13th. Accessed at: https://farmdoc.illinois.edu/publications/where-is-the-bottom

Good, D. 2009. “Corn Acreage Jumps, Stocks are Large.” *farmdoc weekly outlook.* Released Jun. 30th. Accessed at: https://farmdoc.illinois.edu/publications/corn-acreage-jumps-stocks-are-large

Good, D. 2010. “Corn Supply Issues.” *farmdoc weekly outlook.* Released Jul. 6th. Accessed at: https://farmdoc.illinois.edu/publications/corn-supply-issues

Good, D. 2014. "How Burdensome Are Corn Supplies?" *farmdoc daily* (4):130, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, July 14. Accessed at: https://farmdocdaily.illinois.edu/2014/07/how-burdensome-are-corn-supplies.html

Gouel, C. 2020. “The value of public information in storable commodity markets: application to the soybean market.” *American Journal of Agricultural Economics*, 102(3), pp.846-865. Accessed at: https://onlinelibrary.wiley.com/doi/full/10.1002/ajae.12013?casa_token=wMsYHtUa_CsAAAAA%3AmYOc_IBk7Pjw0sDasT7xEt1cMj5kfyTIiash4xjYbIbhGv_mwolEMpwXWLZtxgTZEsD8GsZhz89AK5k

Goyal, R. and Adjemian, M.K. 2021. “The 2019 government shutdown increased uncertainty in major agricultural commodity markets.” *Food Policy*, 102, p.102064. Accessed at: https://www.sciencedirect.com/science/article/pii/S0306919221000415?casa_token=2Hoj1rJ6ob0AAAAA:ATOsxQhEsAa6SKgGkX54m9l7WK_U_NdwyU955DdjZ7fdCBbfmkq68wfNkNTfCmqAAz6w-lIPGw

Harris, L. 2022. “Fertilizer Firms Spread Wealth to Shareholders as Farmers Weather Extreme Prices.” The American Prospect. March 23rd. Accessed at: https://prospect.org/economy/fertilizer-firms-spread-wealth-to-shareholders-farmers-weather-extreme-prices/

Huang, J., Serra, T. and Garcia, P. 2021. “The Value of USDA Announcements in the Electronically Traded Corn Futures Market: A Modified Sufficient Test with Risk Adjustments.” *Journal of Agricultural Economics*, 72(3), pp.712-734. Accessed at: https://onlinelibrary.wiley.com/doi/abs/10.1111/1477-9552.12426?casa_token=8XCZxpvPdvcAAAAA:SbKolqO6x7tiaeAcRuXzgK49Iqzc0KD752zAq4kAT1h7kRMlJJ377KllnqsgkhQ4Xi6ITvoDgtACbg8

Isengildina-Massa, O., Irwin, S.H., Good, D.L. and Gomez, J.K. 2008. “The impact of situation and outlook information in corn and soybean futures markets: Evidence from WASDE reports.” *Journal of Agricultural and Applied Economics*, 40(1), pp.89-103. Accessed at: https://www.cambridge.org/core/journals/journal-of-agricultural-and-applied-economics/article/impact-of-situation-and-outlook-information-in-corn-and-soybean-futures-markets-evidence-from-wasde-reports/C584140E88E03FFB055D4622561132DC

Jordà, Ò. 2005. “Estimation and inference of impulse responses by local projections.” *American economic review*, 95(1), pp.161-182. Accessed at: https://www.aeaweb.org/articles?id=10.1257/0002828053828518

Känzig, D.R. 2021. “The macroeconomic effects of oil supply news: Evidence from OPEC announcements.” *American Economic Review*, 111(4), pp.1092-1125. Accessed at: https://www.aeaweb.org/articles?id=10.1257/aer.20190964

Karali, B., Irwin, S.H. and Isengildina-Massa, O. 2020. “Supply fundamentals and grain futures price movements.” *American Journal of Agricultural Economics*, 102(2), pp.548-568. Accessed at: https://onlinelibrary.wiley.com/doi/full/10.1002/ajae.12012?casa_token=s1qgsN_hjGQAAAAA%3AViu_1mNtZBJ0HHgoaCMcwfT-gA1wQigYbHl4FsOIm5ol4hQTLX2_n-pwLmoGM5SvwDHmTNKTG0ucsFM

Mertens, K. and Ravn, M.O. 2013. “The dynamic effects of personal and corporate income tax changes in the United States.” *American economic review*, 103(4), pp.1212-1247. Accessed at: https://www.aeaweb.org/articles?id=10.1257/aer.103.4.1212

Miranda-Agrippino, S. and Ricco, G. 2023. “Identification with external instruments in structural VARs.” *Journal of Monetary Economics*. Accessed at: https://www.sciencedirect.com/science/article/pii/S0304393223000132?casa_token=L-LyvR1XbHUAAAAA:_MxQgL28uR7FaruF9irb9b5MzpEeMIYZTMffiyjjq_twgQe_zyrUQcqJxMqcHXBo209rYEKIZw

Montiel-Olea, J.L., Stock, J.H. and Watson, M.W. 2016. “Uniform inference in SVARs identified with external instruments.” *Harvard Manuscript*.

