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. Policy makers, the media, and ordinary consumers want to know why it happened. Many factors contribute, 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 2022 invasion of Ukraine, and the excess savings buildup funded 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 over 77 percent of food-at-home inflation 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 nearly 43 percent of the price rise since January, 2020. We further show that supply-side pressure on food prices is increased by poor agricultural and oil supply news, higher global industrial production, and predicted by Google searches for the term "shortage", supply chain pressure, a tighter labor market, and higher prices for farm goods. Demand-driven inflation is decreased by bad crop and oil supply news, tighter monetary policy, and industrial production shocks, but increases are predicted by concern over shortages, supply chain pressure, and excess savings—which reached historic levels through pandemic-era fiscal stimulus.

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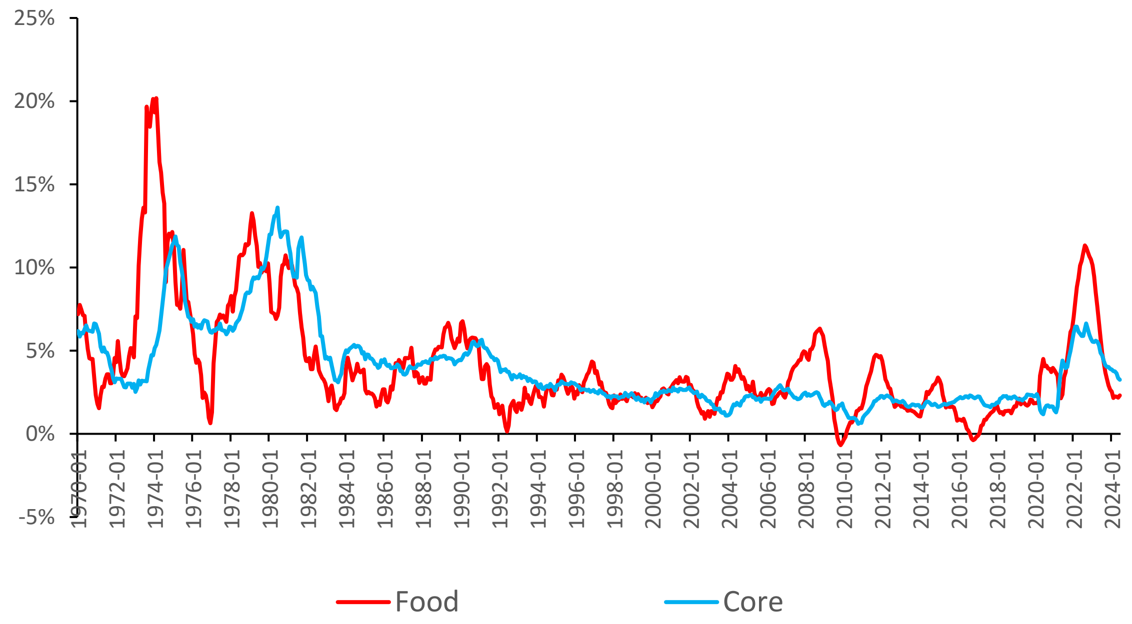
Between 2022-2023, food prices in the United States increased at a historic pace. According to the U.S. Bureau of Labor Statistics (BLS), the price of food paid by urban consumers increased by 11.3 percent over the 12 months ending in August 2022, marking the highest year-over-year increase observed 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 increased 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,[2] since it is more volatile (in part due to more inelastic short-run supply)—the stark difference is notable given the seemingly close relationship between the two series during previous inflationary periods.

[2] 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).

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.

Our research seeks to understand why food prices increased 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 for the recent shock: on the demand side, the rapid growth in real economic output following the COVID-19 shock (CRS, 2021), fueled by historically large fiscal stimulus (de Soyres et al., 2023a); on the supply side, unexpected reductions in productive capacity due to the pandemic-induced lockdowns, the tight labor market 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 in wheat and fertilizer markets 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 generate price increases, that's a sign 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.

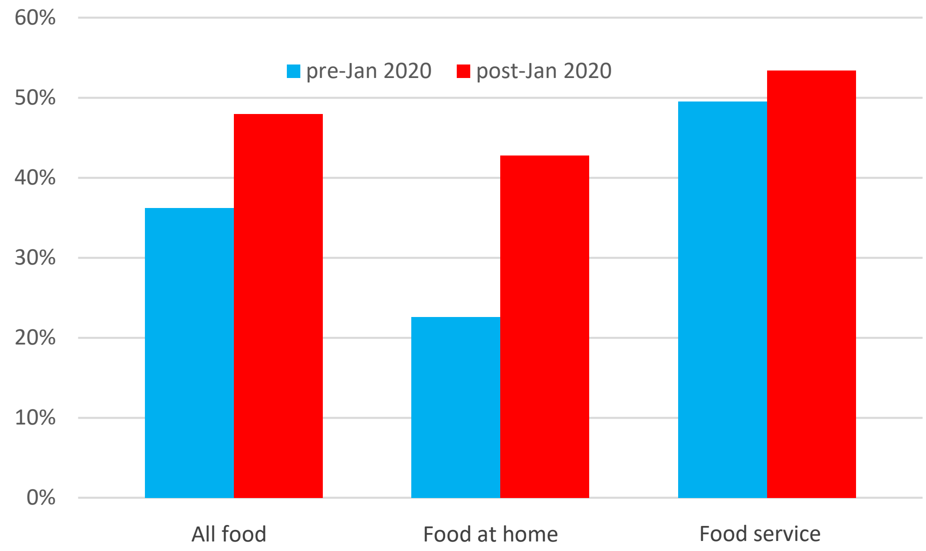
Shapiro (2024) employs category-level regressions to decompose changes in the overall personal consumption expenditure price (PCE) index into supply and demand shocks.[3] PCE data include category-level expenditures at a monthly frequency, as well as indices for price and quantity. Shapiro's model determines 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 shock. Weighting each category according to its share of total U.S. expenditures,[4] the contributions of demand and supply shocks to the overall level of price inflation can be estimated. By decomposing inflation in this way, policy makers can better target their inflation-reducing interventions.

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 to compute it). Model outputs include new data series that represent the overall contribution the demand and supply sides of the market make to food price inflation, permitting the researcher to examine how each contributes to changes in food prices at the category level in near-real time. We find that the supply side of the market tends to dominate observed food price changes before the pandemic, as shown in figure 1. For every dollar Americans paid for food at home (FAH) in January, 1992, they paid an additional 66 cents by December, 2019—

[3] 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).
[4] These are Laspeyres weights.

twenty-eight years later; supply shocks accounted for over 77 percent of that rise. Yet in just the five-and-a-half years from January 2020 - July 2024, FAH prices increased by an additional 41 cents (in 1992 dollars), and demand shocks accounted for over 43 percent of that increase. For the all-food (AF) category, which includes food away from home (FAFH, or "food service"), supply shocks accounted for 36 percent of the 79 cent rise per dollar between 1992-2019, but 48 percent of the subsequent 50 cent rise. The increase is even present for food service itself, although normal inflation in the category is more demand-driven. Between 1992 and 2019, FAFH prices doubled and the demand side explained almost 50 percent of that rise; they explained over 53 percent of the rapid 63 cent rise (in 1992 dollars) beginning with the pandemic shock.

Figure 2. Share of Food Price Increases Explained by the Demand Side, 1992-2024



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

Clearly, 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 timeframe of analysis, spanning over three decades. Our decomposition shows that demand-driven food prices inflation increases substantially in mid-2021 and 2022—just as Americans began to spend down the historic levels of excess savings they built up through fiscal stimulus during the pandemic lockdowns (Abdelrahman and Oliveira, 2023). It also shows that supply-driven inflation begins to spike as Russia invaded Ukraine in 2022, pressuring international wheat and fertilizer markets.

