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The Distributional Consequences of Agricultural Supply News Shocks: Food Prices and Household Welfare[†]

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Abstract

Identifying the causal effect of agricultural production conditions on food prices is challenging because commodity prices respond simultaneously to supply and demand shocks. Exploiting high-frequency field crop futures prices and USDA crop reports, we estimate impacts of agricultural supply news shocks on food markets. A poor harvest news shock that raises field crop prices leads to an increase in food-at-home and food service prices, a decline in food expenditures. Using household-level food price indexes constructed across income quintiles, we find that welfare losses are approximately seven times larger for the lowest-income quintile than for the highest. Counterfactual simulations indicate that, without these shocks, U.S. food inflation during 2021-23 would have peaked up to 1.9 percentage points lower.

Keywords: agricultural commodity prices; food inflation; USDA news; high-frequency identification; SVAR; distributional effects; household welfare

JEL classification: Q11, E31, D12, Q18.

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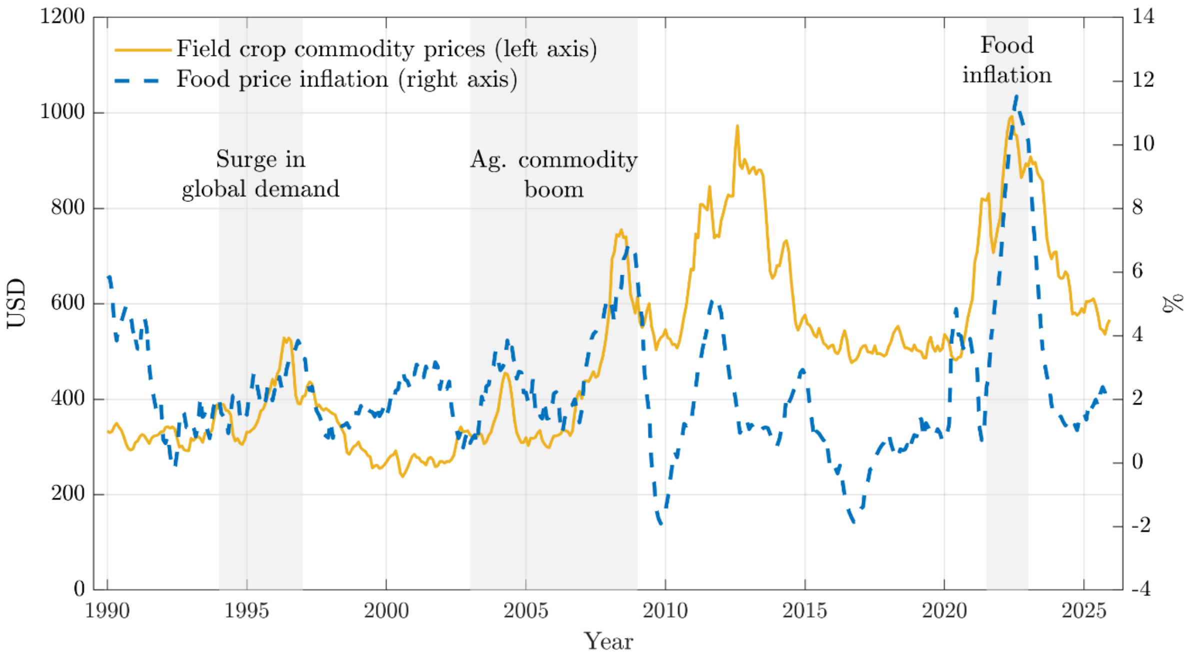
1. Introduction

Field crop prices and food price inflation have moved together throughout the past three decades. The farm share of retail food prices in the United States, however, is now modest. According to the Economic Research Service, the farm share of the U.S. food dollar was around 14 percent in 2023, and the farm share of food-at-home spending was approximately 22 percent (USDA ERS, 2026). Costs of labor, energy, packaging, and transportation dominate what consumers pay at the store. Despite these declining direct linkages, episodes of agricultural commodity volatility continue to be closely associated with food inflation. Figure 1 illustrates that the three major U.S. food inflation episodes of the pass three decades coincided with sharp upward movements in agricultural commodity prices: the surge in emerging-market demand combined with three consecutive poor harvests in the mid-1990s, the agricultural commodity boom of the mid-2000s, and the post-pandemic period of 2021-2023. Several pass-through channels can sustain this association even as the farm share falls: 1) direct cost pass-through from raw commodities to processed products such as cereals, bakery items, fats and oils, and animal-derived foods; 2) indirect channels operating through energy and labor inputs that themselves co-move with agricultural commodities; and 3) second-round currency channels in which a poor U.S. harvest depresses the dollar, raising the local-currency cost of imported food, fertilizer, and energy (Peersman, 2022).

Figure 1. Historical field crop commodity prices and food price inflation (yoy), 1990-2025



Source: USDA National Agricultural Statistics Service (NASS), Bureau of Economic Analysis (BEA), and authors' calculations

Notes: The solid mustard line plots a production-weighted index of field crop spot prices (left axis, USD); the dashed blue line plots year-over-year food price inflation (right axis, percent). Shaded periods denote three major commodity-driven food inflation episodes.

Food price increases impose costs across the income distribution. Food is a non-discretionary expense for nearly all households and is purchased more frequently than almost any other good, so sustained food price increases reduce real consumption and feature prominently in the formation of household inflation expectations (D'Acunto et al., 2021). When food prices rise, households facing nominal budget constraints reduce real spending on other categories. These costs also fall unevenly across the income distribution. Food expenditure shares decline sharply with income. The lowest income quintile in the United States spends around 33 percent of after-tax income to food, a far larger share than higher-income households. Lower-income households are also less able to substitute toward cheaper alternatives or to absorb temporary cost shocks (Cravino, Lan, and Levchenko, 2020; Davidenko and Sweitzer, 2024). The welfare burden of any given food price increase therefore falls hardest on the households least equipped to bear it. Whether different income groups also face heterogeneous price exposure—for example, because they consumer different baskets of food—is a separate question that has received less attention.

Yet the causal contribution of agricultural production conditions to food price changes has not been credibly identified. Two challenges stand in the way. First, commodity prices reflect demand as well as supply. Weather, pests, and crop disease drive field crop production, but rising incomes, increases in field crop demand (e.g., biofuel mandates), and global trade conditions move commodity prices at the same time, so observed price movements cannot be attributed to supply alone. Second, food and commodity prices feed back into each other. Strong food demand pushes commodity prices up, and futures markets price in expected food demand, so even isolated commodity price movements have an ambiguous causal direction with respect to food prices. Identifying the food price effect of agricultural supply therefore requires exogenous variation in commodity prices that is driven purely by supply-side news.

Our paper aims to provide new causal evidence on the dynamic effects of agricultural supply news on food markets and their distributional consequences across U.S. households. Building on Adjemian and Jo (2025), we construct a high-frequency series of agricultural supply news from daily field crop futures price changes around USDA crop production report releases. We embed this news series as an external instrument in a structural vector autoregression (IV-SVAR) model (Stock and Watson, 2012; Mertens and Ravn, 2013) to estimate their impact on food markets.

A negative supply news shock that raises field crop prices by three percent on impact also raises animal feed prices, food-at-home prices, and food service prices significantly. The peak response in the food-at-home price index—approximately 0.3 percent—is broadly consistent with the pass-through implied by the farm share of food-at-home spending. Within food-at-home basket, the shock the largest responses appear in cereals and bakery products, meats and poultry, and fats and oils, components that are most directly linked to field crops and their growing conditions. The dollar depreciates and oil prices rise, consistent with second-round mechanisms that amplify the shock. Consumer inflation expectations rise by approximately 12 basis points after six months. Counterfactual simulations indicate that food inflation during 2021-2023 would have peaked up to 1.9 percentage points lower in the absence of agricultural supply news shocks.

Distributionally, our income-quintile food price indexes reveal that price exposure to a poor harvest news shock is nearly uniform across income groups for food-at-home, but more pronounced in lower-income quintiles for food service. Yet, the welfare consequences differ sharply. Because the budget share devoted to food is far larger for lower-income households than for high-income households (37.7 percent vs. 7.6 percent of after-tax income), the same percentage food price increase is roughly five times more painful, in welfare terms, for the lowest-income household than for the highest. Combined with the larger price exposure low-income households face in food service, the total welfare cost of an agricultural supply news shock is around seven times higher for the lowest income group than for the highest.

Our work relates most directly to a small but growing literature that uses high-frequency identification methods to study commodity- and policy-driven shocks in macroeconomics. Existing work has applied this approach to monetary policy news (Kuttner, 2001; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Bauer and Swanson, 2023, among others), oil supply news (Känzig, 2021), Treasury supply news (Phillot, 2025), USDA supply news (Adjemian and Jo, 2025). Within agricultural economics, an extensive literature documents that USDA reports systematically move commodity futures prices and volatility (Sumner and Mueller, 1989; Isengildina-Massa et al., 2008; Adjemian, 2012; Lehecka, Wang, and Garcia, 2014; Adjemian and Irwin, 2018; Karali, Isengildina-Massa, and Irwin, 2020; Cao and Robe, 2022). More recent work has extended the analysis to the equity prices of agricultural firms (Cao et al., 2024) and to broader macroeconomic indicators (Adjemian and Jo, 2025).

Our approach to identifying the food price effects of harvest shocks differs from two recent papers addressing related questions. Peersman (2022) constructs a global harvest shock index from production residuals and finds that harvest shocks account for nearly one-third of harmonized index of consumer prices (HICP) volatility in Europe. Scott et al. (2025) use drought exposure as an instrument and find positive but imprecisely estimated the effects of drought exposure shocks on U.S. food-at-home prices. Both ex-post measures capture realized supply outcomes. Our news-based instrument captures market expectations updated in real time at multiple points throughout the crop year, before physical production changes are realized; it also captures the full set of supply-side determinants reflected in USDA reports—weather, pests, crop disease, and policy. In addition, by constructing income-group price indexes following Jaravel (2026), we extend this literature to ask not only how much food prices response, but how much each segment of the income distribution loses from a given shock.

The remainder of the paper is organized as follows. Section 2 describes the construction of our agricultural supply news series and presents validations tests. Section 3 lays out our empirical strategy. Section 4 reports baseline impulse responses, while Section 5 documents wider effects on food subcategories, quantities, and inflation expectations. Section 6 develops distributional analysis. Section 7 reports counterfactual simulations of the role of agricultural supply news in recent food inflation. Section 8 concludes with the conclusions.

2. Identifying Agricultural Supply News

2.1. Institutional setting

USDA has produced systematic crop condition reports continuously since 1863. Today, USDA agencies, primarily the National Agricultural Statistics Service (NASS) and the World Agricultural Outlook Board (WAOB), publish nearly five hundred reports each year, ranging from weekly Crop Progress updates to detailed monthly forecasts of supply, use, and prices. We focus on the subset or reports that are most market-relevant and most clearly oriented toward supply.

The monthly World Agricultural Supply and Demand Estimates (WASDE) report, the monthly Crop Production report that is released jointly with WASDE, the Prospective Plantings and Acreage reports, and the Small Grains Summary together account for the bulk of crop-specific supply information released by USDA each year. These reports are prepared under strict lockup conditions, in which final calculations and revisions are conducted in a secure facility without external communication. They are released simultaneously to all market participants at 12:00 p.m. Eastern Time on a fixed schedule. Crop Production and WASDE are released between the ninth and twelfth calendar day of each month. The combination of fixed timing, lockup conditions, and simultaneous release to all participants ensures that the contents of each report are exogenous to market participants at the moment of release. Any post-release price movement reflects the incorporation of new information rather than gradual revelation.

We focus on supply-oriented content, specifically crop production forecasts, planted and harvested acreage estimates, and yield projections, because these are the components most plausibly driven by exogenous shocks to weather, pests, disease, and short-run policy decisions. We exclude price movements on the announcement days of inventory reports such as Grain Stocks, because these reports release information about both supply-side and demand-side determinants—particularly realized usage—and would therefore contaminate a pure supply instrument.

2.2. Constructing the supply news series

Following Adjemian and Jo (2025), we measure USDA supply news as the change in field crop futures prices on USDA report release days. Specifically, for each commodity $i \in$ {corn, oats, rice, soybeans, wheat}, futures expiration $h \in$ {nearby, first deferred, second deferred, third deferred, fourth deferred}, and announcement date (t, d), we compute

$$USDA\ Supply\ News_{t,d,i}^{h} = 100 \times [lnF_{t,d,i}^{h} - lnF_{t,d-1,i}^{h}], \quad (1)$$

where $F_{t,d,i}^{h}$ denotes the settlement price of futures contract h for commodity i on trading day d in month t. Computing log changes between the announcement-day settlement and the prior-day settlement narrows the measurement window to a single trading day around the release, minimizing contamination from unrelated news.