Nakamura, E. and Steinsson, J. 2018*a*. “High-frequency identification of monetary non-neutrality: the information effect.” *The Quarterly Journal of Economics*, 133(3), pp.1283-1330. Accessed at: https://academic.oup.com/qje/article-abstract/133/3/1283/4828341

Nakamura, E. and Steinsson, J. 2018*b*. “Identification in macroeconomics.” *Journal of Economic Perspectives*, 32(3), pp.59-86. Accessed at: https://www.aeaweb.org/articles?id=10.1257/jep.32.3.59

Nielsen, R.L. (Bob). 2021. “Grain Test Weight Considerations for Corn.” Corny News Network, Purdue Univ. Accessed at: https://www.agry.purdue.edu/ext/corn/news/timeless/testweight.html

Pindyck, R.S. 2001. “The dynamics of commodity spot and futures markets: a primer.” *The energy journal*, 22(3). Accessed at: https://www.iaee.org/en/publications/download-instant.aspx?id=1364

Ramey, V.A. 2016. “Macroeconomic shocks and their propagation.” *Handbook of macroeconomics*, 2, pp.71-162. Accessed at: https://www.sciencedirect.com/science/article/abs/pii/S1574004816000045

Rigobon, R. 2003. “Identification through heteroskedasticity.” *Review of Economics and Statistics*, 85(4), pp.777-792. Accessed at: https://direct.mit.edu/rest/article-abstract/85/4/777/57415/Identification-Through-Heteroskedasticity

Rigobon, R. and Sack, B. 2004. “The impact of monetary policy on asset prices.” *Journal of monetary economics*, 51(8), pp.1553-1575. Accessed at: https://www.sciencedirect.com/science/article/pii/S0304393204001138?casa_token=N1R1fEJytc0AAAAA:ytAsVjScyeUeMS8lo4OvgNDuX07-tTLTsJzbQZQxzpM8UD3BDqXlGvS1ykntj1ezYeOznloFhA

Schulz, L. 2022. "Detailing the supply curve for beef." Ag Decision Maker. May 22nd. Accessed at: https://www.extension.iastate.edu/agdm/articles/schulz/SchMay22.html

Stock, J.H., Wright, J.H. and Yogo, M. 2002. "A survey of weak instruments and weak identification in generalized method of moments." *Journal of Business & Economic Statistics*, 20(4), pp.518-529. Accessed at: https://www.tandfonline.com/doi/abs/10.1198/073500102288618658

Stock, J.H. and Watson, M.W. 2012. "Disentangling the Channels of the 2007-2009 Recession (No. w18094)." *Brookings Papers on Economic Activity*. Accessed at: https://collaborate.princeton.edu/en/publications/disentangling-the-channels-of-the-2007-09-recession

Stock, J.H. and Watson, M.W. 2018. "Identification and estimation of dynamic causal effects in macroeconomics using external instruments." *The Economic Journal*, 128(610), pp.917-948. Accessed at: https://academic.oup.com/ej/article/128/610/917/5069563

Sumner, D.A. and Mueller, R.A. 1989. "Are harvest forecasts news? USDA announcements and futures market reactions." *American Journal of Agricultural Economics*, 71(1), pp.1-8. Accessed at: https://onlinelibrary.wiley.com/doi/abs/10.2307/1241769

USDA, Economic Research Service. 2015. *U.S. Drought 2012: Farm and Food Impacts*. Accessed at: https://drought.unl.edu/archive/assessments/USDA-ERS-2012-farm-food-impacts.pdf

USDA, Economic Research Service. 2022. *Food dollar real data*. Updated Nov. 17th. Accessed at: https://www.ers.usda.gov/data-products/food-dollar-series/download-the-data/

USDA Office of the Chief Economist. 2009*b*. "Acreage." Released Jun. 30. Accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/j098zb09z/n296x138b/7h149r817/Acre-06-30-2009.pdf

USDA Office of the Chief Economist. 2008. "World Agricultural Supply and Demand Estimates (WASDE)." Released Oct. 10. Accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/bc386j52m/zc77sq44s/wasde-10-10-2008.pdf

USDA Office of the Chief Economist. 2009*a*. "World Agricultural Supply and Demand Estimates (WASDE)." Released Jan. 12. Accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/t148fh48x/79407x60h/wasde-01-12-2009.pdf

USDA Office of the Chief Economist. 2010. “World Agricultural Supply and Demand Estimates (WASDE).” Released Jun. 10. Accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/3t945q76s/j098zb41q/b8515n719/wasde-06-10-2010.pdf

USDA Office of the Chief Economist. 2009*b*. “Grain Stocks.” Released Jun. 30. Accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/xg94hp534/5m60qt78h/8910jw560/GraiStoc-06-30-2009.pdf