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 (which applies Shapiro's model) does not, and has the added benefits of producing easy-to-interpret results that can be modeled as functions of economic shocks. Our results indicate that supply-side pressure on food prices is increased by poor agricultural and oil supply news, higher global industrial production, and predicted by Google searches for the term "shortage", supply chain pressure, a tighter labor market, and higher prices for farm goods. Demand-driven inflation is decreased by bad crop and oil supply news, tighter monetary policy, and industrial production shocks, but increases are predicted by concern over shortages, supply chain pressure, and excess savings—which reached historic levels through pandemic-era fiscal stimulus.

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:

$$\varepsilon_i^s = \left(q_{i,t} - \sigma^i p_{i,t}\right) - \left(q_{i,t-1} - \sigma^i p_{i,t-1}\right) \tag{2}$$

$$\varepsilon_i^d = \left(\delta^i q_{i,t} + p_{i,t}\right) - (\delta^i q_{i,t-1} + p_{i,t-1}), \tag{3}$$

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 reveals evidence about the existence and direction of category-level shocks, $\varepsilon_{i,t}^s$ or $\varepsilon_{i,t}^d$. We categorize them as follows:

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

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

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

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

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

Because the supply and demand curve can move simultaneously, using unexpected price and quantity changes in (5)-(8) is more accurately referred to as revealing what we term a “net” supply or demand shock. That is, the signs of the model residuals set identify the net result of movements in either or both curves: being assigned a net shock means that the category experienced *at least* that labeled shock, i.e., $\widetilde{\varepsilon_{i,t}^{s}} => \varepsilon_{i,t}^{s}$, as shown in Appendix 1. In the case of simultaneous demand and supply curve shifts, the net shock reveals their combined influence.

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

Once time *t* shocks for each food category are segregated into net 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 (2024), we specify indicator functions that classify whether a food category experienced a net supply or demand shock in period *t*:

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

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

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:

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

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

In (12), $\omega_{i,t-1}$ 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 their twelve-month running product, since inflation rates are multiplicative.

$$\pi_{t,t-12}^{m} = \prod_{k=0}^{11}(1 + \pi_{t-k,t-k-1}^{m}) - 1, \text{ for } m\ \epsilon (sup, dem) \tag{13}$$

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).[5] 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" (i.e., FAH) as nondurable purchases, and "food services" as service expenditures, the latter representing on-premises food consumption (i.e., FAFH). 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.[6] While most of the subcategories have complete observations from Jan. 1959 – present, 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 on. We conduct analysis on the full set of available data, using the first five years of the data to establish a baseline for model estimation, which is conducted using a five-year window.

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 FAH 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 their away-from-home expenditures at limited service eating

[5] 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.
[6] 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.

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. Restaurant expenditures (meals at limited service, other eating, and drinking places) comprise 33% of total American expenditures on food, while alcoholic beverages account for another 14%.

Table 1. Share of Food Expenditures by U.S. residents, by food category, Jan. 1987 – Jul. 2024

Food and beverages purchased for off-premises consumption	*Within group*	*Share of all food*
Food/bev for off-premises total	100%	58.87%
Cereals	5.11%	3.01%
Bakery products	9.05%	5.32%
Beef and veal	4.85%	2.86%
Pork	3.50%	2.06%
Other meats	3.28%	1.93%
Poultry	5.51%	3.24%
Fish and seafood	1.58%	0.93%
Fresh milk	2.58%	1.52%
Processed dairy products	4.90%	2.88%
Eggs	1.14%	0.67%
Fats and oils	2.06%	1.21%
Fruit (fresh)	3.69%	2.17%
Vegetables (fresh)	4.59%	2.70%
Processed fruits and vegetables	3.21%	1.89%
Sugar and sweets	5.19%	3.06%
Food products, not elsewhere classified	15.24%	8.97%
Coffee, tea, and other beverage materials	1.59%	0.94%
Mineral waters, soft drinks, and vegetable juices	8.74%	5.15%
Spirits	3.18%	1.87%
Wine	4.01%	2.36%
Beer	6.93%	4.08%
Food produced and consumed on farms	0.07%	0.04%
Food service		
Food service total	100.00%	41.13%
Elementary and secondary school lunches	1.20%	0.49%
Higher education school lunches	2.29%	0.94%
Meals at limited service eating places	41.90%	17.24%
Meals at other eating places	38.26%	15.74%
Meals at drinking places	0.64%	0.26%
Alcohol in purchased meals	12.82%	5.27%
Food supplied to civilians	2.61%	1.07%
Food supplied to military	0.28%	0.11%

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

Empirical approach

After collecting the relevant data from BEA, like Shapiro (2024) we estimate the shocks to price and quantity for each of the i subcategories in table 1 by running log price and log quantity (index, as provided by BEA) VARs of the form, with constant c:

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

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

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, but rather more gradual preference changes, improvements in technology, or population changes. These regressions are estimated via a rolling five-year window, permitting parameters γ_j^{qp}, γ_j^{qq}, γ_j^{pp} and γ_j^{pq} to vary with time. We use the reduced-form errors in (15) and (16) equations to identify the net supply and demand shocks and sign them according to equations (5)-(8), with some allowance for the ambiguity of definition as a robustness check.

Small reduced form residuals increase the risk of a mis-labeling of net shocks, so like Shapiro (2024) we re-interpret 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 net 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.

Results and discussion

Inflation decomposition

Our baseline findings for the contribution of net 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 from table 1, off-premises food and beverages, 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.[7]

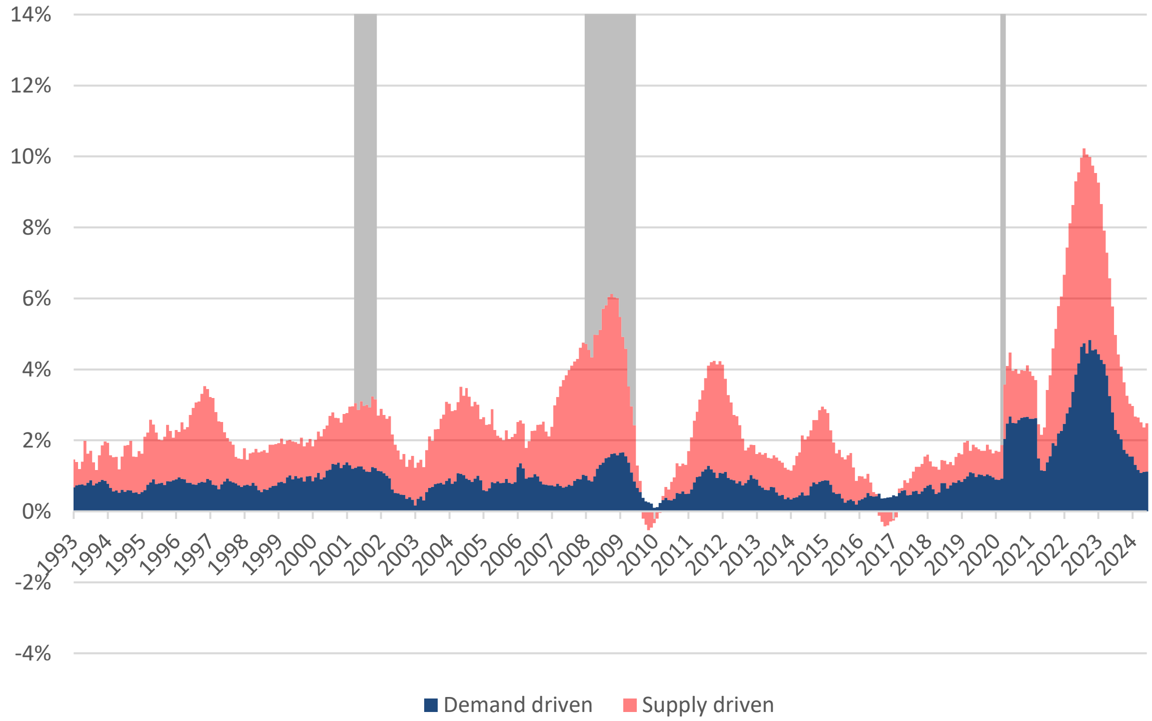
As in figure 2, for most of the three decades in figure 3, supply shocks represent a stronger contributor to food price inflation. This is not surprising, in particular for all-food and FAH shown in panels A and B, since its supply is subject to more unexpected shortages or surpluses than, say, industrial 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 more sensitive to 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, was 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 FAH prices increased relatively swiftly in the lead-up to the financial crisis—