We aggregate across futures maturities for each commodity using the first principal component of the five maturity-specific surprises, which captures the common variation across maturities. We then aggregate across the five field crops using their annual production shares $S_{y,i}$:

$$USDA\ Supply\ News_{t,d}^{h} = \textstyle\sum_i USDA\ Supply\ News_{t,d,i}^{h} \times S_{y,i}. \quad (2)$$

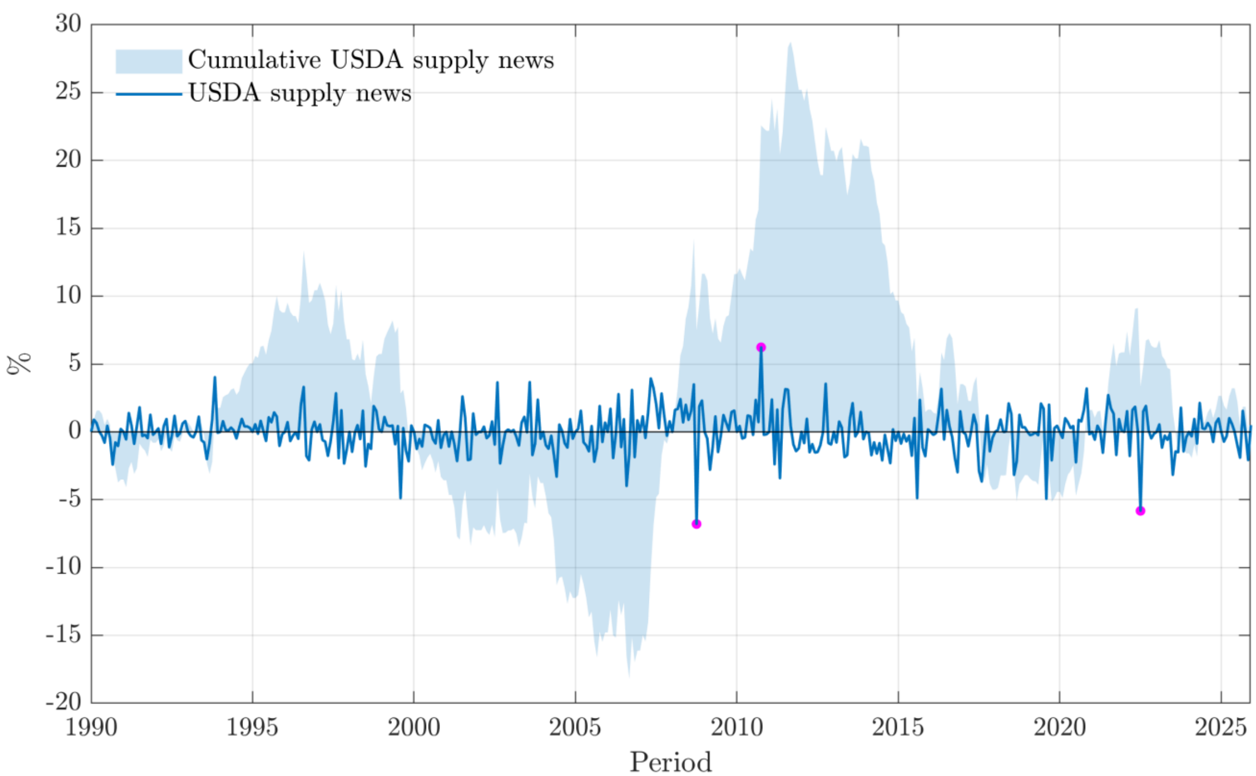
Finally, we collapse the daily news series into a monthly series. For most months, the monthly observation equals the surprise on the single qualifying announcement day. In January, the WASDE report is released on the same day as the Grain Stocks report, so we exclude this announcement from our supply news series. In addition, the October WASDE and Crop Production reports were not published in 2013 and 2015 because of federal government funding disruptions; the corresponding observations are therefore set to zero. By convention, positive realizations indicate negative supply news—a worse-than-expected crop and upward price surprise—and negative realizations indicate positive supply news (a better-than-expected crop and downward price surprise).

As a diagnostic check on the relevance of USDA reports for futures markets, we compare the variance of field crop futures price changes on announcement days to their variance on control days, defined as the same weekday one week after each announcement. Field crop futures price variance is approximately forty percent higher on USDA announcement days than on control days, indicating that USDA reports systematically inject substantial new information into futures markets. Announcement day variance exceeds control day variance by more than forty percent for corn, oats, rice, and soybeans. By contrast, the variance ratio for wheat indicates no announcement day variance premium. The results for each commodity are provided in Appendix Table B.1.

2.3. Narrative validation

The constructed series can be validated against well-known historical episodes. Figure 2 plots the monthly supply news series and its cumulative sum from January 1990 through December 202. Three episodes illustrate the series. In October 2008, USDA raised its corn production forecast by 128 million bushels and its soybean production forecast by 49 million bushels relative to the September WASDE (USDA, 2008); the series correspondingly registers a large negative reading consistent with downward price pressure (positive supply news). In October 2010, USDA cut its corn forecast by 496 million bushels (a 6.7 bushel-per-acre yield reduction), the largest September-to-October yield revision on record at the time (USDA, 2010); our series registers a sharp positive reading. In July 2022, USDA revised wheat production up by 44 million bushels and corn production up by 45 million bushels relative to the June Acreage report (USDA, 2022), and our series shows a negative reading. These narrative checks confirm that the series captures both the direction and rough magnitude of supply news contained in USDA reports.

Figure 2. USDA agricultural supply news series, 1990-2025



Source: Bloomberg terminal, USDA National Agricultural Statistics Service (NASS), and authors' calculations
Notes: The solid line plots the monthly supply news series; the shaded area plots its cumulative sum. Highlighted points correspond to October 2008, October 2010, and July 2022 narrative episodes discussed in the text. The news series is constructed as the first principal component of changes in U.S. agricultural commodity futures prices (relative to their share of domestic production).

2.4. Diagnostic tests

We perform two diagnostic tests to confirm the properties required for use of the series as an external instrument. First, the series is approximately serially uncorrelated. Sample autocorrelations at lags one through twenty are statistically indistinguishable from zero at conventional significance levels (Appendix Figure B.1). This is consistent with USDA supply news being an innovation rather than a persistent component.

Recent macroeconomic research has raised questions about the predictability of high-frequency monetary policy surprises, showing that they may be correlated with other economic news released before FOMC announcements (Cieslak, 2018; Miranda-Agrippino and Ricco, 2021), challenging their interpretation as primitive exogenous shocks and potentially biasing estimates of their dynamic effects (Känzig, 2023). Following Bauer and Swanson (2023*a,b*), we estimate predictive regressions of the form

$$USDA\ Supply\ News_t = \alpha + \beta' X_{t-} + \varepsilon_t, \tag{3}$$

where X_{t-} contains the three-month change in six predictors: the S&P 500 index, the slope of the U.S. Treasury yield curve, broad commodity and agricultural commodity price indexes, the Baltic Dry Index, and the Geopolitical Risk Index of Caldara and Iacoviello (2022). ε_t is the residual term.

Table 1 reports predictive regressions of the USDA news series on lagged financial, commodity, and macroeconomic variables. Across all specifications, no individual predictor is statistically significant at the five percent level, and adjusted R-squared values do not exceed one percent. The yield curve slope coefficient has the largest t-statistic in absolute value ($t \approx 1.87$ in column 1), but does not reach conventional significance and shrinks further once commodity controls are included. Granger causality tests over the variables in our baseline VAR confirm that supply news is not predictable from past values of these variables (Appendix Table B.2). We interpret these results as supporting the exogeneity of our news series with respect to non-USDA economic information.

Table 1. Predictive regressions of USDA supply news on lagged financial, commodity, and macroeconomic variables

USDA supply news	(1) Financials	(2) Commodities	(3) Others
Δ S&P 500	-0.033 (0.081)	-0.024 (0.082)	0.000 (0.082)
Δ Yield curve slope	1.950 (1.042)	1.745 (1.080)	1.695 (1.086)
Δ Comm. price		0.101 (0.159)	0.099 (0.158)
Δ Ag. Comm. price		-0.046 (1.264)	0.264 (1.312)
Δ Baltic Dry Index			0.799 (1.096)
Δ Geopolitical risk			-0.104 (0.223)
R^2	0.010	0.013	0.023
Adjusted R^2	0.005	0.002	0.007
Observations	383	383	383

Notes: This table reports OLS estimates from predictive regressions of the USDA supply news series on three-month-ahead changes in financial, commodity, and macroeconomic variables. Column (1) includes only financial predictors; column (2) adds commodity-price predictors; column (3) adds the Baltic Dry Index and the Geopolitical Risk Index. Each sell reports the coefficient with the heteroskedasticity-robust standard error in parentheses. No predictor is statistically significant at the five percent level in any specification, and adjusted R-squared values do not exceed 0.01, supporting the exogeneity of the supply news series. Sample period: January 1990 – December 2025.

3. Empirical Strategy

The supply news series captures only a portion of true agricultural supply news, and contains classical measurement error (Stock and Watson, 2018). Rather than treat this series directly as the structural shock, we use it as an external instrument to identify the dynamic causal effects of agricultural supply news within a structural VAR.

3.1. SVAR-IV

Let y_t denote an $n \times 1$ vector of endogenous variables. The reduced-form VAR is

$$y_t = b + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{5}$$

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

The reduced-form innovations in (5) are mapped to be structural shocks via

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

where B is a non-singular $n \times n$ structural impact matrix and ε_t is a $n \times 1$ vector of structural shocks. The shocks are mutually uncorrelated (i.e., $var(\varepsilon_t) = \Omega$ is diagonal). From this mapping, the reduced-form residual covariance is

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

For notational convenience, we order the agricultural supply news shock first in ε_t (i.e., $\varepsilon_{1,t}$). Because field crop prices appear first in y_t, identifying the supply news shock requires identifying the first column of B, denoted b_1.

3.2. *Identification with external instrument approach*

Peersman (2022) notes that earlier VAR studies on food price shocks often rely on Cholesky decompositions, implicitly assuming that field crop prices are contemporaneously exogenous. Because demand shocks move agricultural commodity prices within the month, this assumption is unlikely to hold. Such decompositions confound exogenous shocks with endogenous responses. To address this identification problem, we use an external instrument approach that isolates exogenous agricultural supply news shocks and recovers their dynamic causal effects.

Let z_t denote the external instrument, which in this study is the USDA supply news. To identify b_1, the instrument must satisfy

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

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

where $\varepsilon_{1,t}$ is the agricultural supply news shock and $\varepsilon_{2:n,t}$ is the $(n-1) \times 1$ vector of other structural shocks. Equation (8) is the relevance condition, and (9) is the exogeneity condition. Under these conditions, the structural impact vector b_1 is identified up to a scaling factor (Stock and Watson, 2016, 2018; Baumeister and Hamilton, 2024)

$$\tilde{b}_1 \equiv \theta_0 \propto \mathbb{E}\left[z_t u_{2:n,t}\right]/\mathbb{E}\left[z_t u_{1,t}\right], \tag{10}$$

where θ_0 indicates unit-effect normalization and $\mathbb{E}\left[z_t u_{1,t}\right] \neq 0$.

With unit-effect normalization, we can directly estimate the causal effects in policy-relevant units (Stock and Watson, 2018). For interpretation, we scale the structural shock $\varepsilon_{1,t}$ so that it corresponds to an increase of ω (equal to 3 percent in this study) in the real price of U.S. field crop commodities:

$$\tilde{b}_1 \equiv \mathbb{E}\left[z_t u_{2:n,t}\right]/\mathbb{E}\left[z_t u_{1,t}\right] \times \omega. \tag{11}$$

3.3. *Variables and sample*

The baseline model includes seven variables: i) the real field crop spot price index, computed as a production-weighted average of corn, oats, rice, soybeans, and wheat spot prices, deflated by the U.S. consumer price index (CPI); ii) the U.S. producer price index (PPI) for processed foods and feeds; iii) the personal consumption expenditures (PCE) price index for food; iv) the PCE price index for food services; v) real PCE for food; vi) the real spot price of West Texas Intermediate crude oil, deflated by the U.S. CPI; vii) the U.S. real narrow effective exchange rate. All variables are transformed into natural logarithms, so impulse responses are interpreted in percentage changes. The reduced-form VAR is estimated on monthly data from January 1980 to December 2025 with 12 lags, while IV identification is restricted to January 1990 to December 2025. The shorter IV sample reflects pre-1990 conditions—thinner and less liquid futures markets, and government price support programs that stabilized commodity prices—that weakened the relationship between USDA reports and futures price movements (Bowers, Rasmussen, and Baker, 1984; Olson, 2001). Variable descriptions and data sources are reported in Appendix Table C.1, and summary statistics in Appendix Table C.2.

3.4. Instrument relevance and validity

Table 2 reports first-stage statistics from the IV step using six alternative measures of the field crop price surprises—the nearby contract surprise, four deferred-contract surprises, and our preferred composite (the production-weighted first principal component). The first-stage F-statistics associated with the composite measure is 13.59, greater than the conventional weak-instrument threshold of 10. Heteroskedasticity-robust F-statistics are in the same range. Combined with the predictive-regression evidence in Section 2.4, we conclude that our supply news series satisfies the relevance and exogeneity conditions required for SVAR-IV identification.

Table 2. First-stage F-statistics from SVAR-IV

	Nearby	First def.	Second def.	Third def.	Fourth def.	Composite
F-statistic	16.50	17.34	16.97	16.32	14.05	16.39
Robust F-statistic	13.25	14.50	14.14	13.43	11.84	13.59

Notes: The table reports the first-stage F-statistic (Olea and Pflueger, 2013) and its heteroskedasticity-robust counter part from the SVAR-IV model, using six alternative measures of the field crop price surprise as instrument. The composite measure is the production-weighted first principal component across crop maturities (corn, oats, rice, soybeans, and wheat). Sample spans from 1990 to 2025.