USDA Office of the Chief Economist. 2021. “Grain Stocks.” Released Jun. 30. Accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/xg94hp534/pz50ht47k/0g355c356/grst0621.pdf

USDA Office of the Chief Economist. 1994. “Grain Stocks.” Released Jun. 30. Accessed at: https://downloads.usda.library.cornell.edu/usda-esmis/files/xg94hp534/5999n526d/j3860892s/GraiStoc-06-30-1994.pdf

U.S. Department of Agriculture (USDA), Economic Research Service (ERS). November 2022. Food Dollar Series. Accessed at: https://www.ers.usda.gov/data-products/food-dollar-series/documentation.aspx#:~:text=For%20calendar%20year%202021%2C%20the,remainder%20of%20the%20food%20dollar.

U.S. Department of Agriculture (USDA), Economic Research Service (ERS). June 2023. U.S. Rice Exports. Accessed at: https://www.ers.usda.gov/topics/crops/rice/rice-sector-at-a-glance/

Westcott, P.C. and Young, C.E. 2004. “Farm program effects on agricultural production: coupled and decoupled programs.” *Burfisher, M. and Hopkins, J., Editors*. Accessed at: https://www.ers.usda.gov/webdocs/publications/41708/30381_aer838b_002.pdf?v=5870.4

Ying, J., Chen, Y. and Dorfman, J.H. 2019. “Flexible tests for USDA report announcement effects in futures markets.” *American Journal of Agricultural Economics*, 101(4), pp.1228-1246. Accessed at: https://onlinelibrary.wiley.com/doi/abs/10.1093/ajae/aaz013?casa_token=_EyjZ9iNCBAAAAAA:xDKyDrP13_vs1wDHBMUbGiUH5sOQbcS1Kp7qAlHCp8aGyMyEZoggmRJURevMY9b_aYmiIcrvR4gR5NY