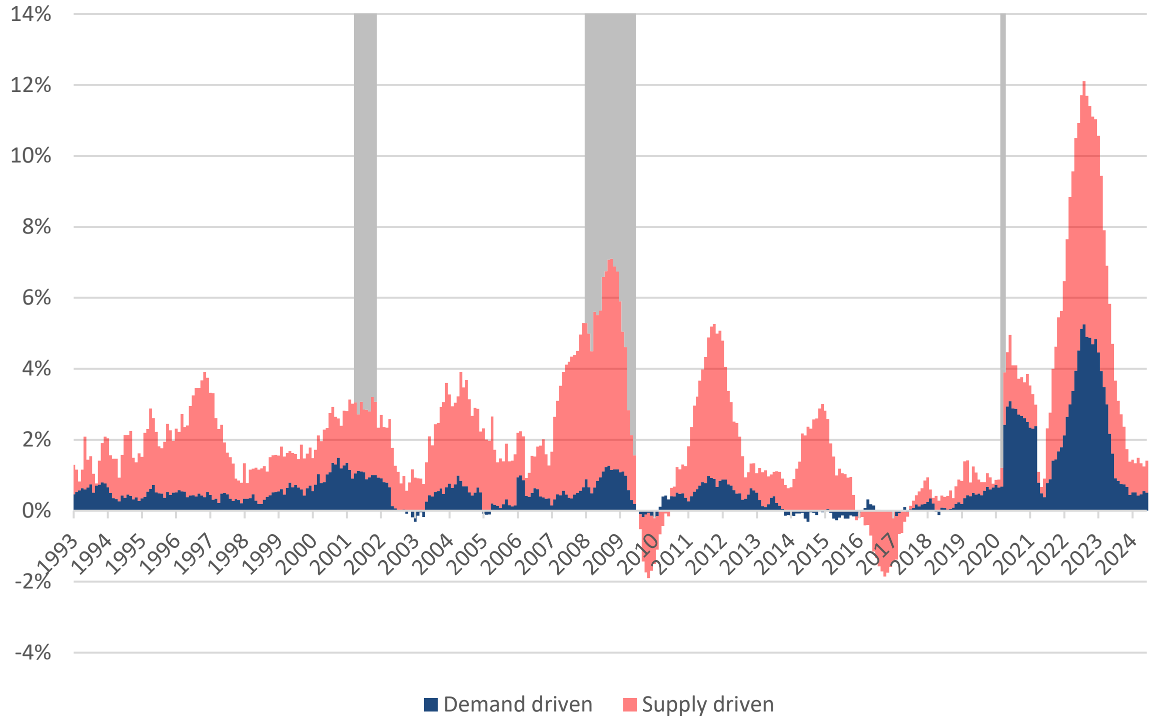
[7] Figure 3 begins in 1993 because, as explained in the text around equations (13), (15), and (16), calculating the year-over-year contributions to inflation requires a twelve-month running sum of the (weighted) shocks displayed in figure 2, which stretches back to January 1992 (following our five-year baseline period to estimate the model; our data series begin in January, 1987).

peaking around a 7 percent rise towards the end of 2008—supply shocks dominated that rise; demand contributions reached just over 1 percentage point, while supply shocks were about six times larger. Yet 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 12 percent, demand shocks contributed over 5 percentage points of that increase—nearly half the measured inflation.

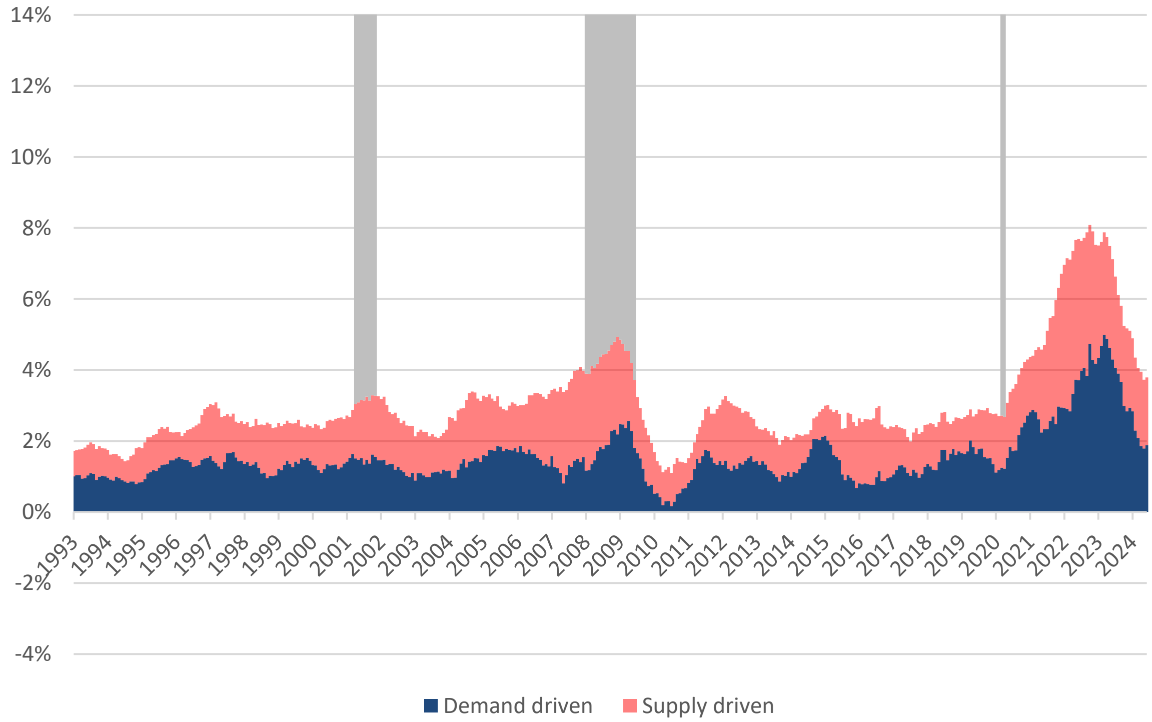
Figure 3. Supply- and demand-driven food price inflation in the United States, year-over-year
Panel A. All food



