Decomposing Food Price Inflation into Supply and Demand Shocks

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Abstract
Recent food price inflation in the United States is comparable to historically sharp increases observed in the 1970s and early-1980s. Many factors contribute to recent food price inflation, including supply chain backups and increased production costs brought on by the Covid-19 pandemic and its aftermath, weaker global markets for wheat and fertilizers following Russia's invasion of Ukraine, and the strong aggregate demand driven in part by historically-large U.S. government stimulus efforts. Using a newly-developed technique to identify the contributions supply and demand shocks make to food price inflation over time, we find that while about 77 percent of the observed food category-level food price changes from the early-1990s up to the pandemic period were due to supply shocks (with the demand side taking up the remaining 23 percent), recent inflation is characterized by demand shocks to a greater degree—accounting for over 40 percent of the food category shocks. We exploit the decomposition to show that while monetary tightening reduces demand-side contributions to food price inflation, poor agricultural supply news increases the supply-side component. We further show how oil supply news, (Google searches for) shortages, industrial production, per-capita income, the job vacancy ratio, and prices for energy, transportation, and farm products relate to supply- and demand-driven food price inflation, dynamically.

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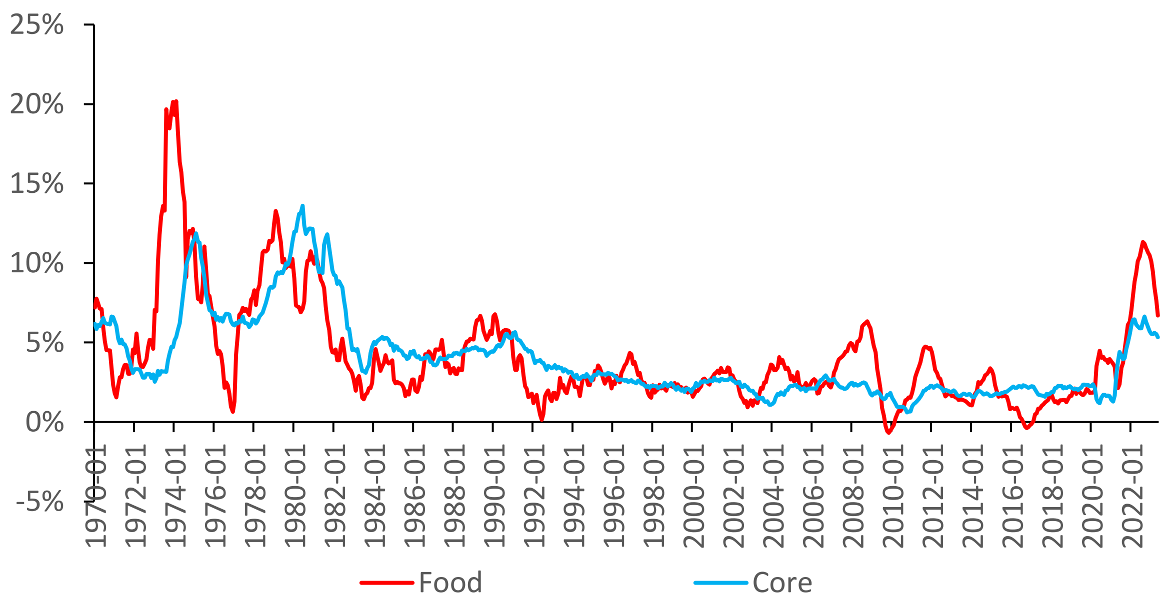
Since 2022, food prices in the United States have increased at a historic pace. According to the U.S. Bureau of Labor Statistics (BLS), the price of food paid by urban consumers increased by 10.6 percent over the 12 months ending in November 2022, marking the highest year-over-year increase observed in more than four decades. As shown in figure 1, food price inflation levels in the 2020s more closely resemble the steep food price inflation of the 1970s and 1980s, compared to the relatively stable intervening decades. Food price rises are concerning because food consumption is unavoidable, and it makes up a greater share of household budgets among lower-income Americans (ERS, 2022). Inflation, definitionally, is widespread across product categories in the economy. Yet, as figure 1 shows, since the onset of the pandemic in early 2020 food prices in the United States are increasing at a faster pace than prices for other goods and services. Although not unprecedented, historically—after all, BLS drops food (and energy) prices from its core inflation series,[1] since it is more volatile (in part due to more inelastic short-run supply)—the difference is notable.

Figure 1. Inflation in the United States (Year over Year)



Source: U.S. Bureau of Labor Statistics and U.S. Bureau of Economic Analysis; author calculations.

[1] The Bureau of Labor Statistics (BLS) Consumer Price Index (CPI) for All Items Less Food and Energy is commonly referred to as the "core" CPI (BLS, 2018). Although core inflation is generally used as a gauge of overall inflation since it is less volatile, including food and energy prices provides a more accurate view of the inflationary situation facing Americans (CRS, 2021).

Our research seeks to understand why food prices are rising so quickly. Prices ration supply and demand, so price increases can occur with positive shifts in demand or negative shifts in supply. Furman (2022) identifies some potential explanations: on the demand side, the rapid growth in real economic output following the COVID-19 shock (CRS, 2021); on the supply side, unexpected reductions in productive capacity due to the pandemic-induced lockdowns, the still-tight labor market following the pandemic recovery produced, and other supply chain issues like intermediate goods shortages and transportation bottlenecks that may have in part been driven by a lockdown-compelled preference shift from services to goods, or disruptions stemming from the Russian invasion of Ukraine. Understanding the source of observed price shocks is important because it informs policymakers about how to approach the issue. If demand-side shocks are generating price increases, that's a sign that policy makers should focus on monetary tools (like adjusting interest rates) and fiscal measures (like refraining from additional stimulus packages). On the other hand, if supply-side factors dominate, policy makers may be able to address food price inflation through infrastructure investments (e.g., improving ports, waterways, highways, or rail networks) that facilitate supply chain efficiency, although this is a longer run prospect.

Shapiro (2023) employs category-level regressions to decompose changes in the overall personal consumption expenditure price (PCE) index into supply and demand shocks.[2] PCE data include category-level expenditures at a monthly frequency, as well as indices for price and quantity. Shapiro's model determines if, from one month to the next, a category experienced a same-direction change in price and quantity, or an opposite direction change (allowing for ambiguousness as well, depending on the size of the shocks relative to cutoffs based on their historical distribution). Same-direction changes are consistent with a demand shock, opposite direction changes indicate a supply

[2] PCE data are the source of the Fed's preferred measure of inflation, while the CPI inflation figures are often referred to by the popular press (CRS, 2021).

shock. Weighting each category according to its share of total U.S. expenditures,[3] the contributions of demand and supply shocks to the overall level of price inflation can be estimated.

We use Shapiro's method and focus on food price rises, for food consumed at home (what the PCE terms "off-premises consumption"), food away from home ("food services"), and a total food category ("all food"; the PCE does not include this measure, but we aggregate its off-premises and food services data into a single index). Model outputs include new data series that represent the overall contribution the demand and supply sides of the market make to food price inflation. This decomposition permits the researcher to examine how each contributes to changes in food prices at the category level. In addition, our approach offers the ability to track how the composition of food price shocks evolves in near-real time. We find that supply shocks tend to dominate observed food price changes before the pandemic, accounting for 77 percent of all food category shocks from January 1992 - December 2019. Yet from January 2020 - April 2023, movements in the demand curve accounted for over 40 percent of observed food shocks. Likewise, demand-driven contributions to food price inflation increased notably beginning with the onset of the pandemic and the recession it sparked. Recent food price inflation is driven by demand shocks to a greater degree than it has been over the last thirty years. And these demand-side contributions are among the most precisely-measured shocks we observe in the analysis timeframe, spanning three decades.

Few papers have addressed recent high rates of U.S. food price inflation. Adjemian et al. (2023) use conventional time series methods (like structural vector autoregressions) to estimate how specific factors affect food prices. Their approach builds on similar models estimated by Baek and Koo (2010), Lambert and Miljkovic (2010), and Irz et al. (2013)—each written not long after the last rapid food price increase toward the end of the first decade of the 2000s. While insightful, the work of these authors relies on identification strategies that make fairly strong assumptions. In contrast, our work

[3] These are Laspeyres weights.