Appendix

A. Historical series of USDA supply surprises for individual field crop commodities in the United States

Figure A.1. Historical series of USDA supply surprises for corn, 1990-2022

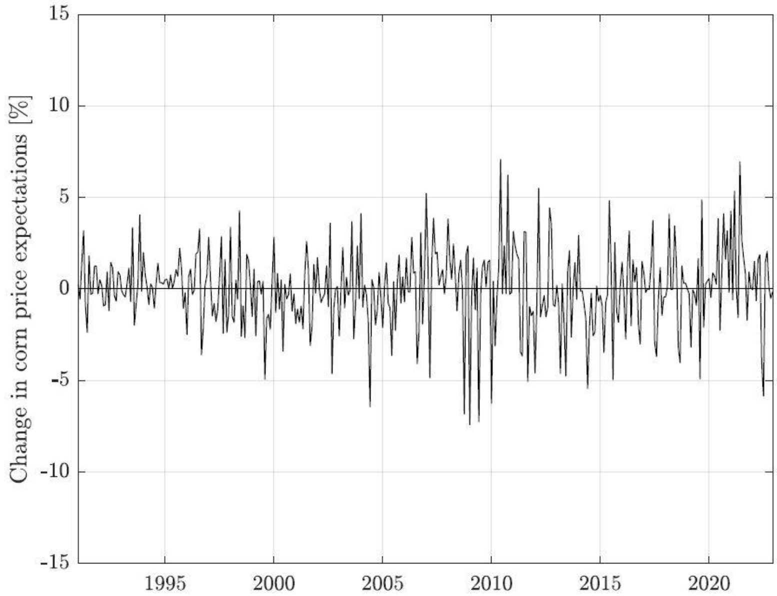


Figure A.2. Historical series of USDA supply surprises for oats, 1990-2022

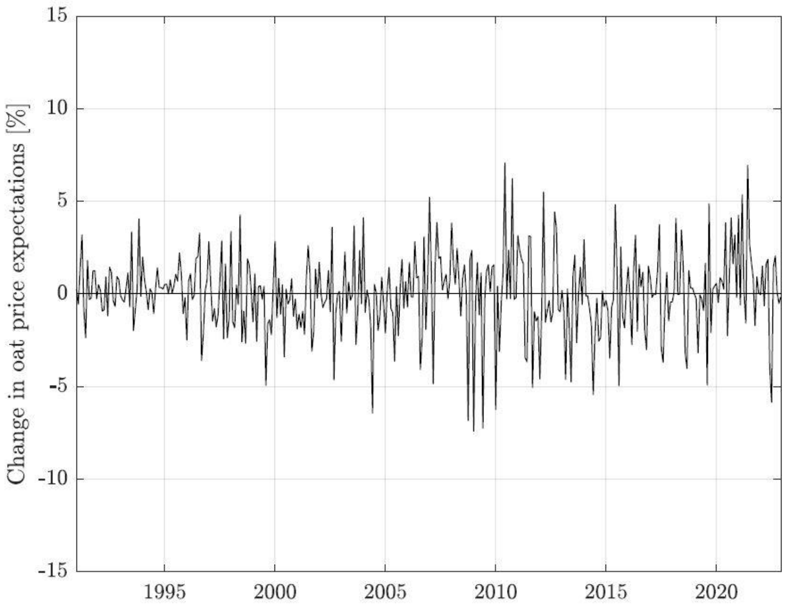


Figure A.3. Historical series of USDA supply surprises for rice, 1990-2022

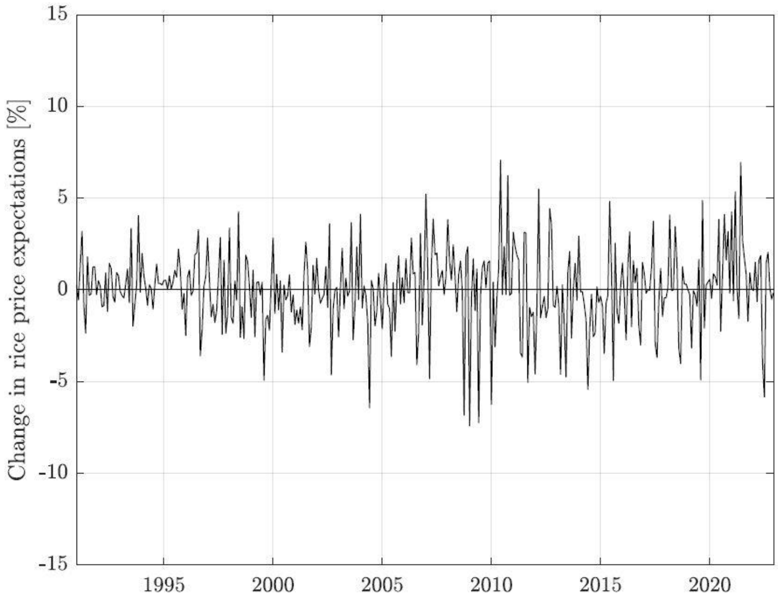


Figure A.4. Historical series of USDA supply surprises for soybeans, 1990-2022

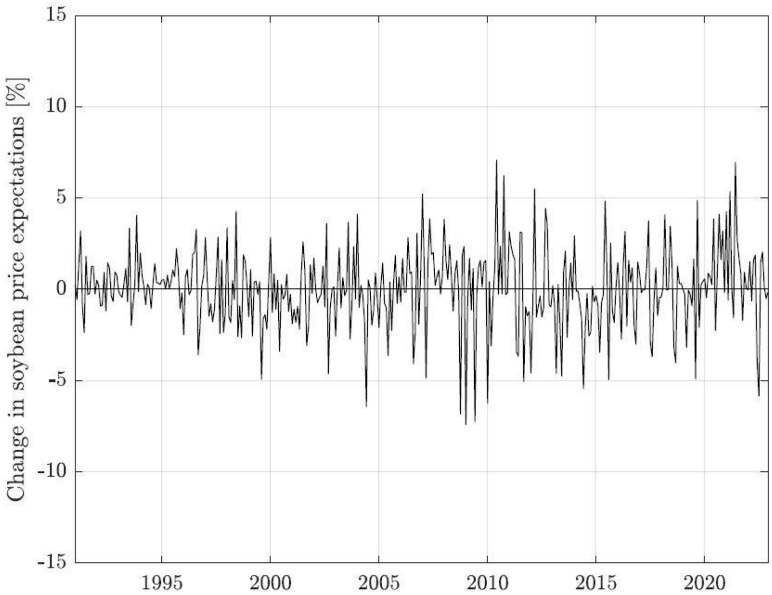
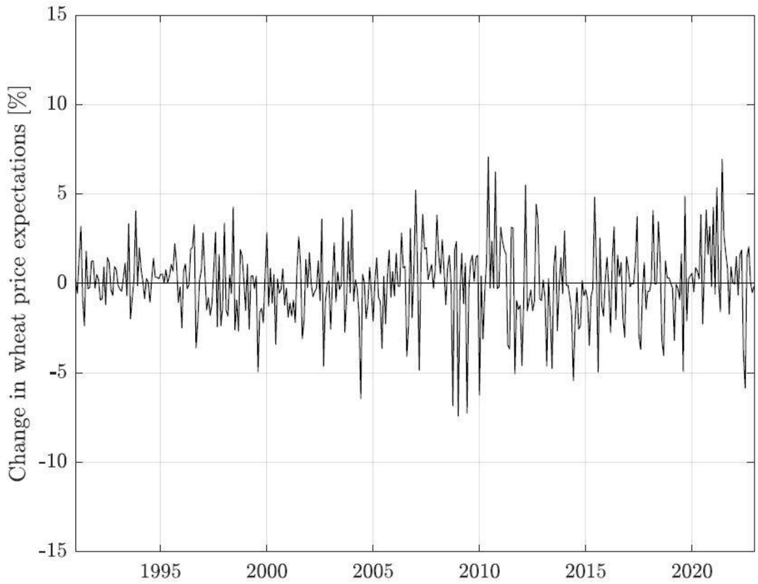