4. Baseline Results

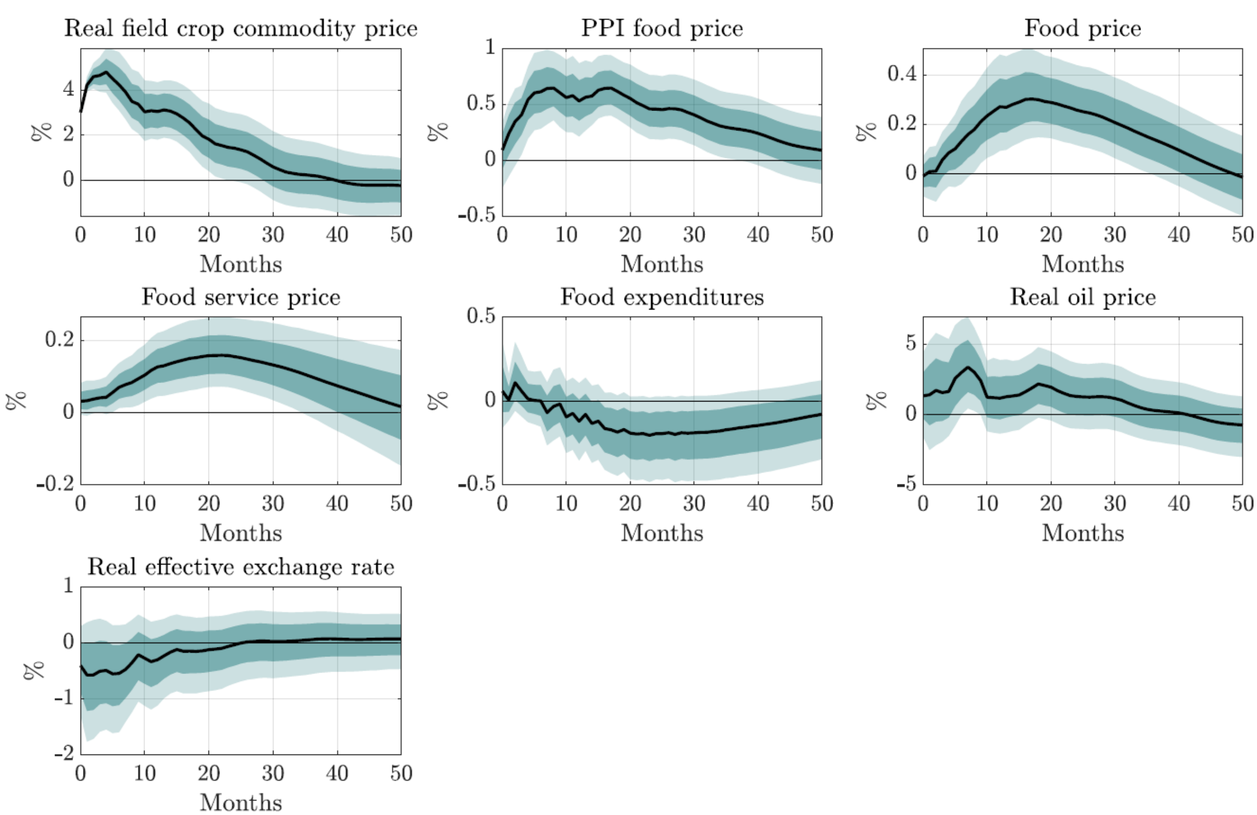
Figure 3 presents impulse response function to a poor harvest news shock—a negative supply news shock that raises the real field crop price by three percent. Each panel displays point estimates with the 68 and 90 percent bootstrap confidence intervals.

The real field crop price rises by three percent by construction of our normalization, peaks at around 4.8 percent within three to four months, and returns to baseline after roughly two years. Producer prices for food respond more gradually, peaking at about 0.6 percent within five months on impact, approximately 13 percent of the field crop price response. The lagged and partial response of producer prices is consistent with intermediate processing margins and inventory adjustment in the food sector, which delays full pass-through from raw commodity prices to producer processed food prices. A poor harvest news also raises retail food prices by 0.30 percent and food service prices by 0.16 percent at their respective peaks. These responses are broadly in line with the predictions implied by USDA's Food Dollar Series, which reports an average farm production share of 7.5 percent for food and 2.5 percent for food service between 1997 and 2023 (USDA ERS, 2026). Applying these shares to the 4.8 percent peak field crop response implies predicted responses of 0.36 percent and 0.12 percent, respectively, under complete pass-through. Our estimated retail food response (0.30 percent) implies approximately 83 percent pass-through, while our estimated food service response (0.16 percent) slightly exceeds the complete pass-through prediction.

On the quantity side, real food expenditures fall by 0.20 percent on impact. Its sign and magnitude are economically intuitive. The modest size of this decline, relative to the 0.30 percent peak in food prices, aligns with the inelasticity of food demand. Households absorb most of the price increase through reduced retail purchasing power. This pattern is also consistent with substitution within the basket (Section 5), in which households shift toward less commodity-intensive products in response to relative price changes.

At its peak, the real oil price rises by more than three percent. Agricultural commodity and oil prices are linked through biofuel demand, which ties corn and soybean prices directly to oil prices, and through shared energy-intensive production inputs such as fertilizer, fuel, and machinery. The U.S. dollar depreciates on impact and remains weaker for several months. A poor harvest reduces expected agricultural export volumes and thereby lowers global demand for the dollar, generating depreciation. Because depreciation raises the dollar cost of imported food, fertilizer, and energy, the second-round currency channel reinforces the direct cost pass-through channel from field crops to food prices (Campa and Goldberg, 2005).

Figure 3. Impulse responses to a poor harvest news shock



Notes: Impulse responses are plotted for a fifty-month horizon. The shock is normalized to a 3 percent increase in the real field crop commodity price (first variable located at upper left of the figure). The solid line represents the point estimate. The dark shaded area indicates the 68 percent confidence interval, and the light shaded area represents the 90 percent confidence interval. These are derived from the moving-block bootstrap with 10,000 replications.

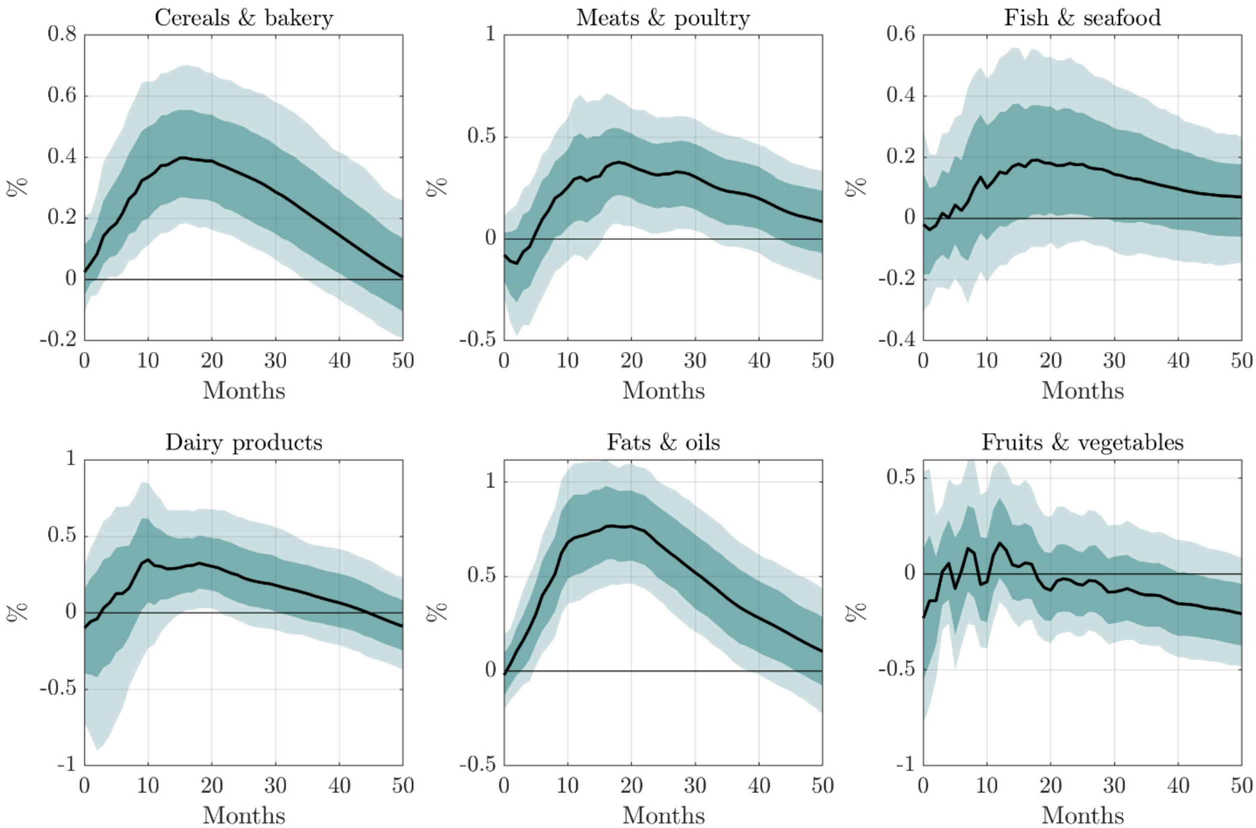
5. Wider Effects

The impulse responses above confirm that agricultural supply news shocks significantly influence aggregate agricultural and food markets. In this section, we go beyond the aggregate effects to examine how the shock transmits to specific components, such as food-at-home subcategory prices and quantities, producer prices, and consumer inflation expectations. Following Känzig (2021), we estimate additional impulse responses by augmenting the baseline VAR with one variable at a time.

5.1. Disaggregated food-at-home prices

Figure 4 displays impulse responses for six PCE food-at-home subcategories. Cereals and bakery products rise by approximately 0.40 percent at peak, meats and poultry by approximately 0.38 percent, dairy products by approximately 0.35 percent, and fats and oils by around 0.77 percent. All four categories are statistically significant at the 90 percent level at the peak horizon. These results align with the input structure of each category. Cereals and bakery rely directly on wheat and corn, meats and poultry and dairy products rely on feed cost pass-through, and fats and oils rely on soybean oil and other vegetable oils. By contrast, fish and seafood, and fruits and vegetables, show small and statistically insignificant responses, reflecting weaker direct relationships with field crops. As a robustness check, we also consider the corresponding CPI categories; results are qualitatively similar (Appendix Figure D.1).

Figure 4. Impulse responses of PCE food-at-home subcategory prices to a poor harvest news shock

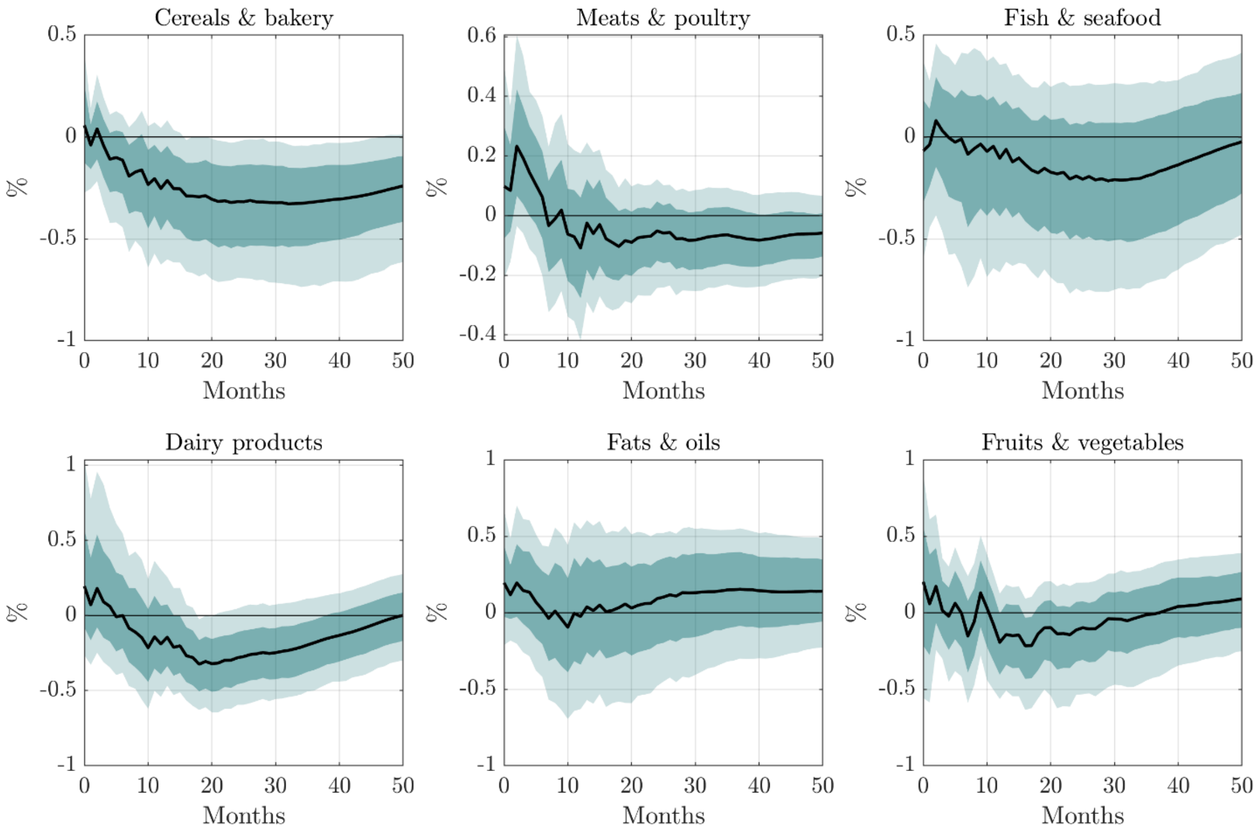


Notes: Data are drawn from the Bureau of Economic Analysis, "Table 2.4.4U. Price Indexes for Personal Consumption Expenditures by Type of Product." The sample spans 1980-2025. Index are expressed relative to 2017=100. Monthly data are seasonally adjusted. Responses are normalized to a 3 percent increase in real field crop prices. The solid line represents the point estimate; the dark shaded area denotes the 68 percent confidence band, and the light shaded area the 90 percent confidence band. Confidence intervals are derived from 1,000 bootstrap replications.