(which applies Shapiro's model) does not, and has the added benefit of producing easy-to-interpret results. Our estimated demand- and supply-driven components can be modeled as functions of exogenous economic shocks, allowing us to examine their association with other macroeconomic developments. We show that monetary tightening curbs the contribution of demand-side factors to food price inflation, while adverse agricultural supply news augments the supply-side component. Additionally, we display the dynamic relationship between supply- and demand-driven food price inflation and several other factors. These include oil supply news, the incidence of shortages (as indicated by Google searches), industrial production, per-capita income, job vacancy ratio, and prices for energy, transportation, and farm products..

Conceptual Model, Data, and Empirical Approach

Identifying supply and demand shocks

Following Shapiro (2023), with quantity and price data for food category *i*, and facing supply curve slope σ^i and demand curve slope δ^i, running the vector autoregression (VAR) model:

$$z_{i,t} = \left[A^i\right]^{-1} \sum_{j=1}^{N} A_j^i z_{i,t-j} + \nu_{i,t} \tag{1}$$

where $A^i = \begin{bmatrix} 1 & -\sigma^i \\ \delta^i & 1 \end{bmatrix}$, $z_i = \begin{bmatrix} q_i \\ p_i \end{bmatrix}$, and j lags produces reduced-form residuals $\nu_i = \begin{bmatrix} \nu_i^q \\ \nu_i^p \end{bmatrix}$. These residuals can be transformed to recover the structural supply and demand shocks $\varepsilon_i = \begin{bmatrix} \varepsilon_i^s \\ \varepsilon_i^d \end{bmatrix}$, where:

$$\varepsilon_i^s = q_i - \sigma^i p_i \tag{2}$$

$$\varepsilon_i^d = \delta^i q_i + p_i, \tag{3}$$

according to:

$$\varepsilon_{i,t} = A^i \nu_{i,t}. \tag{4}$$

Restrictions on the sign of the supply and demand slopes specified in A^i (consistent with basic economic theory) imply restrictions on both the signs of the reduced-form residuals and structural shocks (Calvert Jump and Kohler, 2022). That is, the relationship in (4) indicates how unexpected time *t* shifts in price and quantity for different food categories reveal supply and demand shocks:

$$\text{Pos. Supply Shock: } \nu_{i,t}^{p} < 0 \; and \; \nu_{i,t}^{q} > 0 \rightarrow \varepsilon_{i,t}^{s} > 0 \tag{5}$$

$$\text{Neg. Supply Shock: } \nu_{i,t}^{p} > 0 \; and \; \nu_{i,t}^{q} < 0 \rightarrow \varepsilon_{i,t}^{s} < 0. \tag{6}$$

$$\text{Pos. Demand Shock: } \nu_{i,t}^{p} > 0 \; and \; \nu_{i,t}^{q} > 0 \rightarrow \varepsilon_{i,t}^{d} > 0 \tag{7}$$

$$\text{Neg. Demand Shock: } \nu_{i,t}^{p} < 0 \; and \; \nu_{i,t}^{q} < 0 \rightarrow \varepsilon_{i,t}^{d} < 0 \tag{8}$$

For a given food category *i* at time *t*, same-sign price and quantity residuals from (1) represent a demand shock, while opposite sign residuals represent a supply shock. Likewise, the sign of any demand or supply shock depends on the signs of the residuals.

Determining the contributions of demand and supply shocks to food price inflation

Once time *t* shocks for each food category are segregated into supply and demand shocks according to equations (5)-(8), they can be used to decompose observed food price inflation into the portion driven by each broad side of the market. Once again following Shapiro (2022), we specify indicator functions that classify whether a food category experienced a supply or demand shock in period *t*:

$$\mathrm{I}_{i \in sup,t} = \begin{cases} 1 & if \; \varepsilon_{i,t}^{s} > 0 \; or \; \varepsilon_{i,t}^{s} < 0 \\ 0 & otherwise \end{cases} \tag{9}$$

$$\mathrm{I}_{i \in dem,t} = \begin{cases} 1 & if \; \varepsilon_{i,t}^{d} > 0 \; or \; \varepsilon_{i,t}^{d} < 0 \\ 0 & otherwise \end{cases}. \tag{10}$$

Then the observed price inflation between *t-1* and *t* can be decomposed into supply- ($\pi_{t,t-1}^{sup}$) and demand-driven ($\pi_{t,t-1}^{dem}$) components, each of which represent sums of category-level inflation—classified by type of shock—and weighted by their share of the overall consumption basket. That is:

$$\pi_{t,t-1} = \pi_{t,t-1}^{sup} + \pi_{t,t-1}^{dem}, \text{ where} \tag{11}$$

$$\pi_{t,t-1} = \textstyle\sum_i \mathrm{I}_{i \in sup,t} \, \omega_{i,t} \pi_{i,t,t-1} + \sum_i \mathrm{I}_{i \in dem,t} \, \omega_{i,t} \pi_{i,t,t-1}. \tag{12}$$

In (12), $\omega_{i,t}$ represents the share of time *t-1* expenditures on category *i*, while $\pi_{i,t,t-1}$ is the percent change in price for category *i* between periods *t-1* and *t*. If the frequency of the data are monthly, then the contributions of the supply and demand shocks to year-over-year inflation is the combination of their twelve-month running sums.

$$\pi_{t,t-12} = \pi_{t,t-12}^{sup} + \pi_{t,t-12}^{dem}, \text{ where} \tag{13}$$

$$\pi_{t,t-12}^{m} = \sum_{k=0}^{11} \pi_{t-k,t-k-1}^{m}, \text{ for } m\ \epsilon (sup, dem). \tag{14}$$

Food expenditure, price and quantity data

The U.S. Bureau of Economic Analysis PCE dataset tracks expenditures on goods and services by U.S. resident "persons", defined as households or nonprofit institutions serving households (BEA, 2022).[4] While the CPI represents only urban residents, PCE data include expenditures of both urban and rural Americans. Expenditures are classified into broad categories; the two relevant to food purchases are "food and beverages purchased for off-premises consumption" as nondurable purchases, and "food services" as service expenditures, the latter representing on-premises food consumption (i.e., food away from home). These broad categories are further disaggregated into several levels; we use the lowest level of aggregation available for analysis. For each category, BEA provides price and quantity indices, as well as total expenditure levels at the annual, quarterly, and monthly frequency.[5] While most of the subcategories have complete observations from Jan. 1959 – Apr. 2023, three food service subcategories (meals at limited-service eating places, meals at other eating places, and meals at drinking places) are only available from Jan. 1987 – Apr. 2023. We conduct analysis on the full set of available data, using the first five years of the data to establish a baseline for, e.g., the precision cutoffs we describe below.

[4] This definition includes U.S. residents traveling overseas for a duration of up to one year, as well as government civilian and military personnel stationed overseas, whatever the duration of their deployment.

[5] Quantity, price, and expenditure data are available in the "Underlying Detail" BEA PCE tables 2.4.3U, 2.4.4U, and 2.4.5U tables, respectively.

Specific PCE subcategories included in our analysis, as well as their average expenditure weights over the sample timeframe, are shown in table 1. According to the PCE data, over the last few decades Americans averaged spending about 59% of their food (and beverage) budget on food consumed off-premises, i.e., at home, and the remaining 41% on food away from home. The largest specified at-home food categories include beverages like mineral waters/sodas/vegetable juices and beer, and food like bakery products, poultry, beef and veal, cereals, processed dairy products, and fresh vegetables. U.S. residents concentrated away-from-home expenditures at limited service eating places and "other eating places", including full-service restaurants. The third column in table 1 identifies the average share that each of these thirty subcategories makes up of the all-food category that we construct using PCE food and food service data.