Figure A.5. Historical series of USDA supply surprises for wheat, 1990-2022



B. A comparison of USDA announcement versus control days for individual commodities

Figure B.1. Comparing the USDA announcement to control days for corn

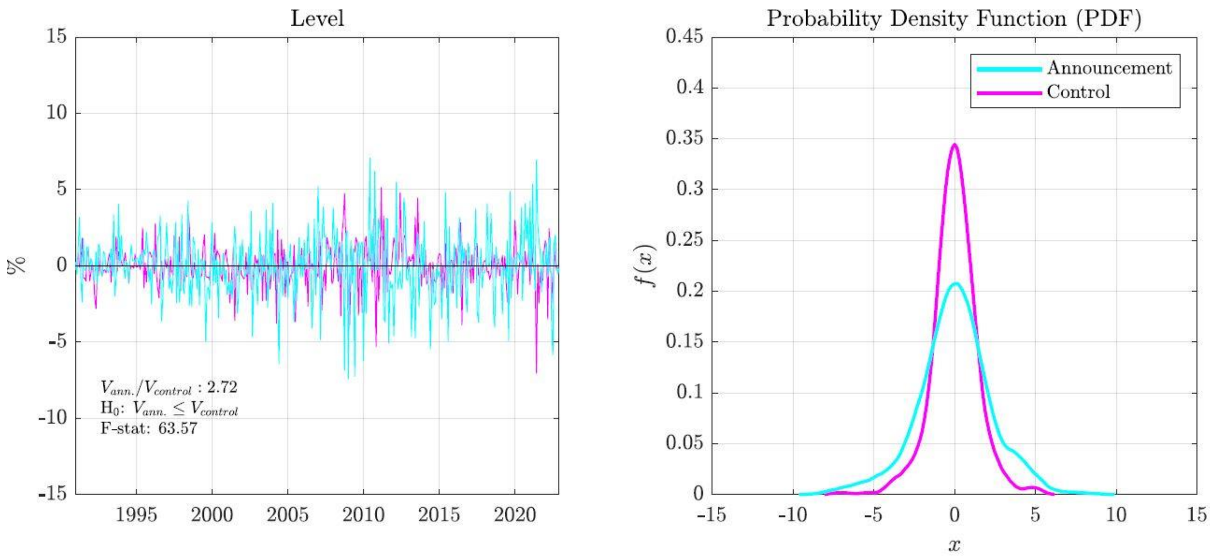


Figure B.2. Comparing the USDA announcement to control days for oats