Panel B. Food at home (FAH), or off-premises food and beverages



Panel C. Food away from home (FAFH), or food service

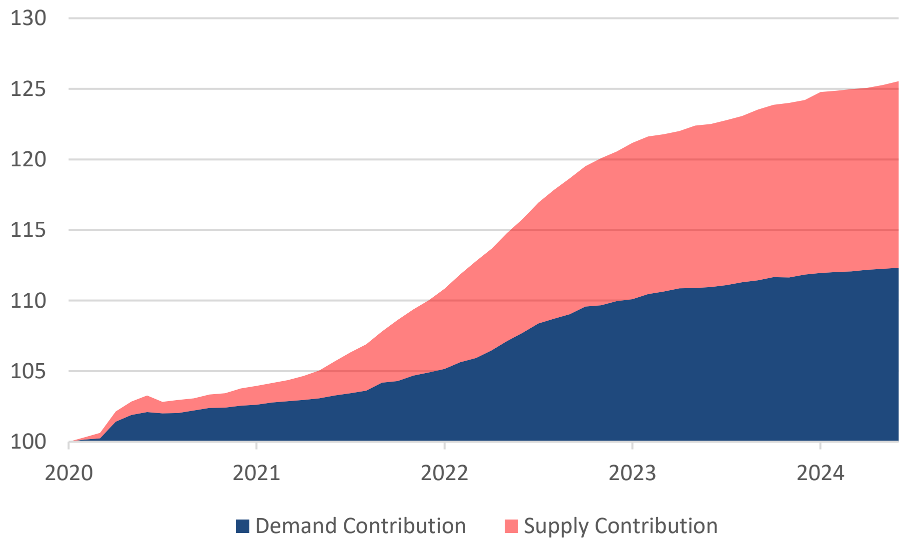


Source: U.S. Bureau of Economic Analysis; author calculations.
Note: Recession periods, as defined by the National Bureau of Economic Research, are shown in dark gray.

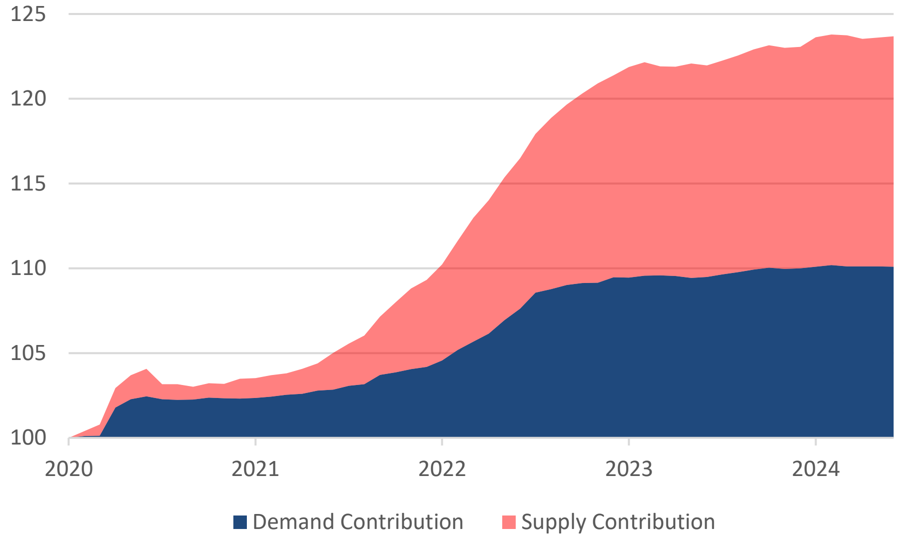
While the panels in figure 3 represent year-over-year inflation, figure 4 represents price increases since the pandemic onset in the indexed (Jan 2020=100) levels. Panels A, B, and C, report that all food, FAH, and FAH prices increased by 26%, 23%, and 28%, respectively, up to July, 2024. In each panel, the contribution of demand side pressure is notably—and relatively larger than the inflation due to supply side shocks—earlier on in the pandemic period. Through the first year of the pandemic, the figure shows that demand shocks in each panel accounted for over 64% of the price increases to all types of food; through the first two years, over 45% were for every type of food. These values are significantly higher than pre-2020 inflation, which was dominated by supply shocks as shown in figure 2.

Figure 4. Contributions of Different Sides of the Market to Food Prices in the United States, Monthly (January 2020 = 100)

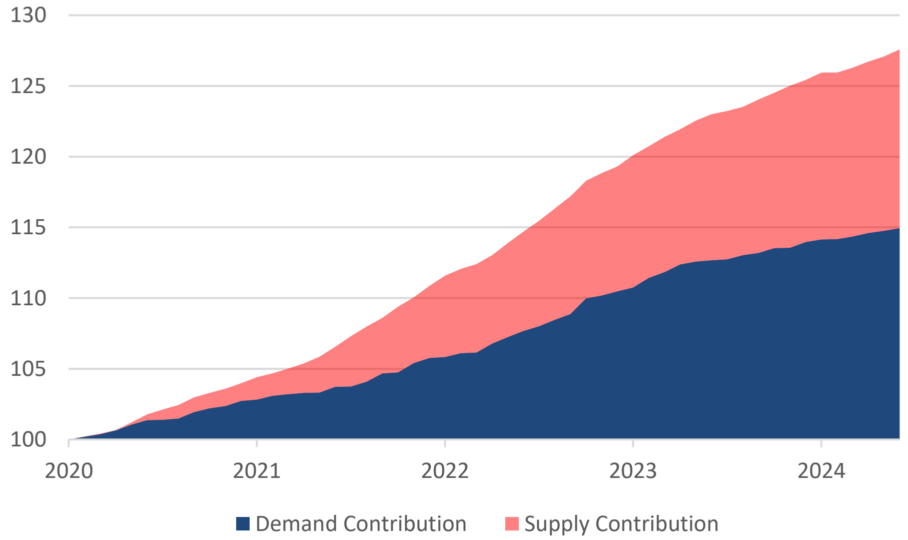
Panel A. All food



Panel B. Food at home (FAH), or off-premises food and beverages



Panel C. Food away from home (FAFH), or food service



Up to now, our estimates leave no space for uncertainty; all unexpected price and quantity shifts in figure 3 are classified as either net 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.[8] In the case of ambiguity, observed price inflation

[8] The more, mid, less, and ambiguous cutoffs work out to represent 42.6, 34.8, 8.8, and 13.9 percent, respectively, of all the food category/time pair shocks in the data.

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 5 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, across panels. However, ambiguity is notable in the FAH price increases (in panel B) during the financial crisis, and then again during the early stages of the pandemic. FAFH prices exhibit more ambiguity, historically; although, it accounts for a significant portion of food price inflation during the first eighteen months of the pandemic. After that, observed food price shocks are far more easily classified into net demand or net supply.