Empirical approach

After collecting the relevant data from BEA, like Shapiro (2023), we estimate the shocks to price and quantity for each of the subcategories *i* in table 1 by running log price and log quantity (index, as provided by BEA) VARs of the form:

$$q_{i,t} = \sum_{j=1}^{12} \gamma_j^{qp} p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{qq} q_{i,t-j} + \nu_{i,t}^{q} \qquad (15)$$

$$p_{i,t} = \sum_{j=1}^{12} \gamma_j^{pp} p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{pq} q_{i,t-j} + \nu_{i,t}^{p}. \qquad (16)$$

Table 1. Share of Food Expenditures by U.S. residents, by food category, Jan. 1987 – Apr. 2023

Food and beverages purchased for off-premises consumption	*Within group*	*Share of all food*
Food/bev for off-premises total	100%	59.03%
Cereals	5.23%	3.09%
Bakery products	9.35%	5.52%
Beef and veal	4.88%	2.88%
Pork	3.54%	2.09%
Other meats	3.34%	1.97%
Poultry	5.74%	3.39%
Fish and seafood	1.56%	0.92%
Fresh milk	2.66%	1.57%
Processed dairy products	4.84%	2.86%
Eggs	1.14%	0.67%
Fats and oils	2.12%	1.25%
Fruit (fresh)	3.49%	2.06%
Vegetables (fresh)	4.64%	2.74%
Processed fruits and vegetables	3.12%	1.84%
Sugar and sweets	5.17%	3.05%
Food products, not elsewhere classified	14.92%	8.81%
Coffee, tea, and other beverage materials	1.46%	0.86%
Mineral waters, soft drinks, and vegetable juices	9.11%	5.38%
Spirits	2.93%	1.73%
Wine	3.73%	2.20%
Beer	6.96%	4.11%
Food produced and consumed on farms	0.07%	0.04%
Food service		
Food service total	100.00%	40.94%
Elementary and secondary school lunches	1.27%	0.52%
Higher education school lunches	2.37%	0.97%
Meals at limited service eating places	41.60%	17.03%
Meals at other eating places	38.64%	15.82%
Meals at drinking places	0.59%	0.24%
Alcohol in purchased meals	12.82%	5.25%
Food supplied to civilians	2.42%	0.99%
Food supplied to military	0.29%	0.12%

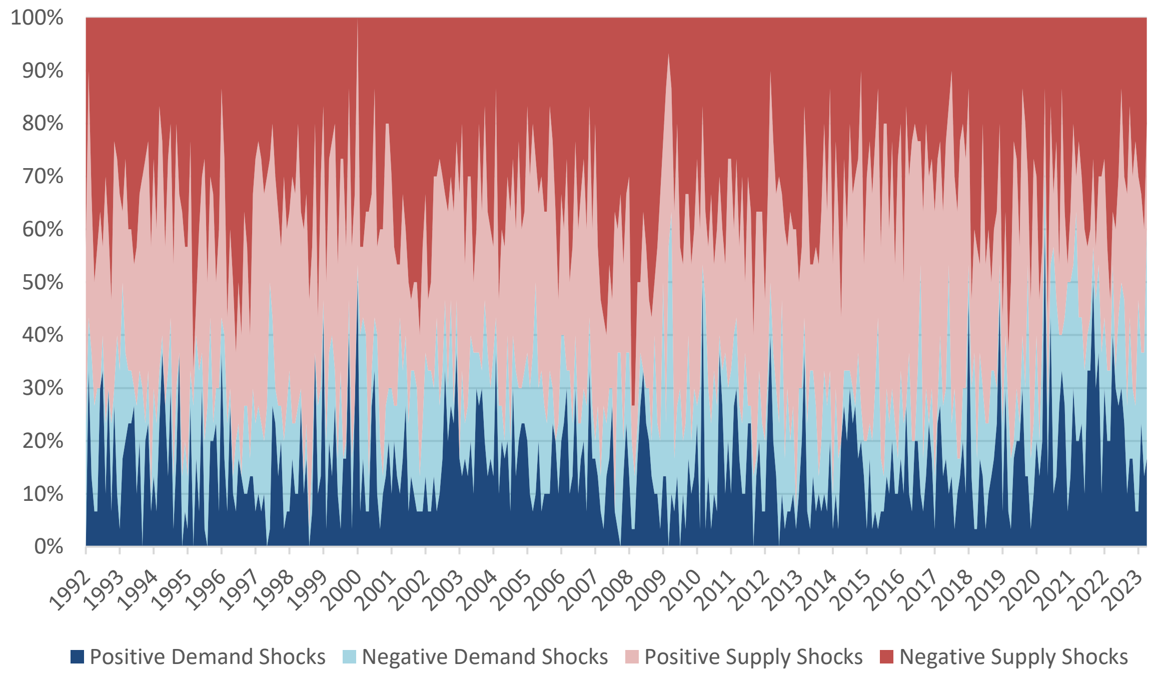
Source: U.S. Bureau of Economic Analysis; author calculations. Totals may not sum to 100% due to rounding.

Regressions in equations (15) and (16) include twelve lags to control for trends in the purchase of food categories that do not represent unexpected shocks. We use the reduced-form errors in those equations to identify the supply and demand shocks and sign them according to equations (5)-(8), with some allowance for the ambiguity of definition as a robustness check.[6] Figure 2 plots the monthly shares of PCE food subcategories—both off-premises and food service—with supply or demand shocks beginning in 1992, assuming no ambiguity in their definition. Dark colors in the figure (positive demand and negative supply shocks) are associated with price increases; light colors (negative demand and positive supply) with price decreases.

For most of the period of observation, supply shocks—whether positive or negative—tend to dominate observed food price changes across food subcategories.[7] From January 1992-December 2019, the supply side accounted for 77 percent of all food category shocks (and demand shifts represented the remaining 23 percent). Yet after that date, coinciding with the onset of the global pandemic, movements in the demand curve accounted for over 40 percent of observed food shocks—nearly a doubling in percentage-point terms. In the figure, while the early part of the pandemic is characterized by (in light blue) inward shifts in demand, (dark blue) positive demand shocks become more prominent as the pandemic wore on. The only other instance when demand shocks approached a similar level of importance, according to the model, was during the 2008 financial crisis, when negative demand shocks spiked in the wake of a sustained period of negative supply shocks.

Figure 2. Shares of PCE food products and services experiencing a supply or demand shock each month, 1992-present

[6] Like Shapiro (2022) we re-define a given food category's contribution to inflation as ambiguous if at least one of the residuals from the regressions in (15)-(16) is within 0.025 food category-specific standard deviations from zero (the idea being that a residual close to zero does not provide enough evidence of a shift in the supply or demand curve). We also report the relative precision of our contribution estimates, defining as less precise, mid precise, and more precise those non-ambiguous inflation contributions whose residuals exceeded a threshold of 0.025, 0.05, and 0.25 food category-specific standard deviations away from zero, respectively.
[7] Note that these are simple averages across subcategories, and are not weighted by expenditure or inflation level.



Source: U.S. Bureau of Economic Analysis; author calculations.

Results and discussion

Inflation decomposition

Our baseline findings for the contribution of supply- and demand-side shocks to overall, year-over-year PCE food price inflation in the United States are displayed in figure 3: panels A, B, and C represent all food subcategories in table 1, off-premises food and beverage, and food service, respectively. For each panel, inflation driven by unexpected shifts in supply is shown in red; demand shift contributions are shown in blue. Recession bars are shown in dark gray. The vertical sum of the two sets of contributions match the observed total food price inflation, by construction.[8]

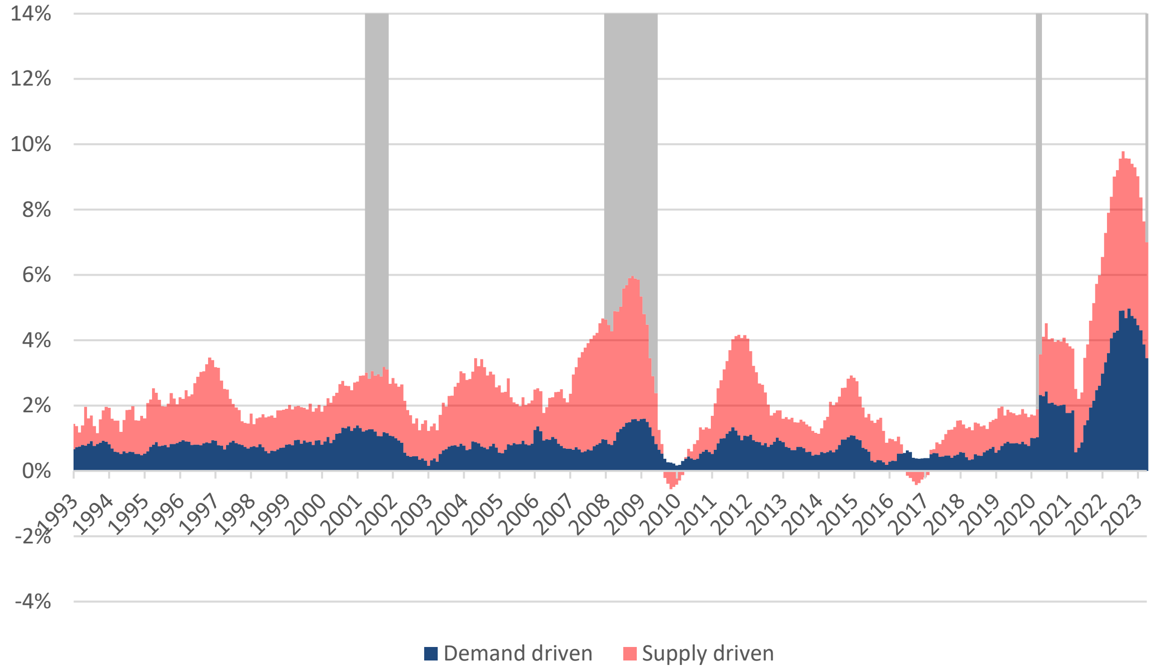
As in figure 2, for most of the three decades in figure 3, supply shocks represent a stronger contributor to food price inflation. This is not surprising, in particular for all-food and off-premises food shown in panels A and B, since its supply is subject to more unexpected shortages or surpluses

[8] Figure 3 begins in 1993 because as explained in equations (9) and (10), calculating the year-over-year contributions to inflation requires a twelve-month running sum of the (weighted) shocks displayed in figure 2, which stretches back to January 1992 (and follows our five-year baseline period to establish the precision cutoffs).