5.2. Disaggregated quantities

Figure 5 illustrates impulse responses of the quantity counterparts to figure 4—that is, real PCE on each food-at-home subcategory. Overall, food subcategory quantities decline slightly, except for fats and oils, which show a small positive but statistically insignificant response. Both cereals and bakery products and dairy products fall by around 0.30 percent at the trough. The relatively muted decline in aggregate food expenditures in the baseline (Section 4) therefore reflects substitution within the food-at-home basket: as the most commodity-intensive categories rise in price, households shift toward less price-responsive categories rather than reducing total food consumption. Fats and oils stand out. While they experience the largest price increase across categories (figure 4), their quantities do not fall. One possibility is that households substitute toward fats and oils as a relatively cheap source of calories when other food prices rise (Drewnowski and Specter, 2004; Drewnowski, 2009).

Figure 5. Impulse responses of PCE food-at-home subcategory quantities to a poor harvest news shock

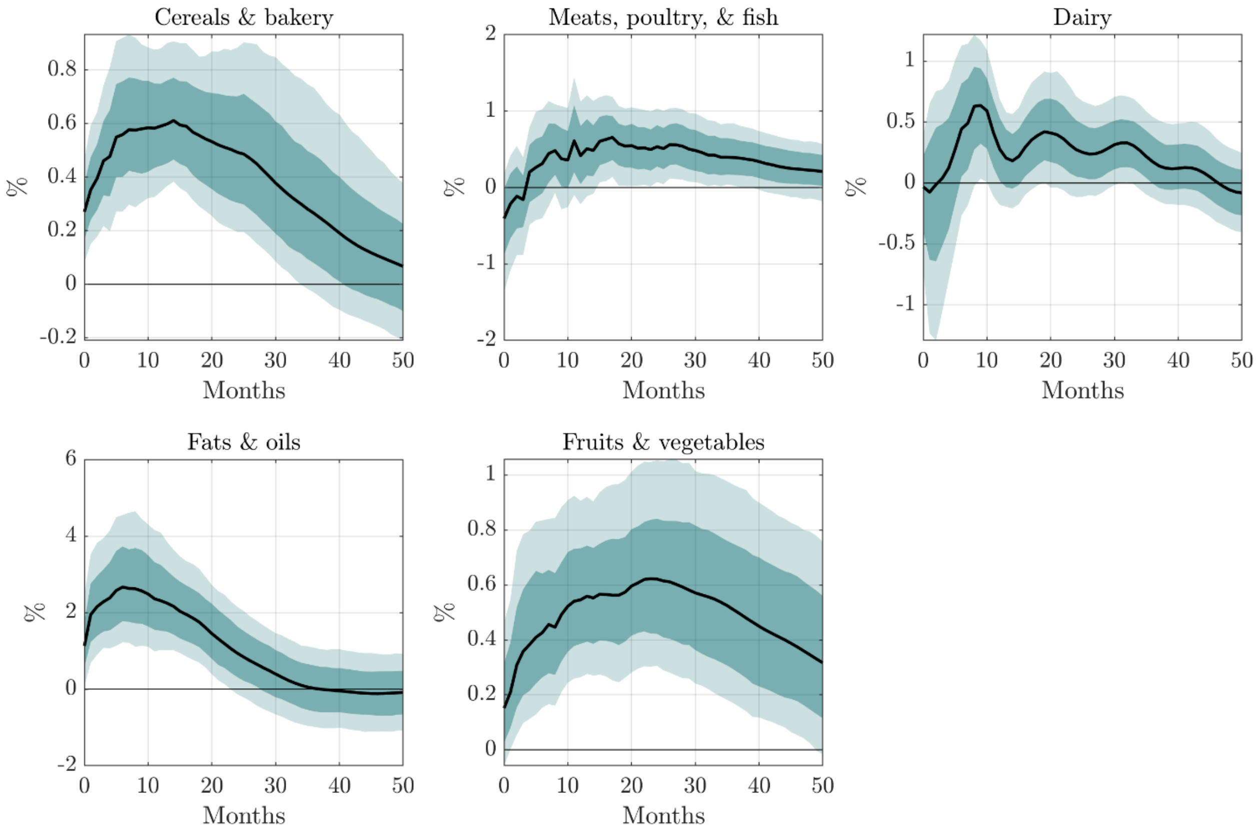


Notes: Data are drawn from the Bureau of Economic Analysis, "Table 2.4.3U. Real Personal Consumption Expenditures by Type of Product, Quantity Indexes." The sample spans 1980-2025. Index are expressed relative to 2017=100. Monthly data are seasonally adjusted. Responses are normalized to a 3 percent increase in real field crop prices. The solid line represents the point estimate; the dark shaded area denotes the 68 percent confidence band, and the light shaded area the 90 percent confidence band. Confidence intervals are derived from 1,000 bootstrap replications.

5.3. Disaggregated producer prices

On average, producer food prices respond more strongly than consumer prices, as displayed in figure 6, reflecting their closer position to agricultural production in the food supply chain. The fats and oils producer price response (2.67 percent) stands out, more than three times the response in any other category. This may be due to the direct cost pass-through from soybean oil, a major input, with limited retail pass-through to consumer prices for fats and oils.

Figure 6. Impulse responses of PPI subcategory prices to a poor harvest news shock



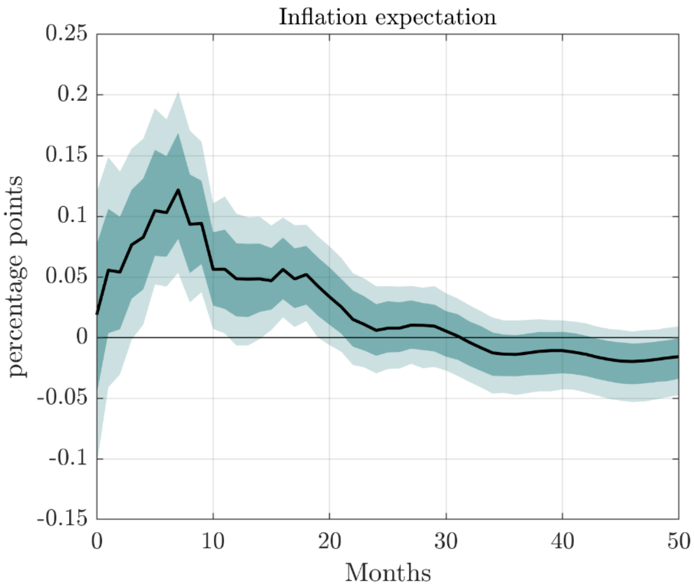
Notes: Data are obtained from Bureau of Labor Statistics (BLS). The sample spans 1980-2025. Index are expressed relative to 1982=100. Responses are normalized to a 3 percent increase in real field crop prices. The solid line represents the point estimate; the dark shaded area denotes the 68 percent confidence band, and the light shaded area the 90 percent confidence band. Confidence intervals are derived from 1,000 bootstrap replications.

5.4. Inflation expectations

Food prices are highly visible to consumers and feature prominently in the formation of inflation expectations (D'Acunto et al., 2021). To examine whether agricultural supply shocks influence household inflation expectations, we add the median one-year-ahead inflation expectation from the University of Michigan Surveys of Consumers to the baseline VAR. Figure 7 reports the response.

A poor harvest news shock raises U.S. household inflation expectations by around twelve basis points after eight months. The response is statistically significant at the 90 percent level and decays over the following two years. The results suggest that consumers directly experience higher prices at grocery stores and restaurants. These realized price increases, concentrated in cereals and bakery, meats and poultry, dairy, fats and oils, and food service, feed into forward-looking inflation expectations. Food prices are also a salient signal of broader inflation conditions, so even sector-specific shocks may shift expectations of aggregate inflation. These channels imply that an episode of agricultural supply news shocks may complicate central-bank communication during periods of food price inflation.

Figure 7. Impulse responses of the U.S. inflation expectation to a poor harvest news shock



Notes: This variable represents median expected price change over the next 12 months from the Surveys of Consumers. Data are from the University of Michigan: Inflation Expectation series, retrieved from FRED (accessed at: https://fred.stlouisfed.org/series/MICH). The sample spans 1980-2025. Responses are normalized to a 3 percent increase in real field crop prices. The solid line shows the point estimate; the dark shaded area denotes the 68 percent confidence band, and the light shaded area the 90 percent confidence band. Confidence intervals are derived from 10,000 bootstrap replications.

6. Distributional Consequences

Food consumption is non-discretionary and accounts for a larger share of household budgets among lower-income Americans (ERS, 2022). In this section, we study how agricultural supply shocks affect different income groups, focusing on the heterogeneity of price exposure and the welfare burden. Food expenditure shares decline sharply with income, so commodity-driven food inflation tends to fall disproportionately on lower-income households. In 2024, the lowest-income quintile (Q1) spent 33 percent of before-tax income on food, while the highest quintile (Q5) spent only 6.4 percent, roughly a fivefold difference (Sinclair and Stewart, 2026). When grocery prices rise, low-income households face sharper trade-offs between food and other necessities such as housing, utilities, and healthcare (Gundersen and Ziliak, 2018). They also have less ability to substitute away from food necessities, both because their consumption baskets are already concentrated in inexpensive staples and because they have less financial slack to absorb temporary cost shocks (Horwich, 2024). An agricultural supply shock that raises food prices can therefore have different welfare implications across the income distribution, and aggregating across households masks this heterogeneity.

6.1. Constructing household-level food price indexes

We construct quintile-specific food price indexes following Jaravel (2026). Using the Consumer Expenditure Survey (CEX) micro-data for 1999-2023, we compute annual expenditure shares for each food subcategory by income quintile. These quintile-specific shares are scaled by BLS price reference scales and blended with the official BLS relative importance weights to ensure consistency with the aggregate CPI. Let $\omega^q_{j,t}$ denote the expenditure weight of food item j for quintile q in month t, constructed from CEX expenditure shares scaled by BLS price reference scales and normalized to sum to 1 within the food sub-basket. The monthly food price index for quintile q is then

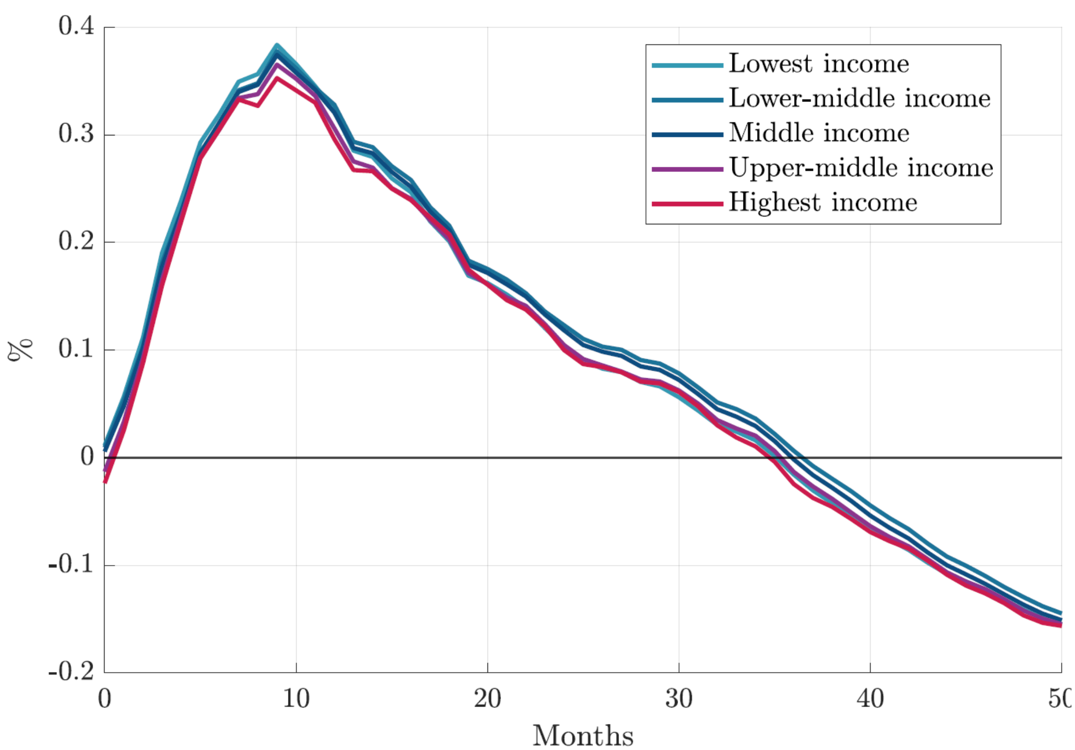
$$P^q_t = P^q_{t-1} \times \left(1 + \sum_{j \in F} \omega^q_{j,t} \cdot \left(\frac{p_{j,t}}{p_{j,t-1}} - 1 \right) \right)$$

where F is the set of food item strata, and $p_{j,t}$ is the BLS price index for item j in month t. We construct separate indexes for food-at-home (53 item strata, SEFA*-SEFT*) and food-away-from-home (5 item strata, SEFV01—SEFV-05). All indexes are set to 100 in January 2002. Summary statistics are reported in Appendix Table C.3.

6.2. Distributional impulse responses

Figures 7 and 8 plot the food-at-home and food-service impulse responses across income quintiles. We estimate additional impulse responses by augmenting the baseline VAR with one variable at a time. For food-at-home, as shown in figure 7, the impulse responses are comparable across the five income groups. The peak impulse response of the lowest-income quintile is approximately 1.09 times that of the highest-income quintile—a difference that, while statistically detectable in some specifications, is economically small. The results reflect the fact that, although income groups differ in the level of food expenditures, the composition of food-at-home spending is relatively similar across quintiles in the United States.