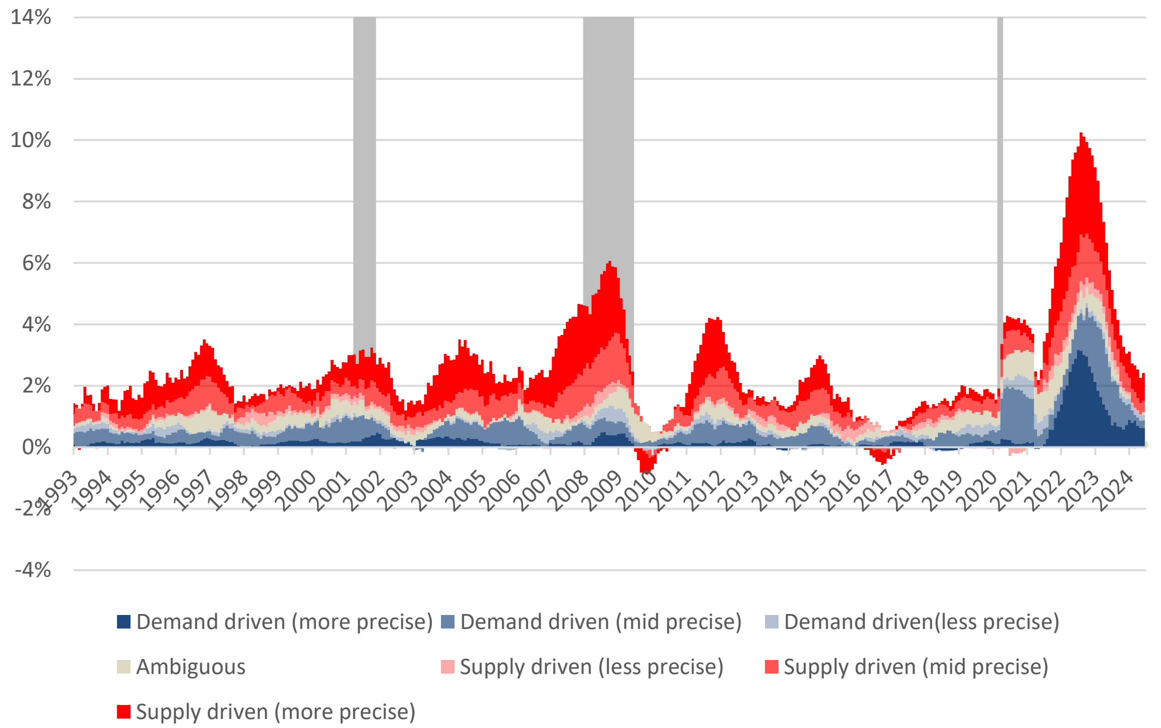
Figure 5 also shows that, in addition to including the largest demand-driven contributions to inflation over the last thirty years, recent food price spikes also exhibit the most *precisely-measured* net demand classifications across all three panels. Across panels, the darkest blue shade is most apparent in the food price rises observed in the aftermath of the pandemic recession. While all food and FAH (panels A and B) include some “more precise” net demand-driven increases in 2020, that pressure on food prices increases substantially in mid-2021 and 2022—just as Americans began to spend down the historic levels of excess savings they built up through fiscal stimulus during the pandemic lockdowns (Abdelrahman and Oliveira, 2023). At the same time, of course, “more precise” supply shocks became more important, as fertilizer prices increased ahead of and in response to Russia’s invasion of Ukraine.[9] Most of the other demand shocks in the panels are measured less precisely, at the mid-level or lower. On the other hand, 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 aftermath. From

[9] An obvious advantage of the model in this paper is that it can decompose rapid price increases like those observed in 2022 into pressure from each side of the market.

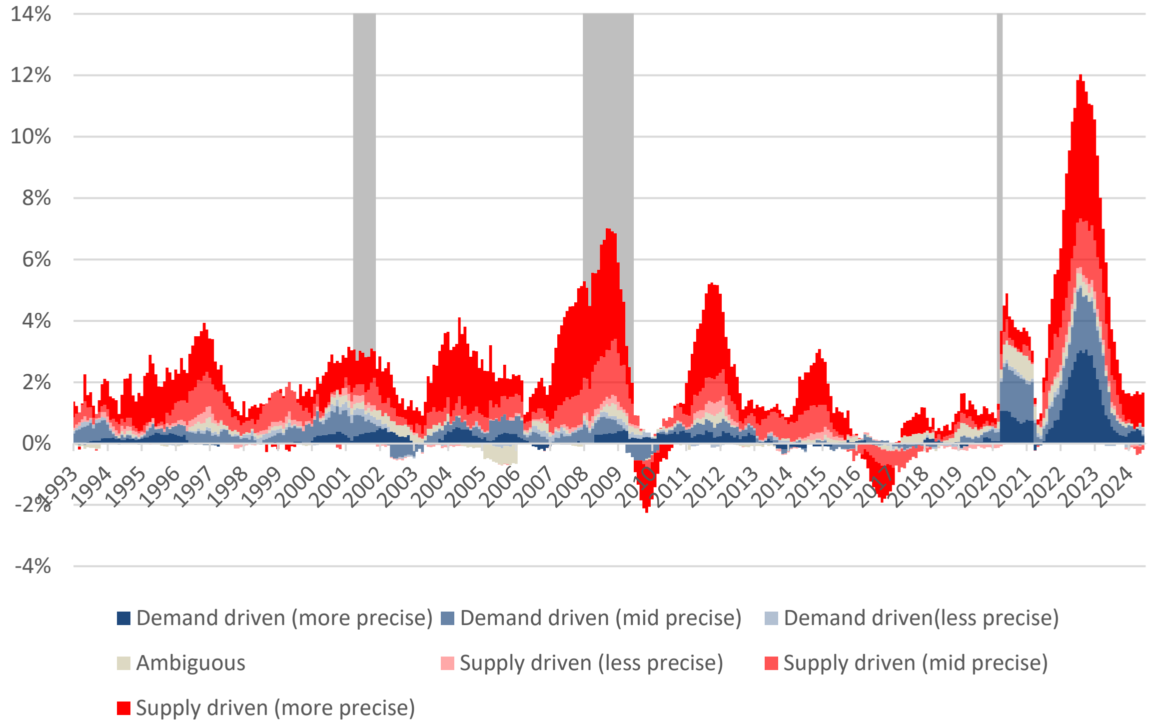
about 2006 through 2013, mid-precise and less-precise supply shocks appear more often. Supply shocks in FAFH inflation (panel C) tend to be less precisely-measured.

Figure 5. Supply- and demand-driven PCE food inflation in the United States with multiple precision cutoffs, year-over-year

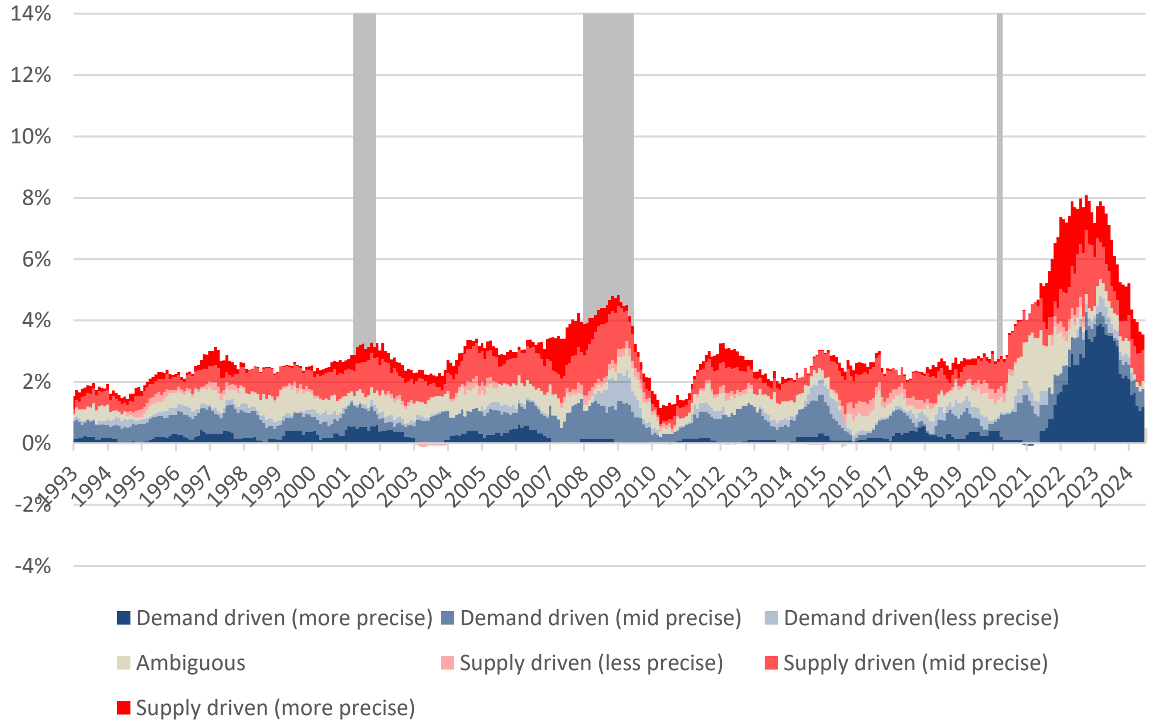
Panel A. All food



Panel B. Food at home (FAH), or off-premises food and beverages



Panel C. Food away from home (FAFH), or 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 predict these demand and supply series, themselves. Specifically, we use local projections (Jordà, 2005)—a method that conducts individual ordinary least squares regressions at each forecast horizon h under study to estimate the predictive relationship between the scaled variable of interest X_t and the cumulative contributions that either side of the market makes to inflation $\pi^m_{t+h,t}$ for $m \in \{sup, dem\}$, as estimated in the previous section.[10] Our local projections are specified as