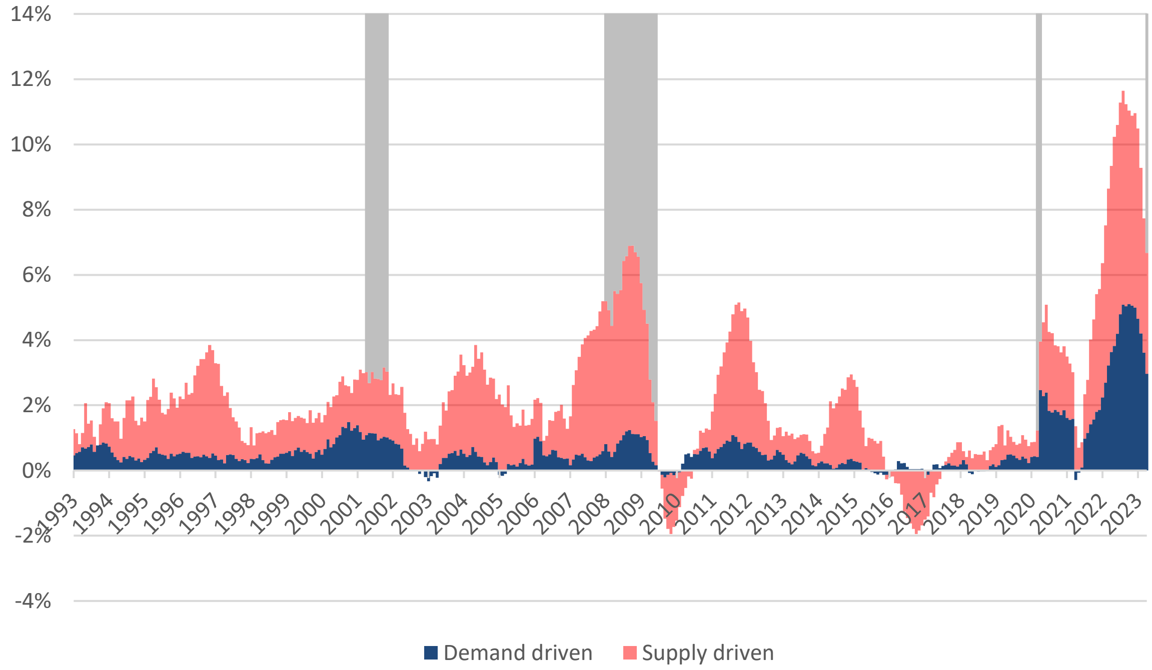
than, say, industrial goods. Farm production is exposed to weather and biological shocks, and can't be scaled up or down as easily as production in a factory. On the other hand, food service inflation is noticeably comprised of demand-side shocks. Again, this is intuitive since the demand for food away from home is more sensitive to income-driven changes in food expenditure; Okrent and Alston (2012) found that average U.S. consumers' budget share for food away from home (at home) fell (increased) during the financial crisis.

For all three panels in figure 3, demand-driven contributions to food price inflation increase sharply beginning with the onset of the pandemic and the recession it sparked in early 2020. Recent food price inflation, exhibiting larger year-over-year increases than it has since the 1970s, is driven by demand shocks to a greater degree than it has been over the last thirty years. This pattern is most evident in panel B of figure 3: while off-premises food prices increased relatively swiftly in the lead-up to the financial crisis—peaking around a 7 percent rise towards the end of 2008—this inflation was dominated by supply shocks. Demand contributions reached just over 1 percentage point, while supply shocks were about six times larger. Yet apart from a brief dip in 2021, demand contributions to the much larger observed food price inflation since the pandemic onset are far more substantial. During a period when year-over-year food price rises at one point exceeded 11 percent, demand shocks contributed about 5 percentage points of that increase—nearly half the measured inflation.

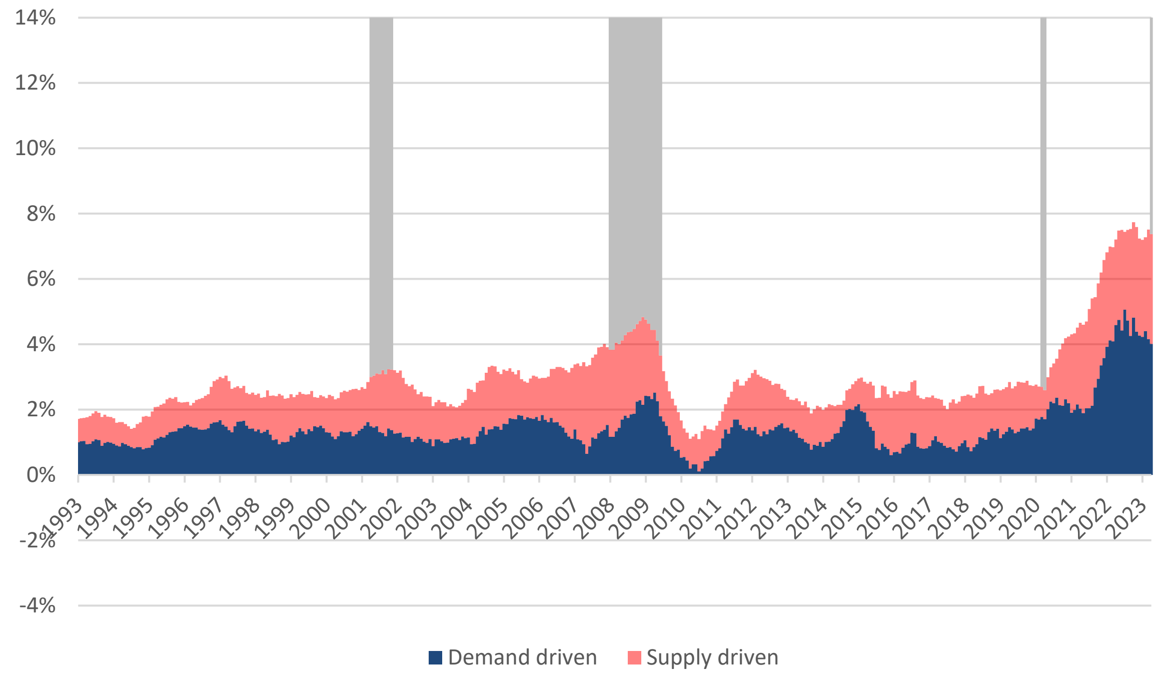
Figure 3. Supply- and demand-driven PCE food inflation in the United States, year-over-year
Panel A. All food



Panel B. Off-premises food and beverages



Panel C. Food service



Source: U.S. Bureau of Economic Analysis; author calculations.
Note: Recession periods, as defined by the National Bureau of Economic Research, are shown in dark gray.