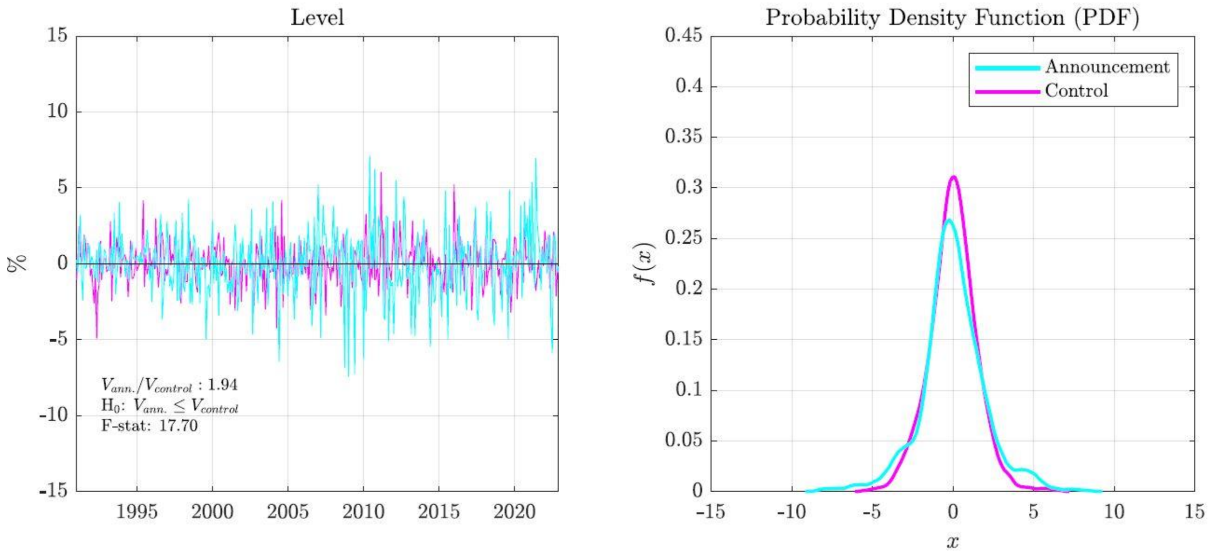


Figure B.3. Comparing the USDA announcement to control days for rice

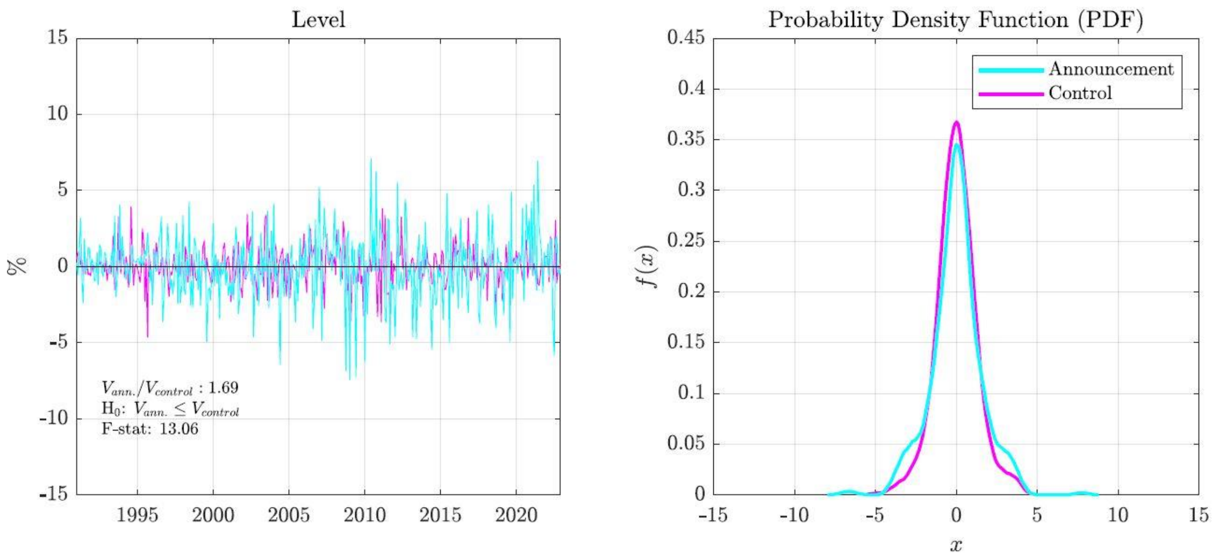


Figure B.4. Comparing the USDA announcement to control days for soybeans

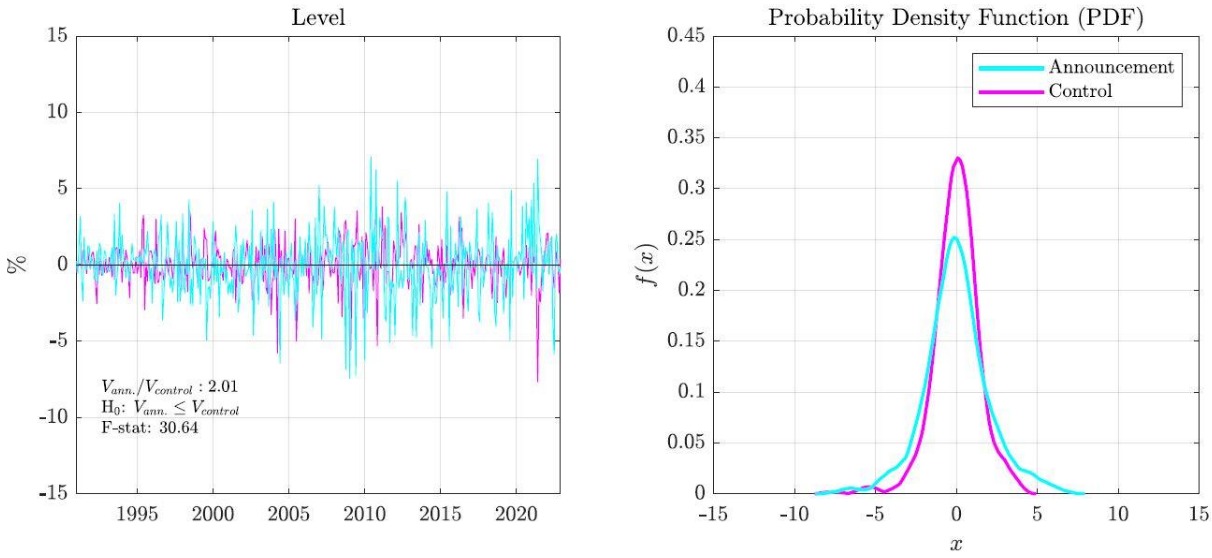
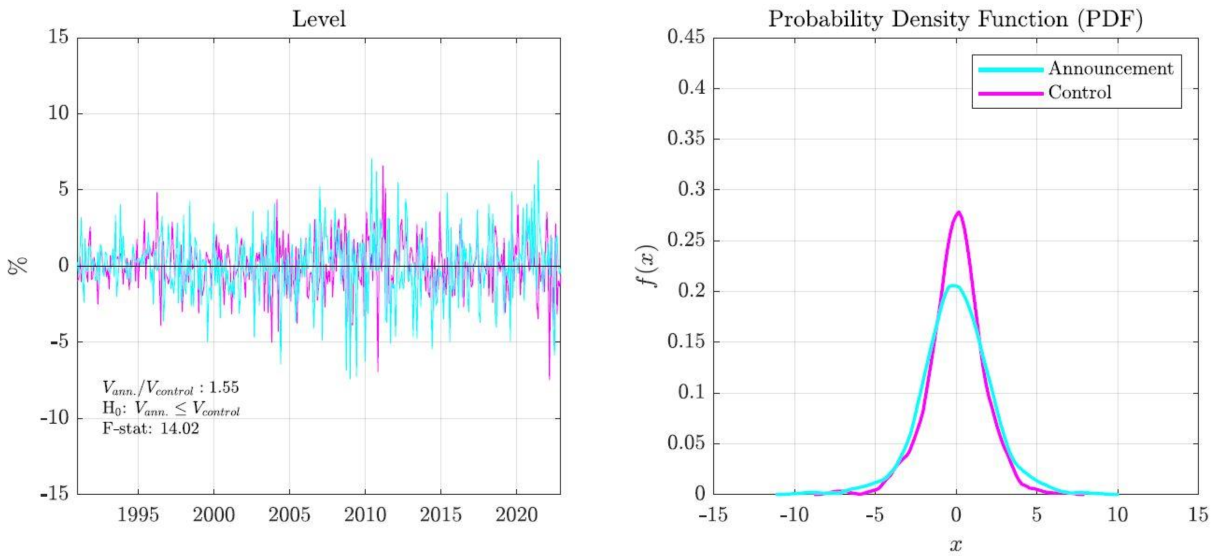