Figure 8. Impulse responses of household-level food-at-home price indexes by income quintile to a poor harvest news shock

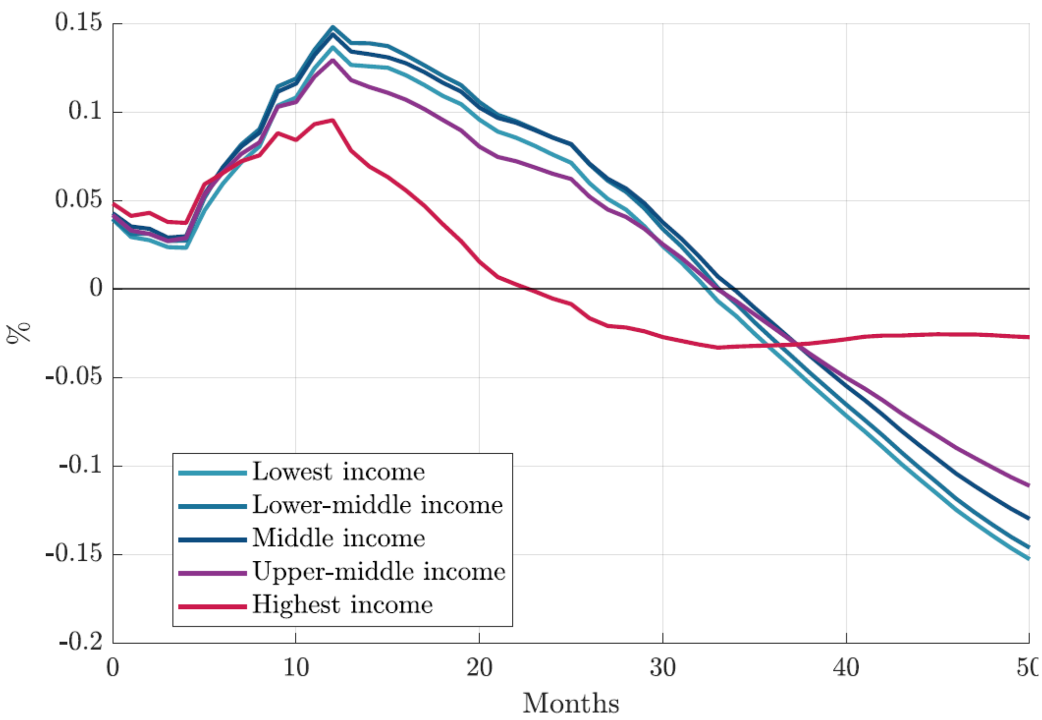


Notes: Each line plots the impulse response for one quintile (Q1 lowest through Q5 highest). Confidence intervals are computed using a moving-block bootstrap with 1,000 bootstrap replications.

For food-away-from home (figure 8), heterogeneity is more pronounced. The lowest-income quintile faces a peak response about 1.43 times that of the highest-income quintiles. This finding implies compositional differences in food service consumption across income groups. Higher-income households spend more at full-service restaurants, where labor and rental costs dominate and pass-through from agricultural commodities is muted; lower-income households spend more at limited-service venues, where commodity-intensive items (e.g., fast food, bakery items) make up a larger share of total cost.

These results show that price exposure to a poor harvest news shock is broadly similar across income groups, with only modest differences in food-at-home prices and somewhat larger differences in food service. To assess the full distributional impact of the shock, however, comparing price responses alone is insufficient. The same percentage food price increase imposes very different welfare burdens because food shares are dramatically larger at the bottom of the income distribution. In the next subsection, we combine the income-specific impulse responses with food expenditure shares to quantify the welfare cost of an agricultural supply news shock by income group.

Figure 9. Impulse responses of household-level food-service (food-away-from-home) price indexes by income quintile to a poor harvest news shock



Notes: Each line plots the impulse response for one quintile (Q1 lowest through Q5 highest). Confidence intervals are computed using a moving-block bootstrap with 1,000 bootstrap replications.

6.3. *Welfare cost calculation*

To translate price exposure into welfare consequences, we compute the welfare cost of an agricultural news shock for each income quintile by combining the quintile-specific impulse responses with food expenditure shares. Specifically, the welfare cost for each quintile is calculated as the product of the peak impulse responses (from figure 9) and the corresponding food expenditure share in income. Table 3 reports the resulting welfare costs. For the lowest-income quintile, the total welfare cost is approximately 0.115 percent of after-tax income (0.099 percent from food-at-home and 0.016 percent from food-away-from home). For the highest-income quintile, the total cost is around 0.017 percent (0.014 percent from food-at-home and 0.003 percent from food-away-from-home). The ratio Q1/Q5 is approximately 6.8, implying that the welfare burden of the shock on the lowest-income quintile is nearly seven times that on the highest-income quintile.

Table 3. Welfare cost of an agricultural supply shock by income quintile

Income group	Food-at-home	Food-away-from-home	Total	Food share (% of income)
Q1 (Lowest)	0.099%	0.016%	0.115%	37.7%
Q2 (Lower-middle)	0.049%	0.010%	0.058%	19.4%
Q3 (Middle)	0.032%	0.008%	0.040%	13.9%
Q4 (Upper-middle)	0.024%	0.006%	0.030%	11.2%
Q5 (Highest)	0.014%	0.003%	0.017%	7.6%

Notes: Welfare costs are reported as the percentage compensating variation from a poor harvest news shock that raises real field crop prices by three percent on impact. For each income quintile, the welfare cost is computed as the peak percentage impulse response multiplied by the corresponding average food expenditure share in after-tax income. Food shares are averaged over 1984-2024 from the Consumer Expenditure Survey.

6.4. *Policy implication*

These distributional findings have implications for food policy and climate adaptation. Our results show that the welfare burden of agricultural supply shocks is concentrated on low-income households, who spend a much larger share of their income on food and energy. This burden is likely to grow in importance, as extreme weather events such as droughts (e.g., the 2022 Mississippi River drought), pest outbreaks, and crop disease have repeatedly reduced expected field crop supply, and climate change is expected to increase the frequency of such events.

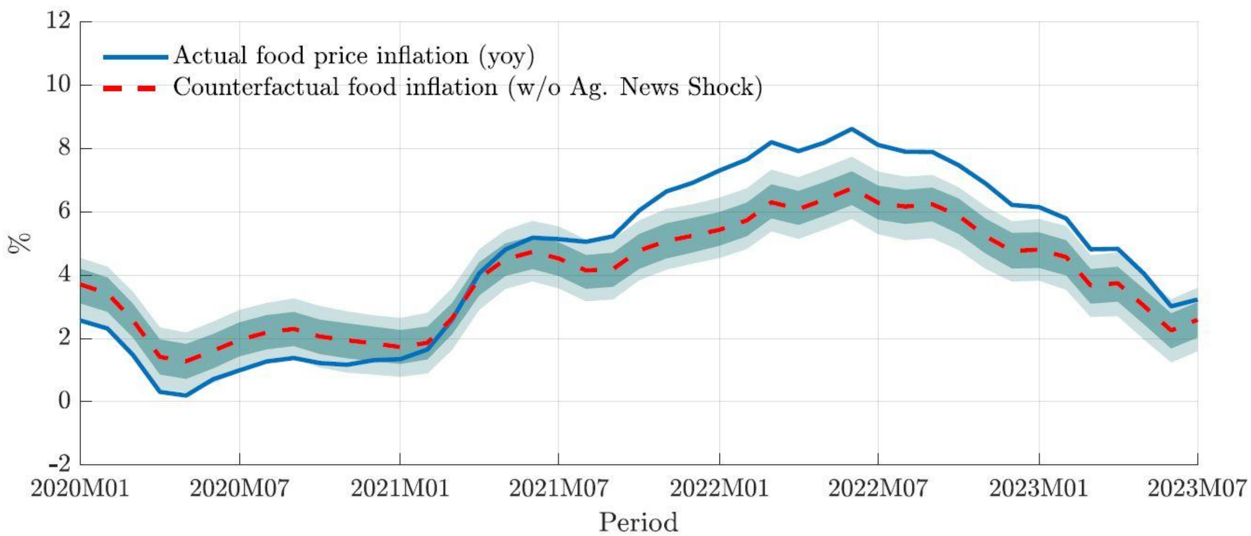
The most direct policy response concerns food assistance. SNAP benefits are tied to the Thrifty Food Plan, which is updated periodically rather than in real time, so benefits lag the food price increases that low-income households actually face. More responsive benefit indexation would better protect the households that bear the largest welfare burden from commodity-driven food inflation. Beyond benefit design, real-time monitoring of agricultural supply conditions could help policy makers anticipate the food security consequences of expected supply shocks before realized food price increases occur.

7. Counterfactual Simulations: 2020–2023

How much did agricultural supply news shocks contribute to the post-pandemic surge in U.S. food inflation? To address this question, we conduct counterfactual simulation using the historical decomposition of our SVAR-IV. Following Stock and Watson (2018), we identify the structural agricultural supply news shocks from the reduced-form VAR residuals via our external instrument, decompose the historical path of food inflation into the contribution of agricultural supply news shocks from the actual series.

Figure 10 illustrates the actual and counterfactual paths for year-over-year food price inflation. The actual series shows food inflation rising from around 2 percent in early 2021 to a peak of around 8.6 percent in mid-2022. The counterfactual path is closely tied to the actual series early in the period but diverges as agricultural supply news shocks contribute increasingly to the rise. The figure shows that food inflation would have been up to 1.9 percentage points lower absent agricultural supply news shocks, with the largest gap occurring in February 2022. However, the post-pandemic food inflation was not driven primarily by agricultural supply news shock; other forces, such as historically large fiscal stimulus, supply chain disruptions, and energy price shocks, also contributed substantially (Adjemian, Li, and Jo, 2026).

Figure 10. Counterfactual food price inflation in the absence of agricultural supply news shocks



Notes: The figure plots actual (solid) and counterfactual (dashed) year-over-year U.S. food price inflation. The counterfactual is constructed by subtracting the historical contribution of agricultural supply news shocks, identified via the SVAR-IV in Section 3, from the actual series over the full sample. The figure displays the over the January 2020 to July 2023 window to focus on the post-pandemic food inflation episode. Shaded areas represent 68 percent and 90 percent confidence bands around the counterfactual, computed using a moving-block bootstrap with 10,000 replications.

8. Conclusions

We construct a high-frequency series of agricultural supply news from daily field crop futures price changes around USDA crop report releases, and use it as an external instrument in a structural VAR of agricultural and food markets in the United States. A poor harvest news shock that raises real field crop prices by three percent, raises food-at-home prices by around 0.3 percent and food service prices by 0.16 percent at peak, with significant pass-through to commodity-intensive subcategories such as cereals and bakery, meats and poultry, dairy and fats and oils. Producer prices for processed foods and feeds respond more strongly, peaking at approximately 0.6 percent. Real food expenditures decline modestly, the US dollar depreciates, oil prices rise, and inflation expectations for the following year rise by around twelve basis points within eight months.

Embedding household-level food price indexes constructed across income quintiles, we show that the welfare cost of an agricultural supply news shock is around seven times larger for the lowest-income quintile than for the highest. This gap is driven largely by heterogeneity in food budget shares rather than by heterogeneity in price exposure. Across income groups, food-at-home prices respond similarly in percentage terms, but the same percentage price increase imposes a far larger welfare burden on households for whom food is a larger share of income. A counterfactual simulation indicates that, without agricultural supply news shocks, U.S. food inflation during 2021-2023 would have been up to 1.9 percentage points lower.

Our findings have implications for food policy. SNAP benefits, tied to the Thrifty Food Plan and updated periodically rather than in real time, lag commodity-driven food inflation. More responsive indexation would better protect the households that bear the largest welfare burden from these shocks. Real-time monitoring of agricultural supply conditions could complement this by anticipating food security consequences of supply shocks before realized food price increases occur.

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Online Appendix

Appendix A. USDA announcement schedule

Table A.1. USDA Crop Production and WASDE announcement schedule, 1990-2025

Month	Publication	Control	Note
1990M02	Feb 12, 1990	Feb 20, 1990	
1990M03	Mar 12, 1990	Mar 19, 1990	
1990M04	Apr 11, 1990	Apr 18, 1990	
1990M05	May 11, 1990	May 18, 1990	
1990M06	Jun 13, 1990	Jun 20, 1990	
1990M07	Jul 13, 1990	Jul 20, 1990	
1990M08	Aug 10, 1990	Aug 17, 1990	
1990M09	Sep 13, 1990	Sep 20, 1990	
1990M10	Oct 12, 1990	Oct 19, 1990	
1990M11	Nov 09, 1990	Nov 16, 1990	
1990M12	Dec 12, 1990	Dec 19, 1990	
1991M02	Feb 12, 1991	Feb 19, 1991	
1991M03	Mar 12, 1991	Mar 19, 1991	
1991M04	Apr 11, 1991	Apr 18, 1991	
1991M05	May 10, 1991	May 17, 1991	
1991M06	Jun 12, 1991	Jun 19, 1991	
1991M07	Jul 12, 1991	Jul 19, 1991	
1991M08	Aug 13, 1991	Aug 20, 1991	
1991M09	Sep 13, 1991	Sep 20, 1991	
1991M10	Oct 11, 1991	Oct 18, 1991	
1991M11	Nov 13, 1991	Nov 20, 1991	
1991M12	Dec 12, 1991	Dec 19, 1991	
1992M02	Feb 12, 1992	Feb 19, 1992	
1992M03	Mar 12, 1992	Mar 19, 1992	
1992M04	Apr 15, 1992	Apr 22, 1992	
1992M05	May 12, 1992	May 19, 1992	
1992M06	Jun 11, 1992	Jun 18, 1992	
1992M07	Jul 10, 1992	Jul 17, 1992	
1992M08	Aug 13, 1992	Aug 20, 1992	
1992M09	Sep 11, 1992	Sep 18, 1992	
1992M10	Oct 09, 1992	Oct 16, 1992	
1992M11	Nov 12, 1992	Nov 19, 1992	
1992M12	Dec 11, 1992	Dec 18, 1992	