Our estimates in figure 3 leave no space for uncertainty, as all unexpected price and quantity shifts are identified as either supply or demand shocks. However, it may be the case that our model misidentifies these shocks if changes in price and quantity are small. To guard against that possibility, we define cutoff values for precision of identification—more, mid, and less—as well as an "ambiguous" category that is left undefined.[9] In the case of ambiguity, observed price inflation for the particular food category is not distinguishable between being supply- or demand-driven, because at least one of the price or quantity shocks is not convincing (i.e., large) enough. Figure 4 plots the contributions to food price inflation produced by the modified model, with darker colors representing greater degrees of identification precision. Ambiguity, plotted in light gray, is generally minimal and only accounts for a small portion of price inflation in most months (in panel C). However, ambiguity in food service shocks peaks in importance over the first eighteen months of the pandemic; after that,

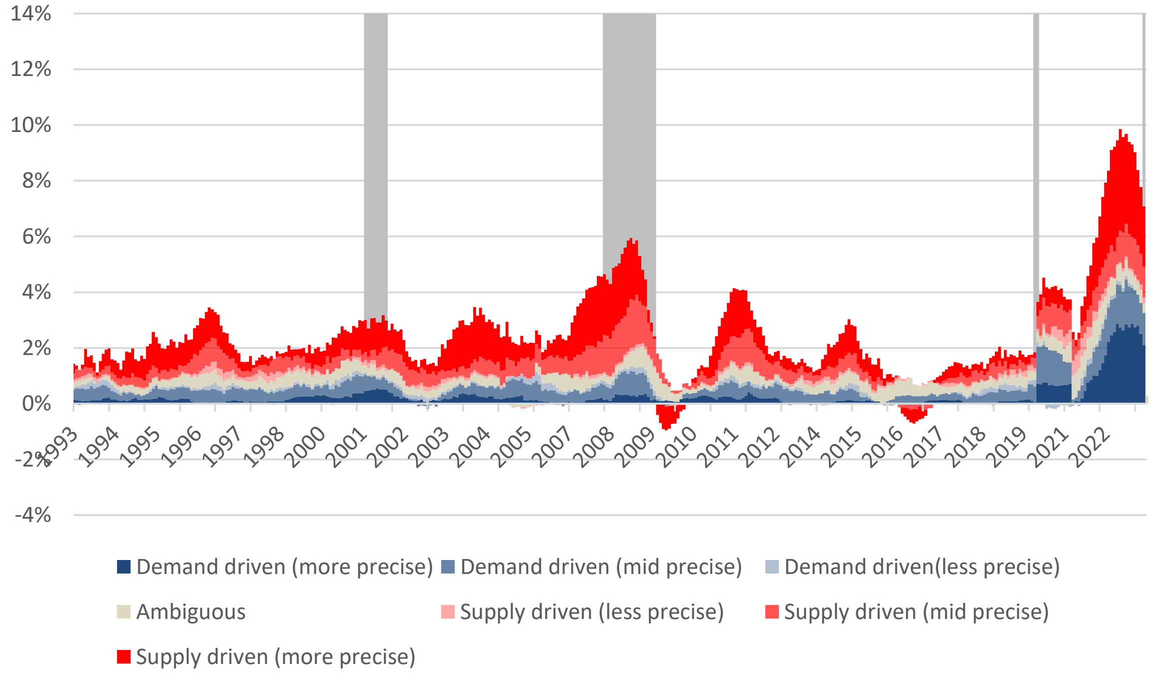
[9] The more, mid, less, and ambiguous cutoffs work out to represent 43.2, 34.0, 8.4, and 14.4 percent, respectively, of all the possible food category/time pair shocks in the data.

observed shocks are far more easily classified. For off-premises food (panel B), ambiguous shocks are most apparent in the 2004-2005 period, when they are associated with a group of products with declining prices.

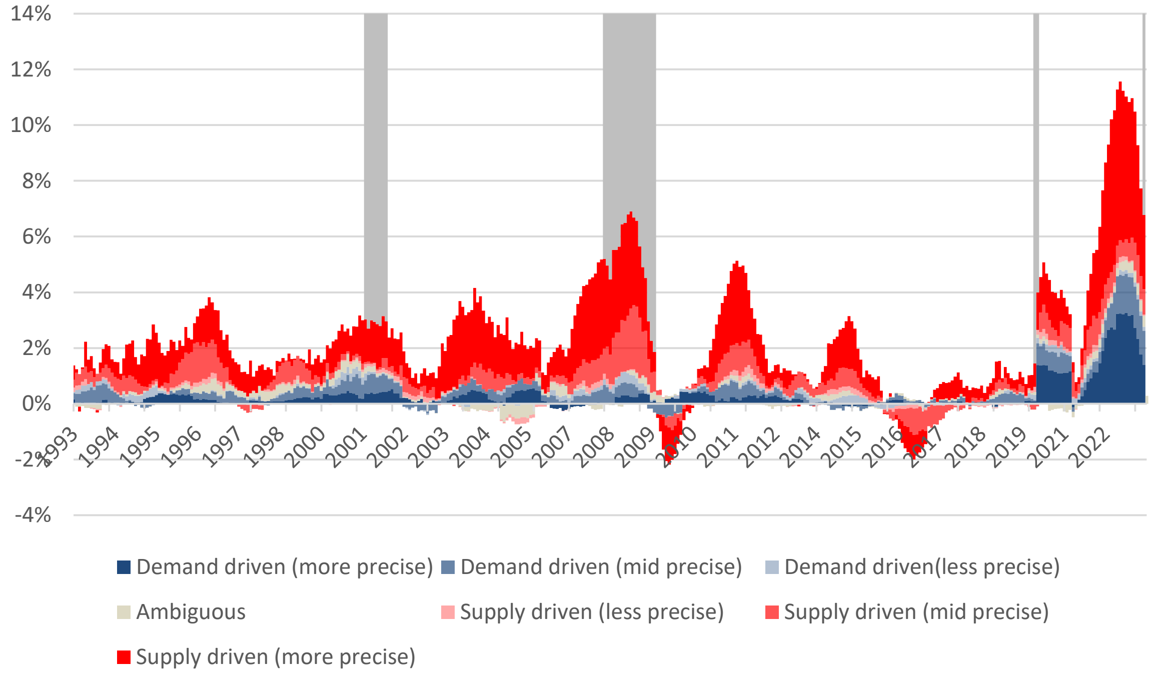
Figure 4 also shows that, in addition to including the largest demand-driven contributions to inflation over the last thirty years, recent food price spikes also exhibit the most *precisely-measured* demand sensitivity across all three panels. For example, the darkest blue shade in panel A is most apparent in the food price rises observed in the aftermath of the pandemic recession. More-precise demand drivers likewise make strong contributions to recent off-premises food and beverage, and food service price inflation in panels B and C, respectively. Most of the other demand shocks in the data are measured less precisely, at the mid-level or lower. On the other hand, most of the supply shocks in panels A and B are measured with a high degree of precision: dark red shocks make up a greater share of the observed supply contributions. Two notable exceptions include the run-up to the financial crisis and its wake. From about 2006 through 2013, mid-precise and less-precise supply shocks appear more often. Supply shocks are less precisely measured for food service inflation in panel C.

Figure 4. Supply- and demand-driven PCE food inflation in the United States with multiple precision cutoffs, year-over-year

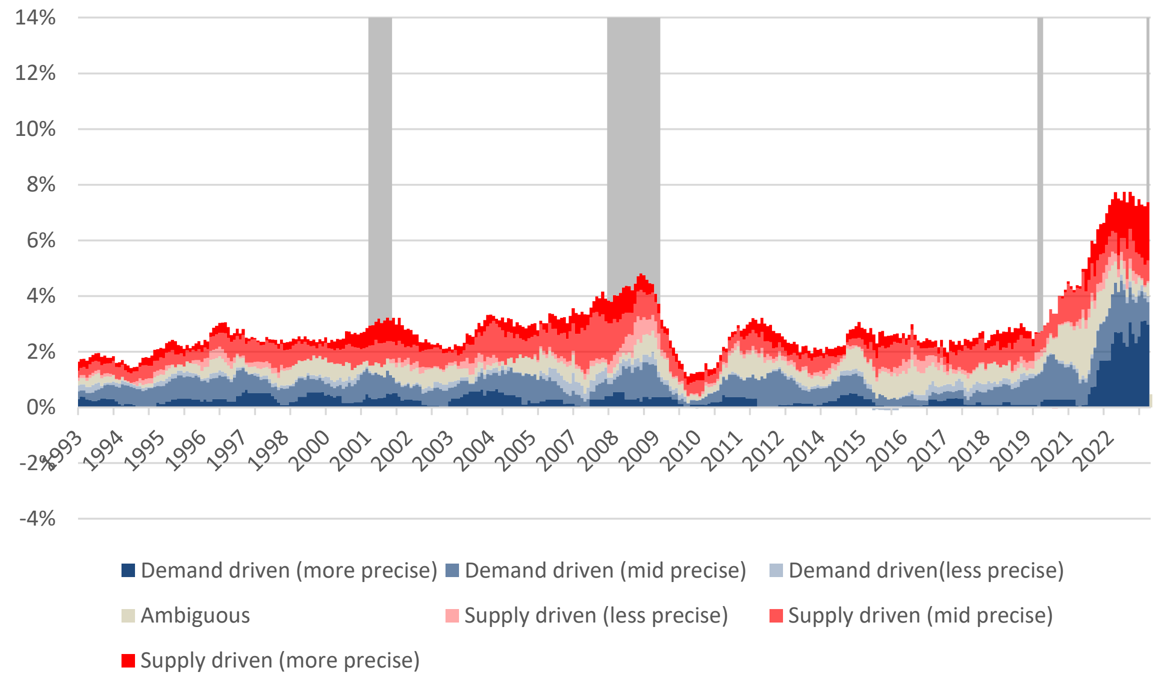
Panel A. All food



Panel B. Off-premises food and beverages



Panel C. Food service



Source: U.S. Bureau of Economic Analysis; author calculations.
Note: Recession periods, as defined by the National Bureau of Economic Research, are shown in dark gray. Darker colors in the figure represent more precisely-measured shocks.