$$\pi^m_{t+h,t-1} = \beta^m_h X_t + A^m_h \sum_{\tau=0}^{6} Y_{t-\tau} + u_{m,t+h} \tag{17}$$

The β coefficients estimated from (17) trace out an impulse response function (IRF), demonstrating how cumulative inflation contributions evolve dynamically following a change in the RHS variable of interest; specifically, they represent the expected cumulative change in m-driven inflation between t and $t+h$. Controls $Y_{t-\tau}$ include the contemporaneous contributions to inflation from the other side of the market and six of its lags, as well as six lags of the dependent variable. As suggested by Jordà (2005), we estimate heteroskedasticity-and-autocorrelation-consistent (HAC) standard errors since the error terms $u_{m,t+h}$ in (17) are likely correlated (Newey and West, 1987).

Because food consumed at home and away from home are different, we estimate (17) with four different dependent variables: supply-side contributions to FAH and FAFH, and demand-side contributions to FAH and FAFH. Our impulse response results are shown in figure 6, which overlays the FAH (or "food", in blue) and FAFH inflation responses (or "service", in orange). Solid lines in the

[10] Our results are robust to estimating (17) with differenced regressors, and 12 lags.

figure represent mean responses. Shaded regions in both panels represent 95% HAC confidence intervals.

All models have a common set of explanatory variables that could affect either side of the market. We add farm product price to the supply-side models, since it is an input cost, and excess savings to the demand-side models, since it has been shown to contribute to recent demand-pull inflation (see, e.g., Aladangady et al., 2022; de Soyres et al., 2023b). We estimate excess savings following a similar method as (Abdelrahman, H. and L.E. Oliveira, 2023), calculating the pre-pandemic BEA Personal Saving cubic trend up to February, 2020, and differencing it from actual Personal Saving; increases in the resulting variable are accumulations, decreases are drawdowns. Because data availability limits this portion of our analysis to the period from February 2004 to October 2023,[11] that is the same span over which we calculate the trend.

Panel A (B) in figure 6 plots the response of supply-driven (demand-driven) inflation to 10% increases in the explanatory variables from their mean over the timeframe of observation—except monetary policy tightening, which is scaled to a 100-basis-point surprise across policy regimes (Bu, Rogers, and Wu, 2021). Vertical axis values represent the cumulative rise in the contribution of that side of the market to food price inflation, and can be interpreted in percentage terms, i.e., 0.2 = a 2% cumulative increase in the PCE food price index (Jan 1992 = 100) between t and $t + h$. The first three IRFs in each panel represent the effects of exogenous shocks on contributions to food service price inflation; each of these are estimated externally. The first, a negative domestic agricultural supply shock estimated by Jo and Adjemian (2024)—which can be thought of as bad news about the upcoming field crop harvest due to a drought—increases in the supply-side's contribution to FAH inflation, by around 0.5% after about a year. It does not significantly affect FAFH, which has a less sensitive cost structure to agricultural shocks. However, panel B shows that the demand-side effect is

[11] Google Trends results are available beginning in January, 2004. The baseline monetary shock series we use is available up to October, 2023.

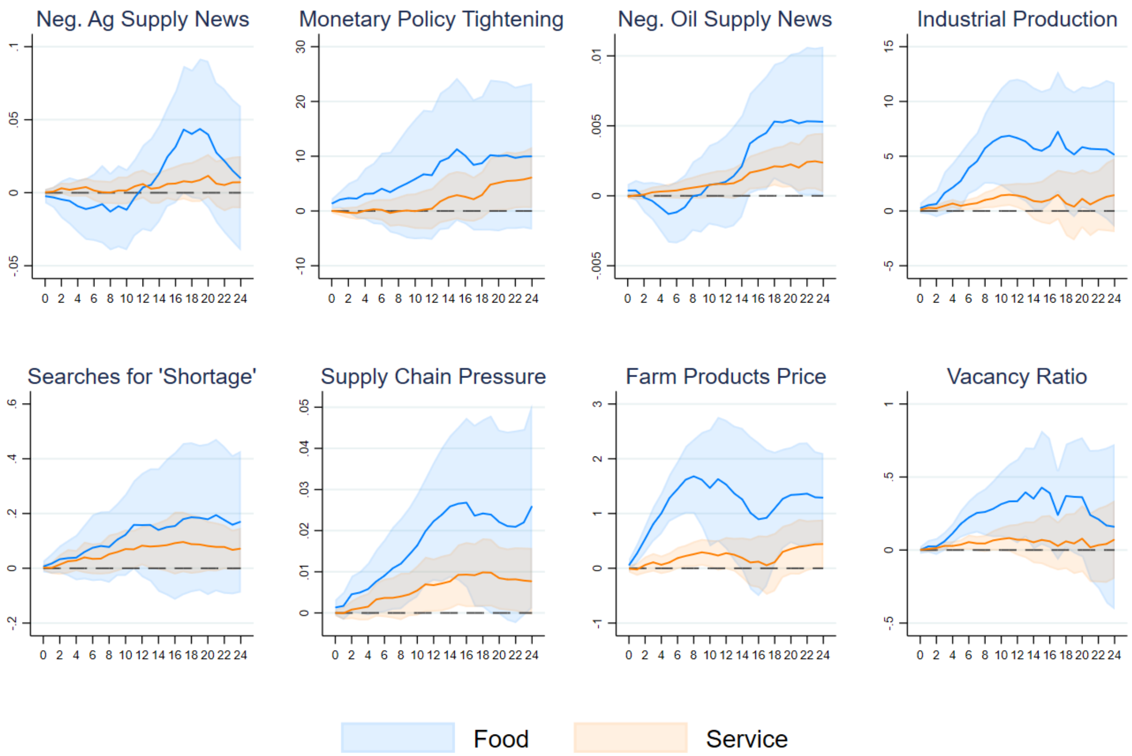
negative for both FAH and FAFH; this may be tied to economic output reduction such shock carries (Jo and Adjemian, 2024). Tighter monetary policy raises the supply-side contribution to FAFH inflation, possibly through higher borrowing costs that (small) firms pass onto consumers. Mean effects of a 100-basis-point shock are large, but they are balanced by the opposite-sign demand-contribution IRFs in Panel B: tighter monetary policy reduces the demand for FAH and FAFH, 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). Unexpected negative oil supply news, as measured by Känzig (2021) and scaled to a 10 percent price decline, likewise significantly raises supply-side pressure on both FAH and FAFH prices. But the effect is small: just 0.04% and 0.02% at the mean, after two years. On the other hand, lower oil prices act as negative demand shocks and reduce demand-driven inflation (see, e.g., Lee and Ni, 2002; Hamilton, 2008; Edelstein and Kilian, 2009).[12] Unexpected increased in global industrial production, as measured by Baumeister and Hamilton (2019), raise supply-driven FAH and FAFH inflation—possibly through increased competition for inputs (like labor, energy, and agricultural commodities), but lower demand-side pressure (although the effect on FAFH is not significant), as the supply of goods including food increases, all else constant.