Figure B.5. Comparing the USDA announcement to control days for wheat



C. F-test results for individual commodities

Table C.1. F-test results for corn

	Front	First def.	Second def.	Third def.	Fourth def.	Comp.
Coefficient	0.237	0.252	0.233	0.247	0.247	0.247
F-statistic	17.43	19.05	15.12	15.19	12.79	16.37
Robust F-statistic	15.39	17.58	14.58	14.67	12.26	15.55
R^2	4.36	4.75	3.81	3.82	3.24	4.11
Adjusted R^2	4.11	4.50	3.56	3.57	2.99	3.86
Observations	384	384	384	384	384	384

Table C.2. F-test results for oats

	Front	First def.	Second def.	Third def.	Fourth def.	Comp.
Coefficient	0.144	0.190	0.216	0.237	0.152	0.202
F-statistic	5.66	7.93	9.13	9.99	3.66	8.37
Robust F-statistic	4.10	5.36	6.22	7.32	2.62	5.75
R^2	1.46	2.03	2.33	2.55	0.95	2.15
Adjusted R^2	1.20	1.78	2.08	2.29	0.69	1.89
Observations	384	384	384	384	384	384

Table C.3. F-test results for rice

	Front	First def.	Second def.	Third def.	Fourth def.	Comp.
Coefficient	0.064	0.061	0.076	0.049	0.041	0.057
F-statistic	0.76	0.54	0.69	0.24	0.14	0.41
Robust F-statistic	0.50	0.46	0.53	0.20	0.11	0.34
R^2	0.20	0.14	0.18	0.06	0.04	0.11
Adjusted R^2	-0.06	-0.12	-0.08	-0.20	-0.22	-0.16
Observations	384	384	384	384	384	384

Table C.4. F-test results for soybeans

	Front	First def.	Second def.	Third def.	Fourth def.	Comp.
Coefficient	0.270	0.281	0.279	0.262	0.269	0.275
F-statistic	15.77	17.03	17.26	14.38	14.35	16.02
Robust F-statistic	15.28	16.66	17.18	14.44	14.25	15.69
R^2	3.97	4.27	4.32	3.63	3.62	4.02
Adjusted R^2	3.71	4.02	4.07	3.38	3.37	3.77
Observations	384	384	384	384	384	384

Table C.5. F-test results for wheat

	Front	First def.	Second def.	Third def.	Fourth def.	Comp.
Coefficient	0.089	0.091	0.101	0.147	0.143	0.108
F-statistic	2.14	2.03	2.26	4.17	3.70	2.58
Robust F-statistic	2.14	1.90	2.22	3.93	3.45	2.61
R^2	0.56	0.53	0.59	1.08	0.96	0.67
Adjusted R^2	0.30	0.27	0.33	0.82	0.70	0.41
Observations	384	384	384	384	384	384