Factors that affect supply- or demand-driven food price inflation

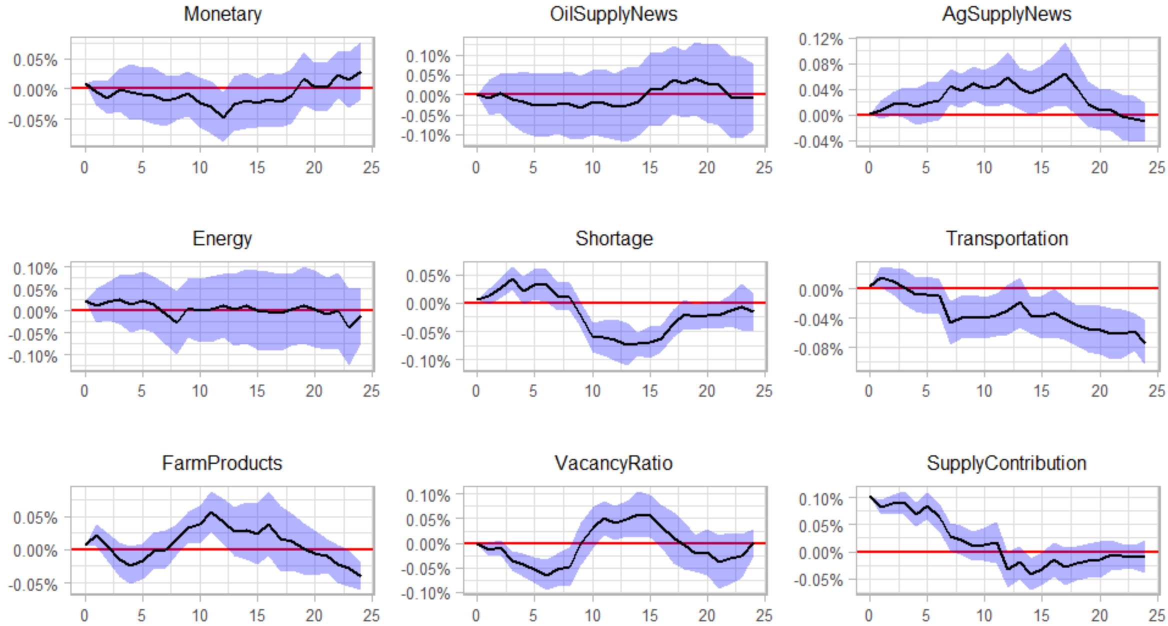
The supply and demand contribution decompositions we estimate describe how shocks to different sides of the market lead food prices to change over time. We use time series methods to explore how certain factors affect these demand and supply series, themselves. Specifically, we use local projections (Jordà, 2005)—a method that conducts individual regressions at each forecast horizon under study—to estimate how the cumulative inflation contributions we measure respond to an initial change in the variable of interest. Although Shapiro (2023) conducts a similar analysis for both headline and core PCE inflation, his analysis doesn't translate perfectly to our focus: a consideration of only food prices. Notably, food prices are left out of the core price series, because they are considered to be too volatile (Luciani and Trezzi, 2019). Moreover, while Shapiro conducts his analysis to verify that his supply and demand decomposition is externally valid for understanding the drivers of headline and core economy-wide (and finds that it is), we are concerned with understanding why supply- and demand-driven contributions to food price inflation vary the way they do. Because food consumed at home and away from home are inherently different, we discuss the way these factors affect them in two separate subsections. For both analyses, we include variables likely to affect either the supply or demand of food. Data availability limits this portion of our analysis to the period from February 2004 to December 2020.

Factors that affect food service price inflation

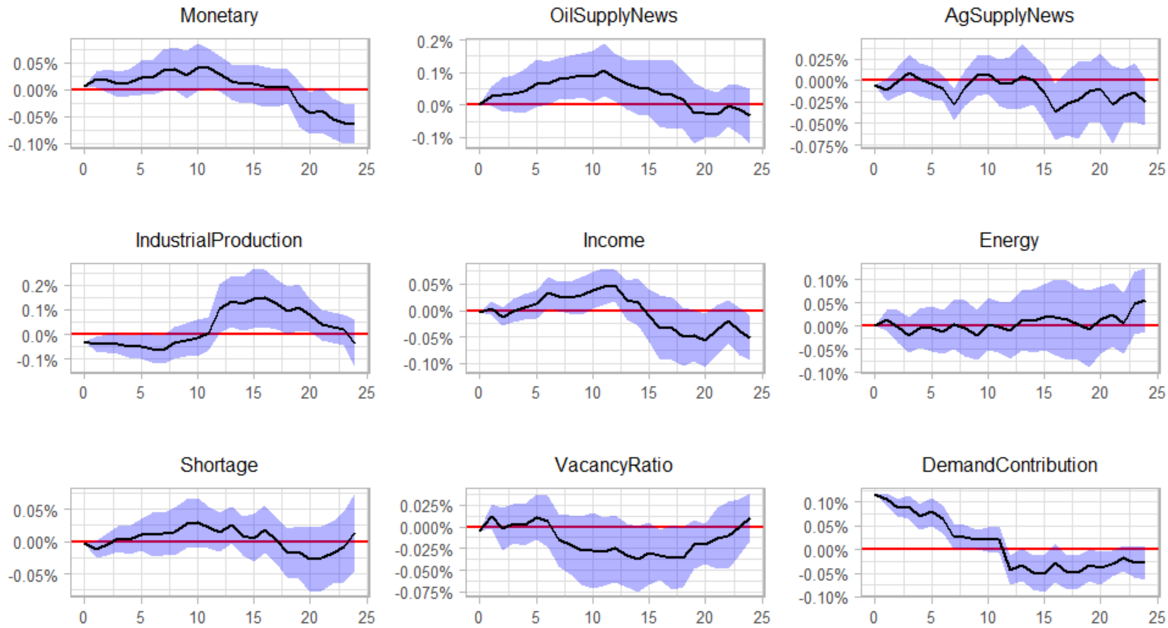
Figure 5 plots the impulse response functions (IRFs) of the supply- (panel A) and demand-driven (panel B) contributions to food service price inflation from a single standard deviation increase in several potential explanatory factors. Mean effects in the figure are shown by a solid black line, while 95% confidence intervals (estimated using Newey-West standard errors to account for any autocorrelation) are shaded blue. The first three IRFs in each panel represent the effects of exogenous shocks on contributions to food service price inflation. The first is a monetary shock that indicates when (conventional or unconventional) policy becomes unexpectedly tighter, as measured by Bu, Rogers, and Wu (2021). Those authors show how rises in that shock series (unexpected monetary contractions) lead to decreases in the CPI—an expected result given that such shocks are theorized to slow inflation by reducing aggregate demand (consumption) in the economy (see, e.g., Smets and Wouters, 2003). In panel A, monetary shocks appear to lead to some short-run decreases in supply-driven food price inflation, but have a stronger effect in panel B, where they lead to significant decreases in the demand-side contribution after an 18-month lag. Unexpected oil supply decreases, as measured by Känzig (2021), lead to negative (at the mean, yet imprecisely-measured) effects on the supply-driven component of food-price inflation; on the other hand, they lead to medium-run increases in the demand-driven series, which echoes Shapiro's (2023) finding for headline inflation. Negative domestic agricultural supply shocks, estimated by Jo and Adjemian (2023), generate both statistically and economically significant increases in the supply-side contribution to inflation as might be expected, while also leading to some small reductions in contributions by the demand side.