Month	Publication	Control	Note
2008M02	Feb 08, 2008	Feb 15, 2008	
2008M03	Mar 11, 2008	Mar 18, 2008	
2008M04	Apr 09, 2008	Apr 16, 2008	
2008M05	May 09, 2008	May 16, 2008	
2008M06	Jun 10, 2008	Jun 17, 2008	
2008M07	Jul 11, 2008	Jul 18, 2008	
2008M08	Aug 12, 2008	Aug 19, 2008	
2008M09	Sep 12, 2008	Sep 19, 2008	
2008M10	Oct 10, 2008	Oct 17, 2008	
2008M11	Nov 10, 2008	Nov 17, 2008	
2008M12	Dec 11, 2008	Dec 18, 2008	
2009M02	Feb 10, 2009	Feb 17, 2009	
2009M03	Mar 11, 2009	Mar 18, 2009	
2009M04	Apr 09, 2009	Apr 16, 2009	
2009M05	May 12, 2009	May 19, 2009	
2009M06	Jun 10, 2009	Jun 17, 2009	
2009M07	Jul 10, 2009	Jul 17, 2009	
2009M08	Aug 12, 2009	Aug 19, 2009	
2009M09	Sep 11, 2009	Sep 18, 2009	
2009M10	Oct 09, 2009	Oct 16, 2009	
2009M11	Nov 10, 2009	Nov 17, 2009	
2009M12	Dec 10, 2009	Dec 17, 2009	
2010M02	Feb 09, 2010	Feb 16, 2010	
2010M03	Mar 10, 2010	Mar 17, 2010	
2010M04	Apr 09, 2010	Apr 16, 2010	
2010M05	May 11, 2010	May 18, 2010	
2010M06	Jun 10, 2010	Jun 17, 2010	
2010M07	Jul 09, 2010	Jul 16, 2010	
2010M08	Aug 12, 2010	Aug 19, 2010	
2010M09	Sep 10, 2010	Sep 17, 2010	
2010M10	Oct 08, 2010	Oct 15, 2010	
2010M11	Nov 09, 2010	Nov 16, 2010	
2010M12	Dec 10, 2010	Dec 17, 2010	

Month	Publication	Control	Note
1993M02	Feb 11, 1993	Feb 18, 1993	
1993M03	Mar 11, 1993	Mar 18, 1993	
1993M04	Apr 13, 1993	Apr 20, 1993	
1993M05	May 12, 1993	May 19, 1993	
1993M06	Jun 11, 1993	Jun 18, 1993	
1993M07	Jul 13, 1993	Jul 20, 1993	
1993M08	Aug 12, 1993	Aug 19, 1993	
1993M09	Sep 10, 1993	Sep 17, 1993	
1993M10	Oct 13, 1993	Oct 20, 1993	
1993M11	Nov 10, 1993	Nov 17, 1993	
1993M12	Dec 10, 1993	Dec 17, 1993	
1994M02	Feb 11, 1994	Feb 18, 1994	
1994M03	Mar 11, 1994	Mar 18, 1994	
1994M04	Apr 13, 1994	Apr 20, 1994	
1994M05	May 10, 1994	May 17, 1994	
1994M06	Jun 09, 1994	Jun 16, 1994	
1994M07	Jul 12, 1994	Jul 19, 1994	
1994M08	Aug 11, 1994	Aug 18, 1994	
1994M09	Sep 12, 1994	Sep 19, 1994	
1994M10	Oct 12, 1994	Oct 19, 1994	
1994M11	Nov 09, 1994	Nov 16, 1994	
1994M12	Dec 09, 1994	Dec 16, 1994	
1995M02	Feb 10, 1995	Feb 17, 1995	
1995M03	Mar 10, 1995	Mar 17, 1995	
1995M04	Apr 11, 1995	Apr 18, 1995	
1995M05	May 11, 1995	May 18, 1995	
1995M06	Jun 12, 1995	Jun 19, 1995	
1995M07	Jul 12, 1995	Jul 19, 1995	
1995M08	Aug 11, 1995	Aug 18, 1995	
1995M09	Sep 12, 1995	Sep 19, 1995	
1995M10	Oct 11, 1995	Oct 18, 1995	
1995M11	Nov 09, 1995	Nov 16, 1995	
1995M12	Dec 12, 1995	Dec 19, 1995	
1996M02	Feb 09, 1996	Feb 16, 1996	
1996M03	Mar 12, 1996	Mar 19, 1996	
1996M04	Apr 11, 1996	Apr 18, 1996	
1996M05	May 10, 1996	May 17, 1996	

Month	Publication	Control	Note
2011M02	Feb 09, 2011	Feb 16, 2011	
2011M03	Mar 10, 2011	Mar 17, 2011	
2011M04	Apr 08, 2011	Apr 15, 2011	
2011M05	May 11, 2011	May 18, 2011	
2011M06	Jun 09, 2011	Jun 16, 2011	
2011M07	Jul 12, 2011	Jul 19, 2011	
2011M08	Aug 11, 2011	Aug 18, 2011	
2011M09	Sep 12, 2011	Sep 19, 2011	
2011M10	Oct 12, 2011	Oct 19, 2011	
2011M11	Nov 09, 2011	Nov 16, 2011	
2011M12	Dec 09, 2011	Dec 16, 2011	
2012M02	Feb 09, 2012	Feb 16, 2012	
2012M03	Mar 09, 2012	Mar 16, 2012	
2012M04	Apr 10, 2012	Apr 17, 2012	
2012M05	May 10, 2012	May 17, 2012	
2012M06	Jun 12, 2012	Jun 19, 2012	
2012M07	Jul 11, 2012	Jul 18, 2012	
2012M08	Aug 10, 2012	Aug 17, 2012	
2012M09	Sep 12, 2012	Sep 19, 2012	
2012M10	Oct 11, 2012	Oct 18, 2012	
2012M11	Nov 09, 2012	Nov 16, 2012	
2012M12	Dec 11, 2012	Dec 18, 2012	
2013M02	Feb 08, 2013	Feb 15, 2013	
2013M03	Mar 08, 2013	Mar 15, 2013	
2013M04	Apr 10, 2013	Apr 17, 2013	
2013M05	May 10, 2013	May 17, 2013	
2013M06	Jun 12, 2013	Jun 19, 2013	
2013M07	Jul 11, 2013	Jul 18, 2013	
2013M08	Aug 12, 2013	Aug 19, 2013	
2013M09	Sep 12, 2013	Sep 19, 2013	
2013M10	—	Oct 18, 2013	*Government Shutdown*
2013M11	Nov 08, 2013	Nov 15, 2013	
2013M12	Dec 10, 2013	Dec 17, 2013	
2014M02	Feb 10, 2014	Feb 18, 2014	
2014M03	Mar 10, 2014	Mar 17, 2014	
2014M04	Apr 09, 2014	Apr 16, 2014	
2014M05	May 09, 2014	May 16, 2014	

Month	Publication	Control	Note
1996M06	Jun 12, 1996	Jun 19, 1996	
1996M07	Jul 12, 1996	Jul 19, 1996	
1996M08	Aug 12, 1996	Aug 19, 1996	
1996M09	Sep 11, 1996	Sep 18, 1996	
1996M10	Oct 11, 1996	Oct 18, 1996	
1996M11	Nov 12, 1996	Nov 19, 1996	
1996M12	Dec 12, 1996	Dec 19, 1996	
1997M02	Feb 12, 1997	Feb 19, 1997	
1997M03	Mar 11, 1997	Mar 18, 1997	
1997M04	Apr 11, 1997	Apr 18, 1997	
1997M05	May 12, 1997	May 19, 1997	
1997M06	Jun 12, 1997	Jun 19, 1997	
1997M07	Jul 11, 1997	Jul 18, 1997	
1997M08	Aug 12, 1997	Aug 19, 1997	
1997M09	Sep 12, 1997	Sep 19, 1997	
1997M10	Oct 10, 1997	Oct 17, 1997	
1997M11	Nov 10, 1997	Nov 17, 1997	
1997M12	Dec 11, 1997	Dec 18, 1997	
1998M02	Feb 11, 1998	Feb 18, 1998	
1998M03	Mar 12, 1998	Mar 19, 1998	
1998M04	Apr 09, 1998	Apr 16, 1998	
1998M05	May 12, 1998	May 19, 1998	
1998M06	Jun 12, 1998	Jun 19, 1998	
1998M07	Jul 10, 1998	Jul 17, 1998	
1998M08	Aug 12, 1998	Aug 19, 1998	
1998M09	Sep 11, 1998	Sep 18, 1998	
1998M10	Oct 09, 1998	Oct 16, 1998	
1998M11	Nov 10, 1998	Nov 17, 1998	
1998M12	Dec 11, 1998	Dec 18, 1998	
1999M02	Feb 10, 1999	Feb 17, 1999	
1999M03	Mar 11, 1999	Mar 18, 1999	
1999M04	Apr 09, 1999	Apr 16, 1999	
1999M05	May 12, 1999	May 19, 1999	
1999M06	Jun 11, 1999	Jun 18, 1999	
1999M07	Jul 12, 1999	Jul 19, 1999	
1999M08	Aug 12, 1999	Aug 19, 1999	
1999M09	Sep 10, 1999	Sep 17, 1999	

Month	Publication	Control	Note
2014M06	Jun 11, 2014	Jun 18, 2014	
2014M07	Jul 11, 2014	Jul 18, 2014	
2014M08	Aug 12, 2014	Aug 19, 2014	
2014M09	Sep 11, 2014	Sep 18, 2014	
2014M10	Oct 10, 2014	Oct 17, 2014	
2014M11	Nov 10, 2014	Nov 17, 2014	
2014M12	Dec 10, 2014	Dec 17, 2014	
2015M02	Feb 10, 2015	Feb 17, 2015	
2015M03	Mar 10, 2015	Mar 17, 2015	
2015M04	Apr 09, 2015	Apr 16, 2015	
2015M05	May 12, 2015	May 19, 2015	
2015M06	Jun 10, 2015	Jun 17, 2015	
2015M07	Jul 10, 2015	Jul 17, 2015	
2015M08	Aug 12, 2015	Aug 19, 2015	
2015M09	Sep 11, 2015	Sep 18, 2015	
2015M10	Oct 09, 2015	Oct 16, 2015	
2015M11	Nov 10, 2015	Nov 17, 2015	
2015M12	Dec 09, 2015	Dec 16, 2015	
2016M02	Feb 09, 2016	Feb 16, 2016	
2016M03	Mar 09, 2016	Mar 16, 2016	
2016M04	Apr 12, 2016	Apr 19, 2016	
2016M05	May 10, 2016	May 17, 2016	
2016M06	Jun 10, 2016	Jun 17, 2016	
2016M07	Jul 12, 2016	Jul 19, 2016	
2016M08	Aug 12, 2016	Aug 19, 2016	
2016M09	Sep 12, 2016	Sep 19, 2016	
2016M10	Oct 12, 2016	Oct 19, 2016	
2016M11	Nov 09, 2016	Nov 16, 2016	
2016M12	Dec 09, 2016	Dec 16, 2016	
2017M02	Feb 09, 2017	Feb 16, 2017	
2017M03	Mar 09, 2017	Mar 16, 2017	
2017M04	Apr 11, 2017	Apr 18, 2017	
2017M05	May 10, 2017	May 17, 2017	
2017M06	Jun 09, 2017	Jun 16, 2017	
2017M07	Jul 12, 2017	Jul 19, 2017	
2017M08	Aug 10, 2017	Aug 17, 2017	
2017M09	Sep 12, 2017	Sep 19, 2017	

Month	Publication	Control	Note
1999M10	Oct 08, 1999	Oct 15, 1999	
1999M11	Nov 10, 1999	Nov 17, 1999	
1999M12	Dec 10, 1999	Dec 17, 1999	
2000M02	Feb 11, 2000	Feb 18, 2000	
2000M03	Mar 10, 2000	Mar 17, 2000	
2000M04	Apr 11, 2000	Apr 18, 2000	
2000M05	May 12, 2000	May 19, 2000	
2000M06	Jun 09, 2000	Jun 16, 2000	
2000M07	Jul 12, 2000	Jul 19, 2000	
2000M08	Aug 11, 2000	Aug 18, 2000	
2000M09	Sep 12, 2000	Sep 19, 2000	
2000M10	Oct 12, 2000	Oct 19, 2000	
2000M11	Nov 09, 2000	Nov 16, 2000	
2000M12	Dec 12, 2000	Dec 19, 2000	
2001M02	Feb 08, 2001	Feb 15, 2001	
2001M03	Mar 08, 2001	Mar 15, 2001	
2001M04	Apr 10, 2001	Apr 17, 2001	
2001M05	May 10, 2001	May 17, 2001	
2001M06	Jun 12, 2001	Jun 19, 2001	
2001M07	Jul 11, 2001	Jul 18, 2001	
2001M08	Aug 10, 2001	Aug 17, 2001	
2001M09	Sep 14, 2001	Sep 21, 2001	
2001M10	Oct 12, 2001	Oct 19, 2001	
2001M11	Nov 09, 2001	Nov 16, 2001	
2001M12	Dec 11, 2001	Dec 18, 2001	
2002M02	Feb 08, 2002	Feb 15, 2002	
2002M03	Mar 08, 2002	Mar 15, 2002	
2002M04	Apr 10, 2002	Apr 17, 2002	
2002M05	May 10, 2002	May 17, 2002	
2002M06	Jun 12, 2002	Jun 19, 2002	
2002M07	Jul 11, 2002	Jul 18, 2002	
2002M08	Aug 12, 2002	Aug 19, 2002	
2002M09	Sep 12, 2002	Sep 19, 2002	
2002M10	Oct 11, 2002	Oct 18, 2002	
2002M11	Nov 12, 2002	Nov 19, 2002	
2002M12	Dec 10, 2002	Dec 17, 2002	
2003M02	Feb 11, 2003	Feb 18, 2003	