D. Data

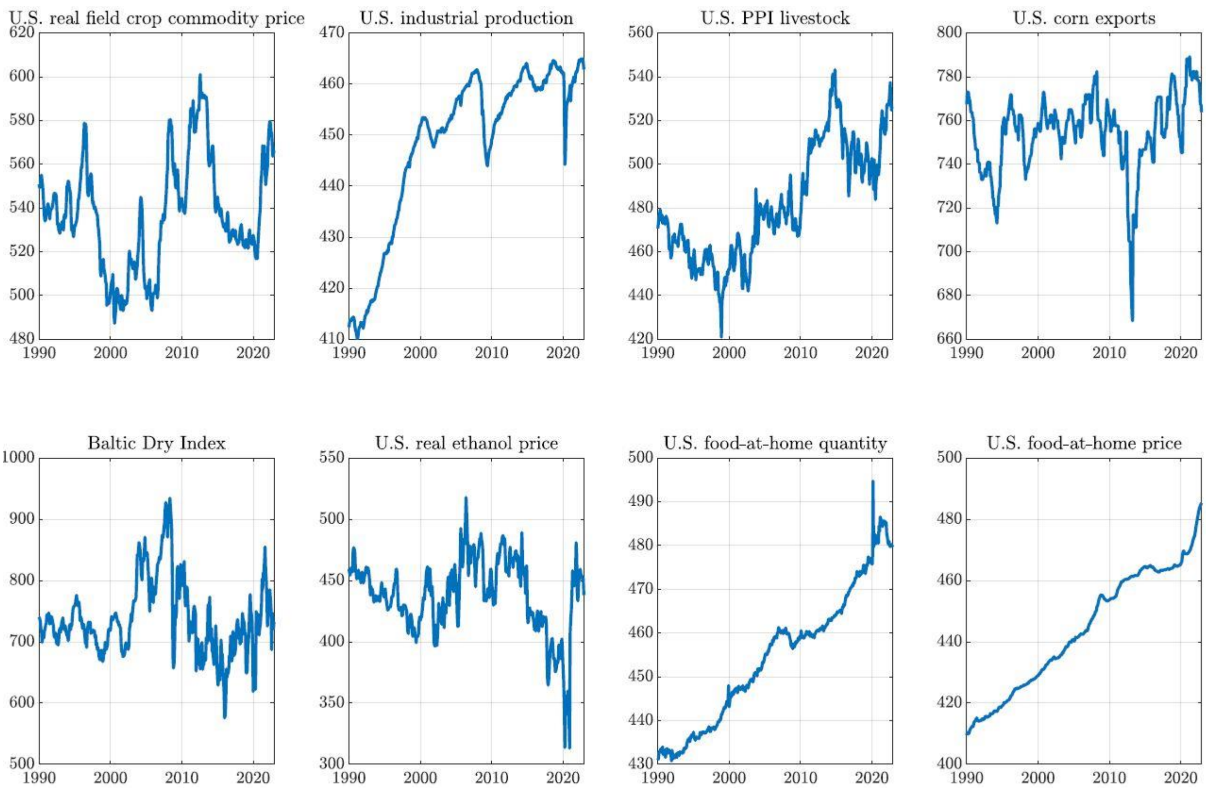
Table D.1. Data description for baseline variables

Variable	Description
U.S. real field crop commodity price	U.S. field crop commodity price (production-weighted) deflated by U.S. Consumer Price Index (CPI)
U.S. industrial production	The real output of manufacturing, mining, and electric and gas utilities in the United States (INDPRO)
U.S. PPI for livestock	Producer price index for livestock in the United States (WPS013)
U.S. corn exports	U.S. corn exports (million bushels)
Baltic Dry Index (BDI)	A financial index that measures the expenses associated with shipping various raw materials, including iron ore, coal, grain, and other bulk commodities, through maritime channels
U.S. real ethanol price	U.S. ethanol price deflated by U.S. Consumer Price Index (CPI)
U.S. food-at-home quantity	Real personal consumption expenditures for food (chain-type quantity index)
U.S. food-at-home price	Personal consumption expenditures for food (chain-type price index)

Table D.2. Data sources and sample period for baseline variables

Variable	Source	Sample period
U.S. real field crop commodity price	USDA National Agricultural Statistics Service Information (NASS) & authors' own calculations	1990M01 - 2022M12
U.S. industrial production	Federal Reserve Economic Data (FRED)	1990M01 - 2022M12
U.S. PPI for livestock	Federal Reserve Economic Data (FRED)	1990M01 - 2022M12
U.S. corn exports	Bloomberg terminal	1990M01 - 2022M12
Baltic Dry Index (BDI)	Bloomberg terminal	1990M01 - 2022M12
U.S. real ethanol price	USDA Economic Research Service (ERS)	1990M01 - 2022M12
U.S. food-at-home quantity	Bureau of Economic Analysis (BEA)	1990M01 - 2022M12
U.S. food-at-home price	Bureau of Economic Analysis (BEA)	1990M01 - 2022M12

Figure D.1. A series of data in the baseline VAR model, 1990-2022



Notes: All variables depicted in the figure are transformed into natural logarithms.

E. Impulse responses of U.S. ethanol production and consumption to agricultural supply news shock to corn