Figure 5 further shows that additional variables that cannot necessarily be classified as exogenous shocks also present some notable associative relationships with the drivers of food price inflation. Global industrial production increases (Baumeister and Hamilton, 2019) lead small short-term reductions and then larger medium-run increases in contributions by the demand side, while per-capita income rises also predict more demand-side inflation in the medium term. Energy price increases predict increases in both supply- and demand-driven inflation, although the supply figures are not measured with precision. Google searches for the term “shortage” lead large, immediate increases in supply-driven inflation (and decreases in the medium run), but predict smaller effects to demand-side contributions; transportation price increases predict similar supply-side effects as shortage searches. Increases in the vacancy ratio, which represents the number of job vacancies for every unemployed person in the United States, at first reduces supply-driven food service inflation and then increase it; its effect on demand-driven inflation is smaller and less precisely measured. Finally, like poor agricultural supply news, increases in farm product prices tend to increase supply-driven food service inflation, as expected.

Figure 5. Impulse responses of PCE food service price inflation to various shocks, in percentage point changes
Panel A. Supply contribution



Panel B. Demand contribution



Notes: Panels in the figure display impulse responses of the decomposed inflation contributions to single standard deviation shocks to the modeled variables. 95% confidence intervals are shown in blue, for Newey-West standard errors. Monetary tightening, negative oil supply shocks, negative agricultural commodity supply shocks, and global industrial production data are drawn from the works of Bu, Rogers, and Wu (2021), Känzig (2021), Jo and Adjemian (2023), and Baumeister and Hamilton (2019), respectively. Shortage data represent a Google trends index of searches for that word. Per capita income, the energy PPI, transportation PPI, and farm products PPI are sourced from the St. Louis Federal Reserve Board (FRED) data. The vacancy ratio is the ratio of job openings to the nationwide unemployment level (from FRED). After November 2000, the numerator in that ratio is calculated using JOLTS data (also from FRED); before then, because JOLTS data are not available, we use Barnichon's (2010) help wanted index.

Factors that affect off-premises food and beverage price inflation

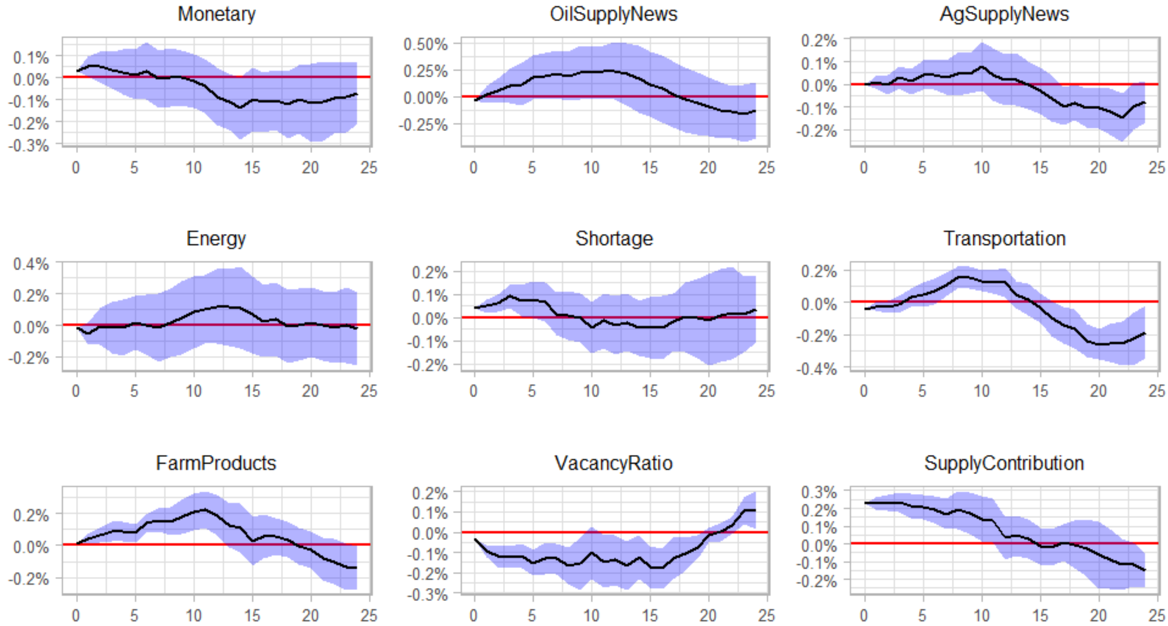
Like figure 5, figure 6 plots IRFs of the supply- (panel A) and demand-driven (panel B) contributions to off-premises food and beverage price inflation. Monetary policy shocks generate small short-run increases for both the supply- and demand-side inflation, but lead to decreases in the medium run. Negative oil supply news shocks raise at-home food-price inflation from both sides of the market, while poor agricultural supply news shocks roughly match the monetary IRFs—at first increasing supply- and demand-driven inflation, and then reducing it over the long run as producers and the downstream food supply chain adjusts.

Elsewhere in figure 6, more Google searches for the term "shortage" are associated with immediate increases in supply and demand-side inflation, while increases in global industrial production lead short-run declines but medium-term rises in demand-driven inflation. The latter uniformly increases following income rises, however. Transportation and farm product price increase lead short- to medium-term increases in supply-driven inflation for off-premises food, but like poor agricultural supply news, this effect changes sign as the market adjusts. The vacancy ratio IRFs carry a somewhat surprising implication, at first: following labor market tightening (i.e., an increase in the number of vacancies per unemployed person), both supply- and demand-driven inflation for off-premises food falls for a period of nearly two years. However, this result is consistent with the findings of Scott, Cowley, and Kreitman (2023), who show that from 2001-2020, food at home prices were negatively correlated with the vacancy ratio.[10]

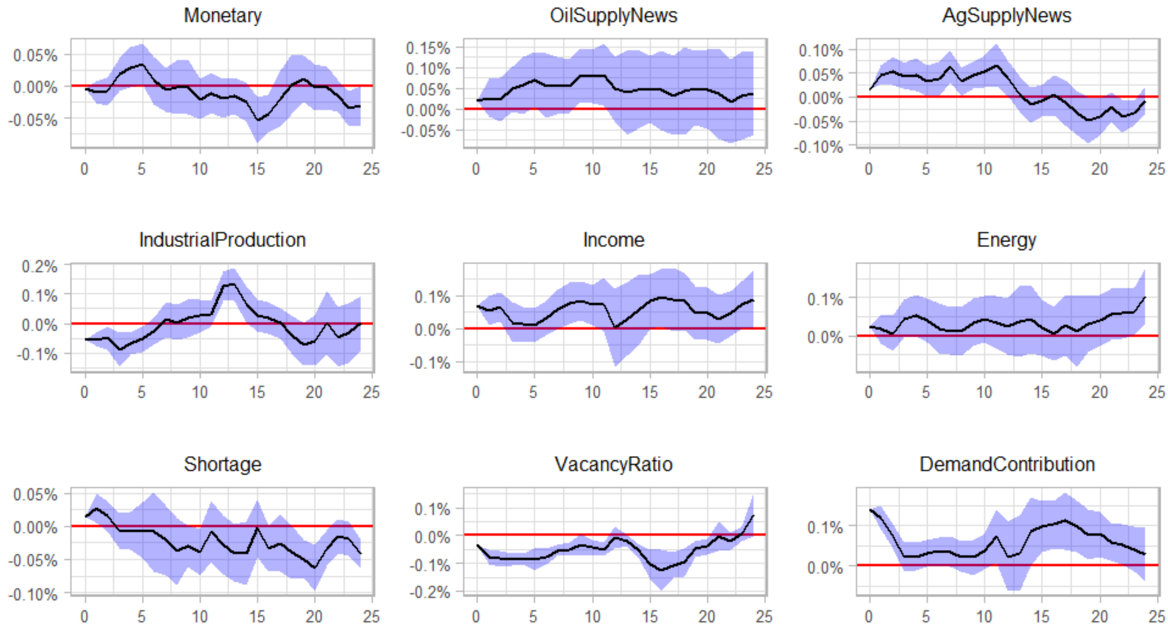
[10] The same authors show that the relationship reverses beginning in 2021, but our data limitations prevent us from including that period in the IRFs we estimate in figures 5 and 6.