Additional variables in figure 6 cannot necessarily be classified as exogenous shocks, but present some notable predictive relationships for food prices. Google searches for "shortage" predict increases in both supply- and demand-driven inflation (although the supply-side effect on FAH is not statistically significant). On the supply side, searches can predict awareness of actual and anticipated shortages, and prices must increase so markets clear; on the demand side, searches may correlate to panic-buying situations, where consumers rush to secure goods, driving up prices. In a similar way, increases in the NY Federal Reserve Board's Global Supply Chain Pressure Index (GSCPI)—which represents disruptions like bottlenecks, delivery delays, and scarcity of critical inputs—predicts rising pressure on FAH and FAFH from both sides of the market. Elevated supply chain pressure raises costs

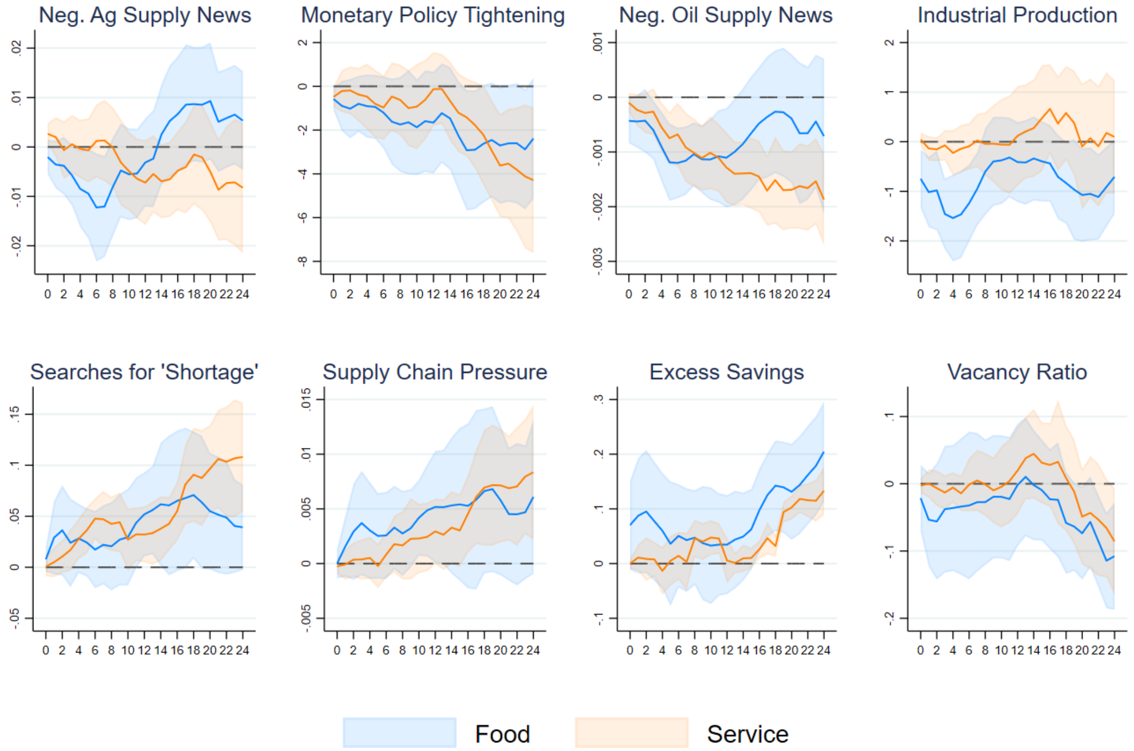
[12] Shapiro (2024) observes a similar effect with respect to headline inflation.

for producers, which they can then pass on to consumers. As in the case of google searches for "shortage", rising GSCPI values can signal weakness in the availability of goods to consumers, pressuring prices higher through precautionary demand. A rising vacancy ratio, which represents the number of job vacancies for every unemployed person in the United States, predicts more short-run supply-driven inflation for FAH and FAFH; this is intuitive since a tight labor market raises labor and therefore production costs. On the other hand, a tighter labor market somewhat surprisingly predicts a reduction in the longer-run demand-side pressure on the price of food. This may be explained by firms that substitute capital for labor as labor markets tighten, leading to weak demand growth, and therefore pressure on food prices. Indeed, as shown in appendix figure A1 when we split the sample into pre-Covid (up to January, 2020) and Covid periods (from that break through October, 2023), the negative IRF is fully explained by the pre-Covid period. The largest vacancy ratios in the data, which occur after the Covid shock, did not predict lower demand-side pressure on food prices. Panel A confirms that rising farm product prices predict increase supply-driven pressure on both FAH and FAFH prices, while panel B results indicate that demand pressure on both is likewise foretold by an increase in excess savings.

Figure 6. Monthly impulse responses of 10% increases in predictive factors variables to contributions to food price inflation, in percentage point changes to an index (Jan 1992 = 100)
Panel A. Supply contribution



Panel B. Demand contribution



Notes and sources: Panels in the figure display impulse responses of the decomposed inflation contributions to scaled 10% increases in the modeled variables from their mean value. 95% confidence intervals are indicated by shaded regions, using Newey-West standard errors. Negative agricultural commodity supply shocks, monetary tightening, negative oil supply shocks, and global industrial production shocks are drawn from the works of Jo and Adjemian (2024), Bu, Rogers, and Wu (2021), Känzig (2021), and Baumeister and Hamilton (2019), respectively. Shortage data represent a Google trends index of searches for that word. The Global Supply Chain Pressure Index is taken from the Federal Reserve Bank of New York, while excess savings are estimated by the authors, as described in the text, using a similar method to Abdelrahman and Oliveira (2023). The farm products PPI is 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.

Policy Implications

Recent food price inflation is the highest on record in over four decades. We show that demand pressures bear more responsibility for that inflation to a larger degree than they have been in the past. Indeed, food prices also increased rapidly in 2007-2008, just before the financial crisis. But in that previous episode, our model results indicate that (especially FAH) food prices increased mostly due to supply pressures. This matches the findings of Headley and Fan (2010), who argue that supply factors like energy prices, export restrictions, precautionary imports, and the demand for biofuels—which in effect reduces the available supply of food commodities for use as food—were more responsible than other factors, like surging demand from China and India.

Explaining why food prices change the way they do—particularly in a time of historic inflation—is important because it informs policymakers about how to approach the issue. According to our empirical findings, tighter monetary policy reduces demand-driven food price inflation. Although we did not similarly model the effect of fiscal policy, because no comparable exogenous series is available, our results with respect to excess savings are consistent with the explanation that pandemic-era fiscal stimulus had a reverse effect: raising the demand-side contribution to food prices after a lag, as households draw them down. On the other hand, we also find that concern over shortages and supply chain pressure costs predict increases in supply-side food price pressure.

Therefore, if food prices are inflated by demand-side shocks, policy makers can focus on monetary tools (like adjusting interest rates) and fiscal measures (like refraining from additional stimulus packages) to reduce inflation. On the other hand, if supply-side factors dominate, policy makers may be able to address food price inflation through infrastructure improvements (e.g., investments in ports, waterways, highways, or rail networks) that enhance supply chain efficiency and reduce the prospect of shortages and rising transport costs. Of course, investments like these operate only at a lag, since it takes time to make infrastructure improvements.