Month	Publication	Control	Note
2017M10	Oct 12, 2017	Oct 19, 2017	
2017M11	Nov 09, 2017	Nov 16, 2017	
2017M12	Dec 12, 2017	Dec 19, 2017	
2018M02	Feb 08, 2018	Feb 15, 2018	
2018M03	Mar 08, 2018	Mar 15, 2018	
2018M04	Apr 10, 2018	Apr 17, 2018	
2018M05	May 10, 2018	May 17, 2018	
2018M06	Jun 12, 2018	Jun 19, 2018	
2018M07	Jul 12, 2018	Jul 19, 2018	
2018M08	Aug 10, 2018	Aug 17, 2018	
2018M09	Sep 12, 2018	Sep 19, 2018	
2018M10	Oct 11, 2018	Oct 18, 2018	
2018M11	Nov 08, 2018	Nov 15, 2018	
2018M12	Dec 11, 2018	Dec 18, 2018	
2019M02	Feb 08, 2019	Feb 15, 2019	
2019M03	Mar 08, 2019	Mar 15, 2019	
2019M04	Apr 09, 2019	Apr 16, 2019	
2019M05	May 10, 2019	May 17, 2019	
2019M06	Jun 11, 2019	Jun 18, 2019	
2019M07	Jul 11, 2019	Jul 18, 2019	
2019M08	Aug 12, 2019	Aug 19, 2019	
2019M09	Sep 12, 2019	Sep 19, 2019	
2019M10	Oct 10, 2019	Oct 17, 2019	
2019M11	Nov 08, 2019	Nov 15, 2019	
2019M12	Dec 10, 2019	Dec 17, 2019	
2020M02	Feb 11, 2020	Feb 18, 2020	
2020M03	Mar 10, 2020	Mar 17, 2020	
2020M04	Apr 09, 2020	Apr 16, 2020	
2020M05	May 12, 2020	May 19, 2020	
2020M06	Jun 11, 2020	Jun 18, 2020	
2020M07	Jul 10, 2020	Jul 17, 2020	
2020M08	Aug 12, 2020	Aug 19, 2020	
2020M09	Sep 11, 2020	Sep 18, 2020	
2020M10	Oct 09, 2020	Oct 16, 2020	
2020M11	Nov 10, 2020	Nov 17, 2020	
2020M12	Dec 10, 2020	Dec 17, 2020	
2021M02	Feb 09, 2021	Feb 16, 2021	

Month	Publication	Control	Note
2003M03	Mar 11, 2003	Mar 18, 2003	
2003M04	Apr 10, 2003	Apr 17, 2003	
2003M05	May 12, 2003	May 19, 2003	
2003M06	Jun 11, 2003	Jun 18, 2003	
2003M07	Jul 11, 2003	Jul 18, 2003	
2003M08	Aug 12, 2003	Aug 19, 2003	
2003M09	Sep 11, 2003	Sep 18, 2003	
2003M10	Oct 10, 2003	Oct 17, 2003	
2003M11	Nov 12, 2003	Nov 19, 2003	
2003M12	Dec 11, 2003	Dec 18, 2003	
2004M02	Feb 10, 2004	Feb 17, 2004	
2004M03	Mar 10, 2004	Mar 17, 2004	
2004M04	Apr 08, 2004	Apr 15, 2004	
2004M05	May 12, 2004	May 19, 2004	
2004M06	Jun 10, 2004	Jun 17, 2004	
2004M07	Jul 12, 2004	Jul 19, 2004	
2004M08	Aug 12, 2004	Aug 19, 2004	
2004M09	Sep 10, 2004	Sep 17, 2004	
2004M10	Oct 12, 2004	Oct 19, 2004	
2004M11	Nov 12, 2004	Nov 19, 2004	
2004M12	Dec 10, 2004	Dec 17, 2004	
2005M02	Feb 09, 2005	Feb 16, 2005	
2005M03	Mar 10, 2005	Mar 17, 2005	
2005M04	Apr 08, 2005	Apr 15, 2005	
2005M05	May 12, 2005	May 19, 2005	
2005M06	Jun 10, 2005	Jun 17, 2005	
2005M07	Jul 12, 2005	Jul 19, 2005	
2005M08	Aug 12, 2005	Aug 19, 2005	
2005M09	Sep 12, 2005	Sep 19, 2005	
2005M10	Oct 12, 2005	Oct 19, 2005	
2005M11	Nov 10, 2005	Nov 17, 2005	
2005M12	Dec 09, 2005	Dec 16, 2005	
2006M02	Feb 09, 2006	Feb 16, 2006	
2006M03	Mar 13, 2006	Mar 20, 2006	
2006M04	Apr 10, 2006	Apr 17, 2006	
2006M05	May 12, 2006	May 19, 2006	
2006M06	Jun 09, 2006	Jun 16, 2006	

Month	Publication	Control	Note
2021M03	Mar 09, 2021	Mar 16, 2021	
2021M04	Apr 09, 2021	Apr 16, 2021	
2021M05	May 12, 2021	May 19, 2021	
2021M06	Jun 10, 2021	Jun 17, 2021	
2021M07	Jul 12, 2021	Jul 19, 2021	
2021M08	Aug 12, 2021	Aug 19, 2021	
2021M09	Sep 10, 2021	Sep 17, 2021	
2021M10	Oct 12, 2021	Oct 19, 2021	
2021M11	Nov 09, 2021	Nov 16, 2021	
2021M12	Dec 09, 2021	Dec 16, 2021	
2022M02	Feb 09, 2022	Feb 16, 2022	
2022M03	Mar 09, 2022	Mar 16, 2022	
2022M04	Apr 08, 2022	Apr 14, 2022	
2022M05	May 12, 2022	May 19, 2022	
2022M06	Jun 10, 2022	Jun 17, 2022	
2022M07	Jul 12, 2022	Jul 19, 2022	
2022M08	Aug 12, 2022	Aug 19, 2022	
2022M09	Sep 12, 2022	Sep 19, 2022	
2022M10	Oct 12, 2022	Oct 19, 2022	
2022M11	Nov 09, 2022	Nov 16, 2022	
2022M12	Dec 09, 2022	Dec 16, 2022	
2023M02	Feb 08, 2023	Feb 15, 2023	
2023M03	Mar 08, 2023	Mar 15, 2023	
2023M04	Apr 11, 2023	Apr 18, 2023	
2023M05	May 12, 2023	May 19, 2023	
2023M06	Jun 09, 2023	Jun 16, 2023	
2023M07	Jul 12, 2023	Jul 19, 2023	
2023M08	Aug 11, 2023	Aug 18, 2023	
2023M09	Sep 12, 2023	Sep 19, 2023	
2023M10	Oct 12, 2023	Oct 19, 2023	
2023M11	Nov 09, 2023	Nov 16, 2023	
2023M12	Dec 08, 2023	Dec 15, 2023	
2024M02	Feb 08, 2024	Feb 15, 2024	
2024M03	Mar 08, 2024	Mar 15, 2024	
2024M04	Apr 11, 2024	Apr 18, 2024	
2024M05	May 10, 2024	May 17, 2024	
2024M06	Jun 12, 2024	Jun 20, 2024	

Month	Publication	Control	Note	Month	Publication	Control	Note
2006M07	Jul 12, 2006	Jul 19, 2006		2024M07	Jul 12, 2024	Jul 19, 2024	
2006M08	Aug 11, 2006	Aug 18, 2006		2024M08	Aug 12, 2024	Aug 19, 2024	
2006M09	Sep 12, 2006	Sep 19, 2006		2024M09	Sep 12, 2024	Sep 19, 2024	
2006M10	Oct 12, 2006	Oct 19, 2006		2024M10	Oct 11, 2024	Oct 18, 2024	
2006M11	Nov 09, 2006	Nov 16, 2006		2024M11	Nov 08, 2024	Nov 15, 2024	
2006M12	Dec 11, 2006	Dec 18, 2006		2024M12	Dec 10, 2024	Dec 17, 2024	
2007M02	Feb 09, 2007	Feb 16, 2007		2025M02	Feb 11, 2025	Feb 18, 2025	
2007M03	Mar 09, 2007	Mar 16, 2007		2025M03	Mar 11, 2025	Mar 18, 2025	
2007M04	Apr 10, 2007	Apr 17, 2007		2025M04	Apr 10, 2025	Apr 17, 2025	
2007M05	May 11, 2007	May 18, 2007		2025M05	May 12, 2025	May 19, 2025	
2007M06	Jun 11, 2007	Jun 18, 2007		2025M06	Jun 12, 2025	Jun 20, 2025	
2007M07	Jul 12, 2007	Jul 19, 2007		2025M07	Jul 11, 2025	Jul 18, 2025	
2007M08	Aug 10, 2007	Aug 17, 2007		2025M08	Aug 12, 2025	Aug 19, 2025	
2007M09	Sep 12, 2007	Sep 19, 2007		2025M09	Sep 12, 2025	Sep 19, 2025	
2007M10	Oct 12, 2007	Oct 19, 2007		2025M10	—	Oct 10, 2025	*Government Shutdown*
2007M11	Nov 09, 2007	Nov 16, 2007		2025M11	Nov 14, 2025	Nov 21, 2025	
2007M12	Dec 11, 2007	Dec 18, 2007		2025M12	Dec 09, 2025	Dec 16, 2025	

Notes: The table lists every monthly USDA Crop Production/ WASDE release used to construct the supply news series, with the matched control date (the same weekday one week after each announcement). January announcements are excluded because the January WASDE is released on the same day as the Grain Stocks report. October 2013 and October 2025 had no publication due to federal government shutdowns; the corresponding control dates are reported but the months are excluded from the announcement sample.

Appendix B. Additional diagnostic tests

In this Appendix, we collect supplementary diagnostic results. Table B.1 reports summary statistics of USDA supply news series for field crops used in this analysis. Figure B.1 displays the sample autocorrelation function of the USDA supply news series and confirms that autocorrelations at lags 1-20 are statistically indistinguishable from zero. Table B.2 reports Granger causality test p-values from regressions of the supply news series on lagged values of each baseline VAR variable, and on all of them jointly; no individual variable or joint specification rejects the null at conventional significance levels.

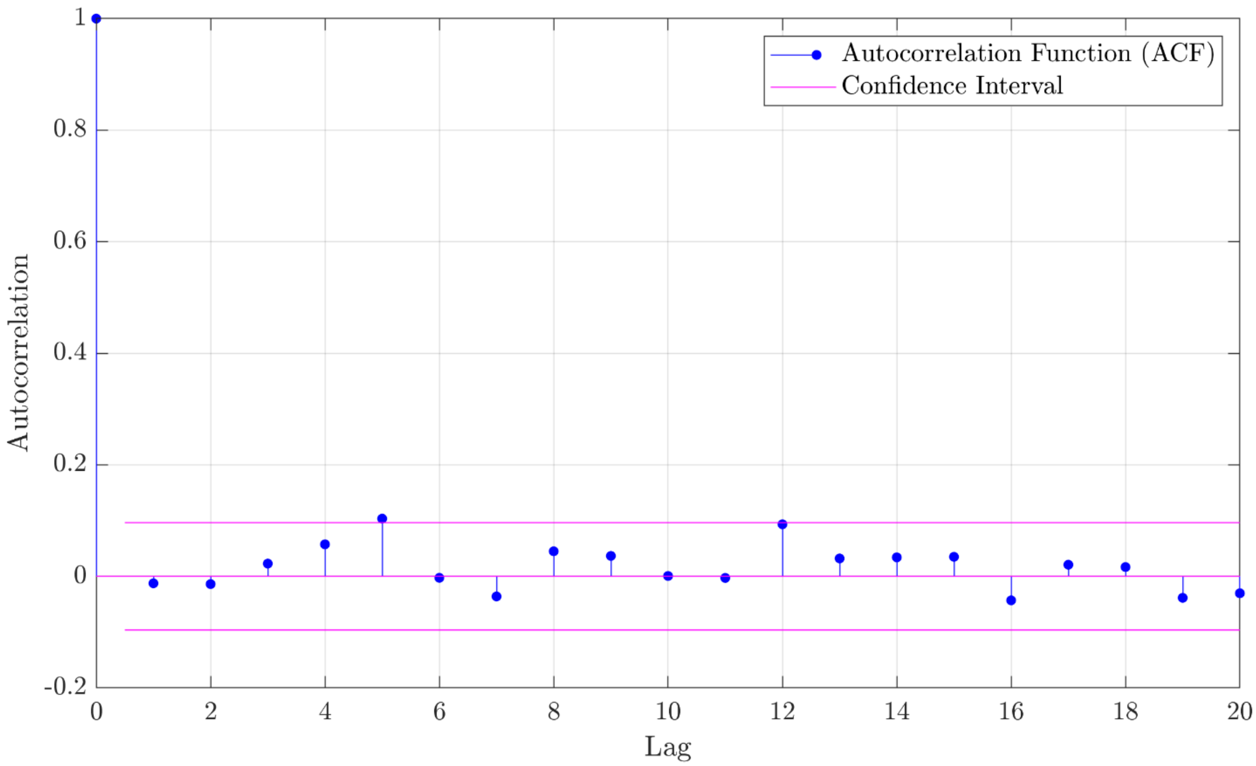
Table B.1. Descriptive statistics of USDA supply news, by commodity

	Corn			Oats			Rice		
	Std. Dev.	*Min*	*Max*	*Std. Dev.*	*Min*	*Max*	*Std. Dev.*	*Min*	*Max*
Surprises (%)									
Announcement	1.81	-6.74	5.86	1.80	-7.68	6.00	1.47	-6.88	7.60
Control	1.40	-7.03	5.13	1.48	-4.98	5.96	1.22	-4.64	4.08
Variance ratio		1.67			1.48			1.45	
Period		1990–2025			1990–2025			1990–2025	

	Soybeans			Wheat		
	Std. Dev.	*Min*	*Max*	*Std. Dev.*	*Min*	*Max*
Surprises (%)						
Announcement	1.68	-7.27	6.33	1.75	-6.83	8.38
Control	1.41	-7.67	3.82	1.75	-7.47	7.27
Variance ratio		1.42			1.00	
Period		1990–2025			1990–2025	

Source: Bloomberg terminal, USDA National Agricultural Statistics Service (NASS), and authors' calculations
Notes: The table reports the standard deviation, minimum, and maximum of percentage daily futures price changes on USDA announcement days and on matched control days, for each of the five field crops. Control days are defined as the same weekday one week (7 days) after each announcement; when this date falls on a market holiday, the control is shifted backward by one trading day. The variance ratio is the ratio of announcement-day variance to control-day variance. The control sample contains 396 observations and the announcement sample contains 394. The October WASDE and Crop Production reports were not released in 2013 and 2025 due to federal government funding disruptions, so these two months are excluded from the announcement sample, but their matched control days remain observable and are included. Sample period is January 1990 – December 2025.