Figure 6. Impulse responses of PCE off-premises food and beverage price inflation to various shocks, in percentage point changes

Panel A. Supply contribution



Panel B. Demand contribution



Notes: Panels in the figure display impulse responses of the decomposed inflation contributions to single standard deviation shocks to the modeled variables. 95% confidence intervals are shown in blue, for Newey-West standard errors. Monetary tightening, negative oil supply shocks, negative agricultural commodity supply shocks, and global industrial production data are drawn from the works of Bu, Rogers, and Wu (2021), Känzig (2021), Jo and Adjemian (2023), and Baumeister and Hamilton (2019), respectively. Shortage data represent a Google trends index of searches for that word. Per capita income, the energy PPI, transportation PPI, and farm products PPI are sourced from the St. Louis Federal Reserve Board (FRED) data. The vacancy ratio is the ratio of job openings to the nationwide unemployment level (from FRED). After November 2000, the numerator in that ratio is calculated using JOLTS data (also from FRED); before then, because JOLTS data are not available, we use Barnichon's (2010) help wanted index.

Conclusion

We use a recently developed framework to decompose PCE food prices inflation into supply- and demand-driven components. Our analysis focuses on three categories of food consumption: food consumed at home, food away from home ("food services"), and all food. While supply shocks, on average, accounted for about 77 percent of the food category-level food price changes observed in the United States from the early-1990s up to the end of 2019, demand shocks account for 40 percent of the shocks observed during the period of record inflation since the onset of the pandemic in 2020. We show that the demand side is a prominent factor behind the price increases observed in food consumed both at home and away from home; this is consistent with the findings of Adjemian et al. (2023), who use a different identification method to show that demand-side factors became more important in explaining food price inflation after the onset of the pandemic. We find that at-home food price increases are much more prominent during and following the pandemic recession than during the financial crisis and follow-on economic recovery in the late 2000s and early-2010s. In addition, the demand shocks we identify—for both types of food consumption—are more precisely-measured than at (least at) anytime over the last thirty years. That is, we have more confidence about the (substantial) role that the demand side plays in recent food price increases than we do for other food price changes since the early-1990s.

Academic work exploring the nature and causes of recent U.S. food price inflation is still quite modest. Most existing studies that examine this topic employ conventional time series methods, such as structural VAR, to estimate the impact of specific factors on food prices. While informative, these techniques rely on identification strategies that may involve overly strong assumptions. Our work, in contrast, employs a more flexible approach and has the additional benefit of producing results that are easily interpretable. Furthermore, the demand- and supply-driven components we estimate can be modeled as functions of exogenous economic shocks, allowing us to study the association between their trajectory and other macroeconomic developments. In particular, we examine the effects of unforeseen alterations in monetary policy, oil supply, and agricultural supply on the contribution to food price inflation from both the demand and supply sides of the market. Additionally, we analyze the dynamic relationships between these series and variables such as Google searches related to shortages, industrial production levels, per-capita income, job vacancy ratios, and prices for energy, transportation, and farm products.

We intend to build on the macro-level findings in this article using similar methods to study micro-level shocks in individual markets going forward. One of the ancillary benefits of Shapiro's model is that it can provide insight into the nature of inflation in near real-time—a valuable data set, especially from a policy-making perspective. Using scanner data that provides granular information on household and retailer level expenditures, prices, and quantities, we will investigate how demand and supply shocks operate on food prices paid by consumers across the United States. We anticipate that measuring, for instance, the impact of category-specific supply across temporal and spatial dimensions will better highlight (geographic and nodal) areas where policy makers might target infrastructure investments, in order to reduce the threat of future stockouts or related supply-chain stress.

References

Adjemian, M.K., S. Arita, S. Meyer, and D. Salin. 2023. "Factors Affecting Recent Food Price Inflation in the United States." *Applied Economic Perspectives and Policy*. https://doi.org/10.1002/aepp.13378

Jo, J., and M.K. Adjemian. 2023. "Measuring the Effects of Agricultural Supply News." *Working paper*. Accessed at:

Baek, J., and W.W. Koo. 2010. "Analyzing Factors Affecting U.S. Food Price Inflation." *Canadian Journal of Agricultural Economics*, 58:303-320. https://doi.org/10.1111/j.1744-7976.2010.01186.x

Barnichon, R. 2010. "Building a Composite Help-Wanted Index." *Economics Letters,* 109(3): 175-178. Accessed at: https://www.sciencedirect.com/science/article/abs/pii/S0165176510002934

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

Benigno, G., J. di Giovanni, J.J.J. Groen, and A.I. Noble. 2022. "The GSCPI: A New Barometer of Global Supply Chain Pressures." *Federal Reserve Bank of New York Staff Reports*, no. 1017. Accessed at: https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr1017.pdf

Bu, C., J. Rogers, and W. Wu. 2021. "A unified measure of Fed monetary policy shocks," *Journal of Monetary Economics,* 118: 331-349. https://doi.org/10.1016/j.jmoneco.2020.11.002

Calvert Jump, R., and K. Kohler (2022): "A history of aggregate demand and supply shocks for the United Kingdom, 1900 to 2016," *Explorations in Economic History*, 85. 101448. p. 101448. https://doi.org/10.1016/j.eeh.2022.101448

Congressional Research Service (CRS). 2021. "Inflation in the Wake of Covid-19." *CRS Report #R46890*. Accessed at: https://crsreports.congress.gov/product/pdf/R/R46890

Economic Research Service of the USDA (ERS). 2022. "Food spending as a share of income declines as income rises." *Chart of note*. Accessed at: https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=58372

Furman, J. 2022. "This Inflation is Demand-Driven and Persistent." Project Syndicate. April 20th. Accessed at: https://www.project-syndicate.org/commentary/inflation-demand-driven-persistent-by-jason-furman-2022-04

Irz., X., J. Niemi, and X. Liu. 2013. "Determinants of Food Price Inflation in Finland—The Role of Energy." *Energy Economics*, 63: 656-663. https://doi.org/10.1016/j.enpol.2013.09.023

Jordà, Ò. 2005. "Estimation and inference of impulse responses by local projections." *American Economic Review*, 95(1):161–182, 2005. Accessed at: https://doi.org/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

Lambert, D. K., & Miljkovic, D. 2010. “The sources of variability in US food prices.” *Journal of Policy Modeling*, *32*(2), 210-222. https://www.sciencedirect.com/science/article/pii/S0161893810000025?casa_token=VvV4dIIvffsAAAAA:jVqa1v6fWuXO1Wlyst35-nqXJhzHEPL5dHqp5LDAiyjyBEA2ji4Q7jSxl8_NFN9fETAFk-ohgQ

Luciani, M., and R. Trezzi. 2019. “Comparing Two Measures of Core Inflation: PCE Excluding Food & Energy vs. the Trimmed Mean PCE Index.” *FEDS Notes*, August 2nd. Board of Governors of the Federal Reserve System. Accessed at: https://www.federalreserve.gov/econres/notes/feds-notes/comparing-two-measures-of-core-inflation-20190802.html

Okrent, A., and Alston, J., 2012. “The demand for disaggregated food-away-from-home and food-at-home products in the United States.” *USDA-ERS Economic Research Report,* 139. Accessed at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2171315

Scott, F., C. Cowley, and T. Kreitman. 2023. “Tight Labor Markets Have Been a Key Contributor to High Food Inflation.” Federal Reserve Bank of Kansas City, *Economic Bulletin*, April 19. Accessed at: https://www.kansascityfed.org/Economic%20Bulletin/documents/9493/EconomicBulletin23ScottCowleyKreitman0419.pdf

Shapiro, A.H. 2023. “Decomposing Supply and Demand Driven Inflation.” Federal Reserve Bank of San Francisco Working Paper 2020-29. https://drive.google.com/file/d/1AlyWvR9DC-XQq_-BdJRVMmdgCl-N7ba8/view

Smets, F., and R. Wouters. 2003. “An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area.” *Journal of the European Economic Association*, 1(5): 1123-1175. https://doi.org/10.1162/154247603770383415

U.S. Bureau of Economic Analysis (BEA). 2022. *NIPA Handbook: Concepts and Methods of the U.S. National Income and Product Accounts.* U.S. Department of Commerce. Washington, D.C.

U.S. Bureau of Labor Statistics (BLS). 2018. *BLS Handbook of Methods*. U.S. Dept. of Labor. Washington, D.C.

U.S. Bureau of Labor Statistics (BLS). 2022. *Economic News Release: Consumer Price Index Summary*. Dec. 16th. Accessed at: https://www.bls.gov/news.release/cpi.nr0.htm