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 the overwhelming majority of food price increases observed in the United States from the early-1990s up to the end of 2019 (over 77 percent of the FAH price increase), demand shocks offer far more explanatory power 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. In addition, the demand shocks we identify—for both types of food consumption—are more precisely-measured than at anytime over the last thirty years; 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 shocks to monetary policy, oil supply, agricultural supply, and industrial production 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, supply-chain backups, excess savings, labor market tightness, and the price of 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, since it offers insight into how inflation-reducing interventions can be targeted. 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.

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Appendix 1. Net Shocks are Set Identified

Net supply or demand shocks in this paper are identified by the sign pattern of the model residuals. Furthermore, they are set identified; they imply *at least* the existence of that type of shock. But simultaneous shocks can occur on both sides of the market. To prove that the existence of a net shock requires an underlying structural shock of that type, we begin with the model in equations (1)-(4), and suppress subscripts, and assume a no-shock prior period without loss of generality. For any subcategory of food the relationship between the structural shocks and reduced-form residuals is then given by

$$\varepsilon = Av$$

which implies that structural shocks are given by

$$\varepsilon_s = v_q - \sigma v_p$$

$$\varepsilon_d = \delta v_q + v_p$$

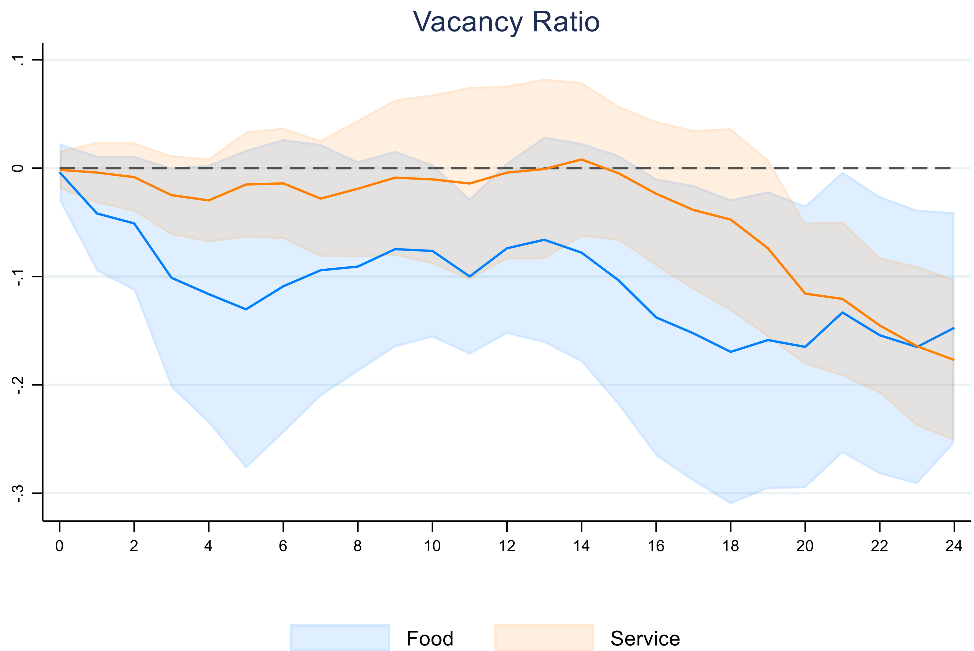
Recall that a net supply shock $\widetilde{\varepsilon_s}$ or a net demand shock $\widetilde{\varepsilon_d}$, is characterized according to equations (5) - (8). A *positive net demand shock* is assigned in the case of reduced form residuals $v_q > 0$ and $v_p > 0$. Assuming that food category demand curves slope downward, δ>0, requiring that $\varepsilon_d > 0$. Likewise, a *negative net demand shock* is assigned in the case of reduced form residuals $v_q < 0$ and $v_p < 0$; given that δ>0, in that case the underlying structural demand shock ε_d must also be negative. Still, in either case an underlying structural supply shock could exist. For example, if $\widetilde{\varepsilon_d} > 0$, $v_q > \sigma v_p$

permits $\varepsilon_s > 0$, while $v_q < \sigma v_p$, which could occur when supply is very inelastic, permits an opposite signed structural supply shock $\varepsilon_s < 0$.

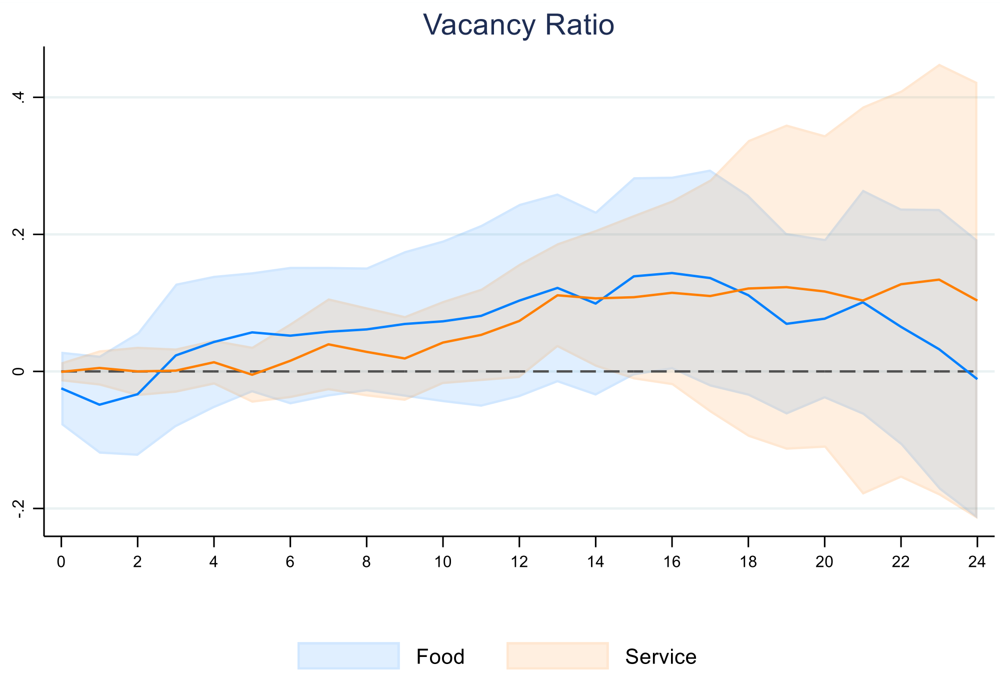
A *positive net supply shock* is assigned in the case of reduced form residuals $v_q > 0$ and $v_p < 0$. Assuming that food category supply curves slope upward, σ>0, requiring that $\varepsilon_s > 0$. Similarly, a *negative net demand shock* is assigned in the case of reduced form residuals $v_q < 0$ and $v_p > 0$; that requires a negative underlying structural demand shock ε_s, since $\sigma > 0$. Once again, a non-zero structural demand shock could co-exist. For example, if $\widetilde{\varepsilon_s} > 0$, $\delta v_q > v_p$ permits $\varepsilon_d > 0$, while $\delta v_q < v_p$ a negative structural demand shock, $\varepsilon_d > 0$.

Figure A1. Monthly impulse responses of 10% increases in the vacancy ratio to contributions to food price inflation, in percentage point changes to an index (Jan 1992 = 100)

Panel A. Pre-Covid period: January 2004 – December, 2019



Panel B. Covid-period: January 2020 – October, 2023


Vacancy Ratio
.4
.2
0
-.2
0
2
4
6
8
10
12
14
16
18
20
22
24
Food
Service