Figure B.1. Sample autocorrelation function of the USDA supply news series



Source: Bloomberg terminal and authors' calculations
Notes: The horizontal lines indicate the 95 percent confidence intervals.

Table B.2. Granger causality test

	P-value
USDA supply news	0.4741
Field crop price	0.2540
PPI food price	0.7891
PCE food price	0.4731
PCE food service price	0.3085
Food expenditures	0.2805
Oil price	0.6025
Exchange rate	0.6416
CPI	0.2801
S&P500	0.9968
All	0.5167

Notes: The table reports p-values from Granger causality tests of whether each variable predicts the USDA supply news series. The lag order is 12, consistent with the baseline VAR specification. The row labeled "All" reports the *p*-

value for the joint test that none of the variables jointly predict the news series. P-values above conventional thresholds indicate failure to reject the null of no predictability.

Appendix C. Data description and source

Table C.1. Data description and source for selected variables

Variable (Unit)	Description	Source
A. Instrument		
USDA supply news (%)	First principal component of daily changes in field crop futures prices (corn, oats, rice, soybeans, and wheat) around regulatory announcements from World Agricultural Supply and Demand Estimates (WASDE), weighted by production shares	Bloomberg terminal; WASDE; USDA NASS
B. Baseline		
Real field crop spot price	Production-weighted composite of the Chicago Board of Trade (CBOT) corn, oats, rice, soybeans, and wheat futures price (nearby through fourth deferred contract), weighted by annual production shares and deflated by CPI	Bloomberg terminal; USDA NASS; BLS
Processed food and feeds PPI (index, 1982=100)	Producer price index for processed foods and feeds	BLS
PCE food price (index, 2017=100)	Personal consumption expenditures for food (chain-type price index)	BEA
PCE food service price (index, 2017=100)	Personal consumption expenditures for food services (chain-type price index)	BEA
Real PCE for food (Billions of Dollars)	Personal consumption expenditures for food, deflated by PCE for food price index	BEA
Real oil price (Dollars per Barrel)	Spot crude oil price: West Texas Intermediate (WTI), deflated by CPI	FRED; BLS
Exchange rate (index, 2020=100)	Real narrow effective exchange rate for United States	BIS
C. Wider Effects		
PCE food price indices		
Cereal and bakery (index, 2017=100)	Personal Consumption Expenditures price index for cereals and bakery products	BEA
Meats and poultry (index, 2017=100)	Personal Consumption Expenditures price index for milk, dairy products, and eggs	BEA
Fish and seafood (index, 2017=100)	Personal Consumption Expenditures price index for fish and seafood	BEA
Dairy products (index, index, 2017=100)	Personal Consumption Expenditures price index for milk, dairy products, and eggs	BEA
Fats and oils (index, 2017=100)	Personal Consumption Expenditures price index for fats and oils	BEA

Fruits and vegetables (index, 2017=100)	Personal Consumption Expenditures price index for fresh fruits and vegetables	BEA
Real PCE food quantity indices		
Cereal and bakery (index, 2017=100)	Personal Consumption Expenditures quantity index for cereals and bakery products	BEA
Meats and poultry (index, 2017=100)	Personal Consumption Expenditures quantity index for milk, dairy products, and eggs	BEA
Fish and seafood (index, 2017=100)	Personal Consumption Expenditures quantity index for fish and seafood	BEA
Dairy products (index, index, 2017=100)	Personal Consumption Expenditures quantity index for milk, dairy products, and eggs	BEA
Fats and oils (index, 2017=100)	Personal Consumption Expenditures quantity index for fats and oils	BEA
Fruits and vegetables (index, 2017=100)	Personal Consumption Expenditures quantity index for fresh fruits and vegetables	BEA
Consumer food price indices		
Cereals and bakery CPI (index, 1982-84=100)	Consumer Price Index for all urban consumers: cereals and bakery products in U.S. city average	BLS
Meats and poultry CPI (index, 1982-84=100)	Consumer Price Index for all urban consumers: meats, poultry, fish, and eggs in U.S. city average	BLS
Dairy CPI (index, 1982-84=100)	Consumer Price Index for all urban consumers: dairy and related products in U.S. city average	BLS
Fats and oils CPI (index, 1982-84=100)	Consumer Price Index for all urban consumers: fats and oils in U.S. city average	BLS
Fruits and vegetables CPI (index, 1982-84=100)	Consumer Price Index for all urban consumers: fruits and vegetables in U.S. city average	BLS
Producer price index for food		
Cereals and bakery PPI (index, 1982=100)	Producer price index for processed foods and feeds: cereals and bakery products	BLS
Meats, poultry, and fish PPI (index, 1982=100)	Producer price index for processed foods and feeds: meats, poultry, and fish	BLS
Dairy PPI (index, 1982=100)	Producer price index for processed foods and feeds: dairy products	BLS
Fats and oils PPI (index, 1982=100)	Producer price index for processed foods and feeds: fats and oils	BLS
Fruits and vegetables (index, 1982=100)	Producer price index for processed foods and feeds: processed fruits and vegetables	BLS
D. Other Variables		

Crude oil price (Dollars per Barrel)	Spot crude oil price: West Texas Intermediate (WTI)	Federal Reserve Bank of St. Louis
Consumer price index (index, 1982-84=100)	Consumer price index for all urban consumers: all items in U.S. city average	BLS
S&P 500 (index)	Stock market index tracking the stock performance of 500 leading companies listed on stock exchanges in the United States	Bloomberg terminal
Treasury slope (percent)	10-year Treasury constant maturity 3-month Treasury constant maturity	Federal Reserve Bank of St. Louis
Baltic Dry Index (BDI)	Baltic exchange dry bulk index, measuring shipping rates for vessels carrying dry commodities	Bloomberg terminal
Bloomberg commodity index (BCOM)	This index provides broad exposure to commodities	Bloomberg terminal
Bloomberg agriculture sub index (BCOMAG)	A commodity group subindex of the Bloomberg commodity index, including futures on coffee, cotton, soybeans, soybean oil, soybean meal, sugar and wheat	Bloomberg terminal
Geopolitical Risk (GPR) index	The GPR index measures the frequency of newspaper articles mentioning adverse geopolitical events such as wars, terrorism, and international tensions, based on the text of major U.S. and international newspapers	Dario and Iacoviello (2022)
Consumer inflation expectations (%)	University of Michigan Survey of Consumers: median expected price change over the next 12 months	University of Michigan

Table C.2. Summary statistics: baseline variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Real field crop price	552	90.04	25.58	31.88	167.23
PPI for food	552	503.26	30.43	450.98	563.15
PCE food price	552	432.73	30.34	370.77	487.33
PCE food service price	552	421.16	39.93	339.23	497.17
Real PCE for food	552	206.94	22.46	170.44	255.35
Real oil price	552	307.80	45.62	186.63	412.05
Exchange rate	552	448.42	11.41	429.70	475.59

Notes: Sample period is from 1980 to 2025. All variables are expressed in natural logarithms. Real field crop price and real oil price are deflated by the U.S. CPI; Real PCE for food is deflated by PCE for food price index.

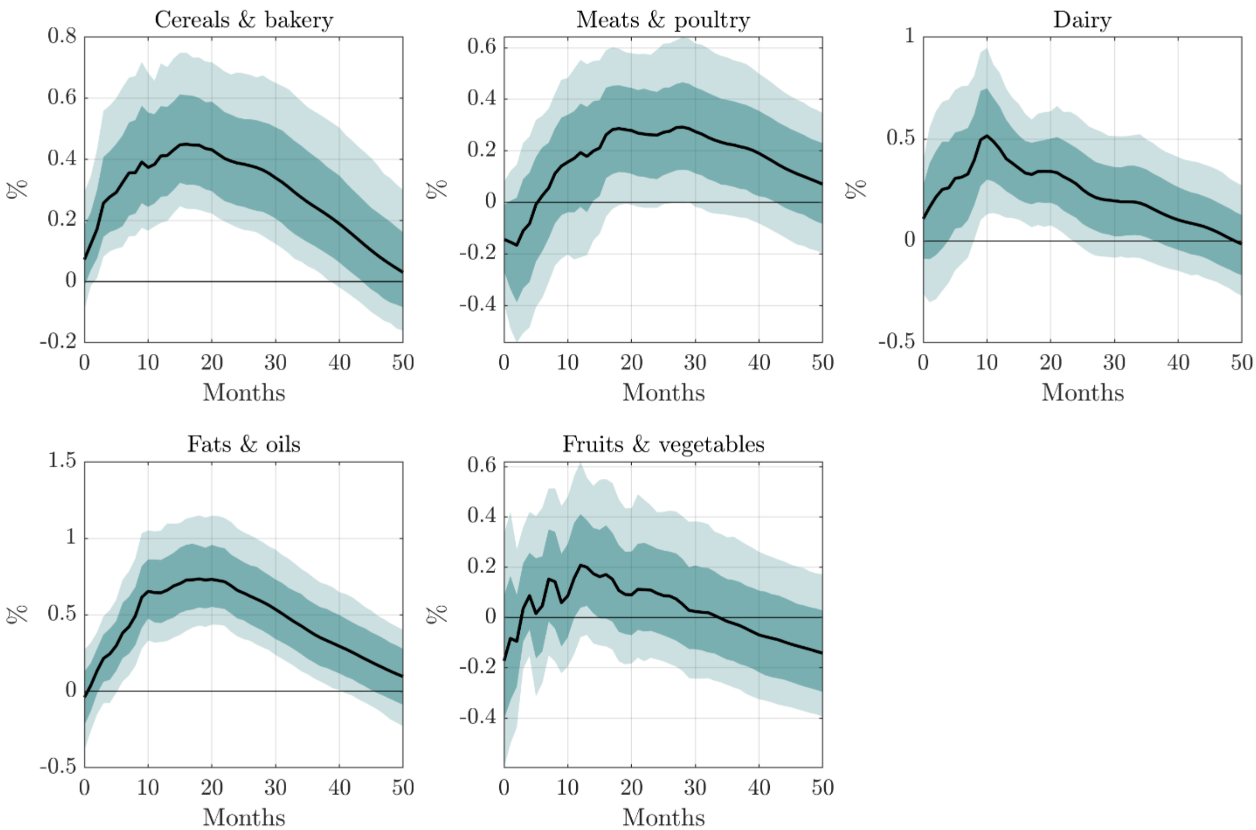
Table C.3. Summary statistics: distributional food CPI by income quintile

Variable	Obs.	Mean	Std. Dev.	Min	Max
Panel A: Food-at-Home D-CPI					
Food-at-Home, Q1 (Lowest)	312	541.3417	17.0176	511.5074	574.5206
Food-at-Home, Q2 (Lower-middle)	312	541.0548	17.0573	511.1279	574.0911
Food-at-Home, Q3 (Middle)	312	540.9498	16.9663	511.2605	573.9273
Food-at-Home, Q4 (Upper-middle)	312	541.0151	16.8604	511.5476	573.8535
Food-at-Home, Q5 (Highest)	312	542.2643	16.8877	512.8136	575.0403
Panel B: Food-away-from-Home D-CPI					
Food-away-from-Home, Q1 (Lowest)	312	550.7487	22.7838	513.9040	597.3613
Food-away-from-Home, Q2 (Lower-middle)	312	550.3749	22.6895	513.8740	596.8043
Food-away-from-Home, Q3 (Middle)	312	550.2810	22.6453	513.8735	596.6301
Food-away-from-Home, Q4 (Upper-middle)	312	550.2580	22.5519	513.9075	596.2263
Food-away-from-Home, Q5 (Highest)	312	550.4859	22.4105	513.9883	595.9721

Notes: All variables are expressed in natural logarithms. D-CPI series are constructed following Jaravel (2026) using Consumer Expenditure Survey (CEX) micro-data and BLS monthly price series. DCPI-FAH = Distributional CPI for Food-at-Home (53 item strata). DCPI-FAFH = Distributional CPI for Food-away-from-Home (5 item strata). Q1-Q5 denote income quintiles ranked by after-tax household income. Sample spans from January 1999 to December 2024.

Appendix D. Consumer Price Index (CPI) subcategories

Figure D.1. Impulse responses of CPI food-at-home subcategory prices to a poor harvest news shock



Notes: Data are obtained from Bureau of Labor Statistics (BLS). The sample spans 1980-2025. Index are expressed relative to 1982-1984=100. Responses are normalized to a 3 percent increase in real field crop prices. The solid line represents the point estimate; the dark shaded area denotes the 68 percent confidence band, and the light shaded area the 90 percent confidence band. Confidence intervals are derived from 1,000 bootstrap replications.