The Anatomy of U.S. Food Price Inflation

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Abstract

Surging food prices disproportionately burden low-income households, affect inflation expectations, and influence political outcomes. Between January 2020 and August 2025, U.S. food prices increased 30%, the steepest rise in more than four decades. We show this episode was structurally different from prior surges, including the 2008 Global Financial Crisis. Decomposing prices into supply- and demand-driven components and attributing each to macroeconomic channels, we find that labor scarcity and logistics disruptions—not commodity prices—dominated the supply side, while fiscal transfers and then wage growth account for an unprecedented demand-side contribution. Wage growth sustained elevated prices for four years through both labor costs and household income, a pattern absent in earlier episodes. Our work reveals underappreciated vulnerabilities in food-system resilience, illuminates how compound shocks generate persistent inflation, and shows why effective response must address logistics, labor, and wage pressure—not commodity availability alone.

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Food prices touch nearly every dimension of household welfare. They take up a larger share of low-income household budgets than other essentials[1], anchor inflation expectations across the broader economy[2], and even shape political outcomes[3]. Sustained food inflation therefore has consequences that extend well beyond the supermarket. Between January 2020 and August 2025, American consumers experienced a 30% increase in food prices, including a 12.4% rise over the 12 months ending in August 2022 according to the U.S. Bureau of Economic Analysis (BEA)[4]—the sharpest annual advance in more than four decades, and faster than inflation in other goods and services. Food consumption is unavoidable, and the welfare consequences fall hardest on the households least able to absorb them. Naturally, the general public, the media, academics, and policy makers want to know *why*. Researchers have offered a variety of explanations for the economy-wide inflationary surge[5], including on the demand side the rapid growth in real economic output following the COVID-19 shock[6], fueled in part by historically-large fiscal stimulus[7]. On the supply side, factors such as pandemic-induced lockdowns, a tight labor market, and supply chain bottlenecks—as well as disruptions in wheat and fertilizer markets due to the Russian invasion of Ukraine—also played a role. While related work applies conventional time series methods that rely on strong assumptions[8–11], few clearly differentiate between these explanations. So, the public is left to wonder whether the post-pandemic food price inflation episode was driven by familiar mechanisms—chiefly commodity price spikes, as in 2008—or by something else?

We show that it was structurally different by separating food price changes into supply- and demand-driven components using the joint behavior of category-level prices and quantities[12], and then attributing each component to observable macroeconomic channels—farm input costs, energy costs, supply chain disruptions, and sectoral labor costs on the supply side; the business cycle, financial market stress, fiscal stimulus, and income on the demand side—using a Shapley value decomposition[13–15]. Our analysis focuses on food consumed at home (FAH, or "off-premises consumption") and food consumed away from home (FAFH, or "food service"), yielding a complete, additive accounting of food price inflation over time.

We illustrate our findings by comparing the two most recent food price inflation episodes observed in the United States: the pandemic shock and its aftermath, and the Global Financial Crisis (GFC) of 2008–2009. Our results confirm that the two spikes had fundamentally different anatomies. Pandemic-era demand shocks accounted for almost 40% of the peak price increase, attributable mostly to fiscal transfers and wage growth, while supply chain disruptions made up a large share of the supply-driven inflation. In contrast, commodity price spikes dominated the supply-driven component of GFC-era food price rises, while the demand side had almost no explanatory power. Most strikingly, wage growth remained associated with elevated prices through both sides of the market simultaneously for four years—a dual-channel transmission with no clear analog in earlier episodes. These findings carry implications for our understanding of inflation under compound shocks, for food-system resilience, and for consumer welfare and the distributional consequences of policy responses, which we discuss in turn.

Results

Our analysis proceeds in two stages. First, we use a Shapiro decomposition[12] to separate food price inflation into the portions driven by supply and demand shocks, based on the joint behavior of category-level prices and quantities (see Methods). This tells us *how much* of each food price episode was driven by each side of the market, but not *why*. In the second stage, we apply a Shapley value decomposition[13,14] that divides each component's variation among observable macroeconomic channels, producing a complete, additive accounting. These attributions are associational rather than causal, but the first stage cleanly separates supply from demand; combining that identification with timing patterns of attribution, channels selected according to theoretical priors, and cross-episode contrasts provides a clear understanding of *why* each episode unfolded as it did. Channel variables are purged of seasonality and trend and the decomposition is centered on the component mean (see Methods). A positive Shapley value at a given date means the channel's recent behavior is associated with above-normal inflation on that side of the market; a negative value indicates below-normal pressure. By tracking these attributions over time, we identify which forces most likely pushed food inflation above its baseline during each episode, and when one force gave way to another. Because our channels cannot capture all variation, we include an unexplained residual. Our central findings are robust to alternative precision thresholds for classifying stage 1 shocks (see Supplementary Note A4). From here, we present the supply- and demand-side attributions in turn, then compare the two episodes.

Two different food price inflation episodes

Our baseline findings for the contribution of supply- and demand-side shocks to year-over-year (yoy) food price inflation as measured by the monthly U.S. BEA personal consumption expenditures (PCE) index are displayed in figure 1. For each panel, inflation driven by unexpected shifts in supply is shown in orange, while demand pressure is shown in blue. The vertical sum of the two sets of contributions matches the total observed food price inflation, by construction. Panels a & b represent all food consumed, the weighted average of FAH (in Panels c & d) and FAFH (in Panels e & f). Darker colors in the right-hand side panels are measured more precisely; the gray portion is labeled "ambiguous" because it is below the precision cutoff.

For most of the three decades in the figure, supply shocks account for the clear majority of U.S. food price inflation. This is not surprising for FAH, since its provision is closely tied to crop supply and cannot be scaled up or down as easily as, e.g., industrial goods, due to weather and biological shocks. The same is true for FAFH, although it is relatively more sensitive to demand-side shocks—this is intuitive since demand for food at eateries is more susceptible to income changes. What is striking is that the most-precisely measured demand shocks in the figure appeared only recently.

This fact is highlighted by the two notable food price spikes that occur in the data: they illustrate a marked change in the nature of domestic food price inflation. During the GFC, supply shocks overwhelmingly dominated FAH; the demand-side contributed barely at all. The pandemic episode was qualitatively different. FAH inflation registered twice as high as it did during the GFC, and though supply pressure was strikingly similar in magnitude—representing nearly all the initial price increase—by mid-2021 the demand-side contribution surged to nearly half the yoy increase. For FAFH, the demand side actually became the *majority* contributor during the pandemic rise. By late 2025 FAH inflation and its supply-demand composition returned to levels more in line with its historical pattern, but FAFH inflation remained elevated and demand-oriented. Our second stage analysis reveals that these two episodes differed not only in the responsible side of the market, but in the specific channels most likely to be responsible.

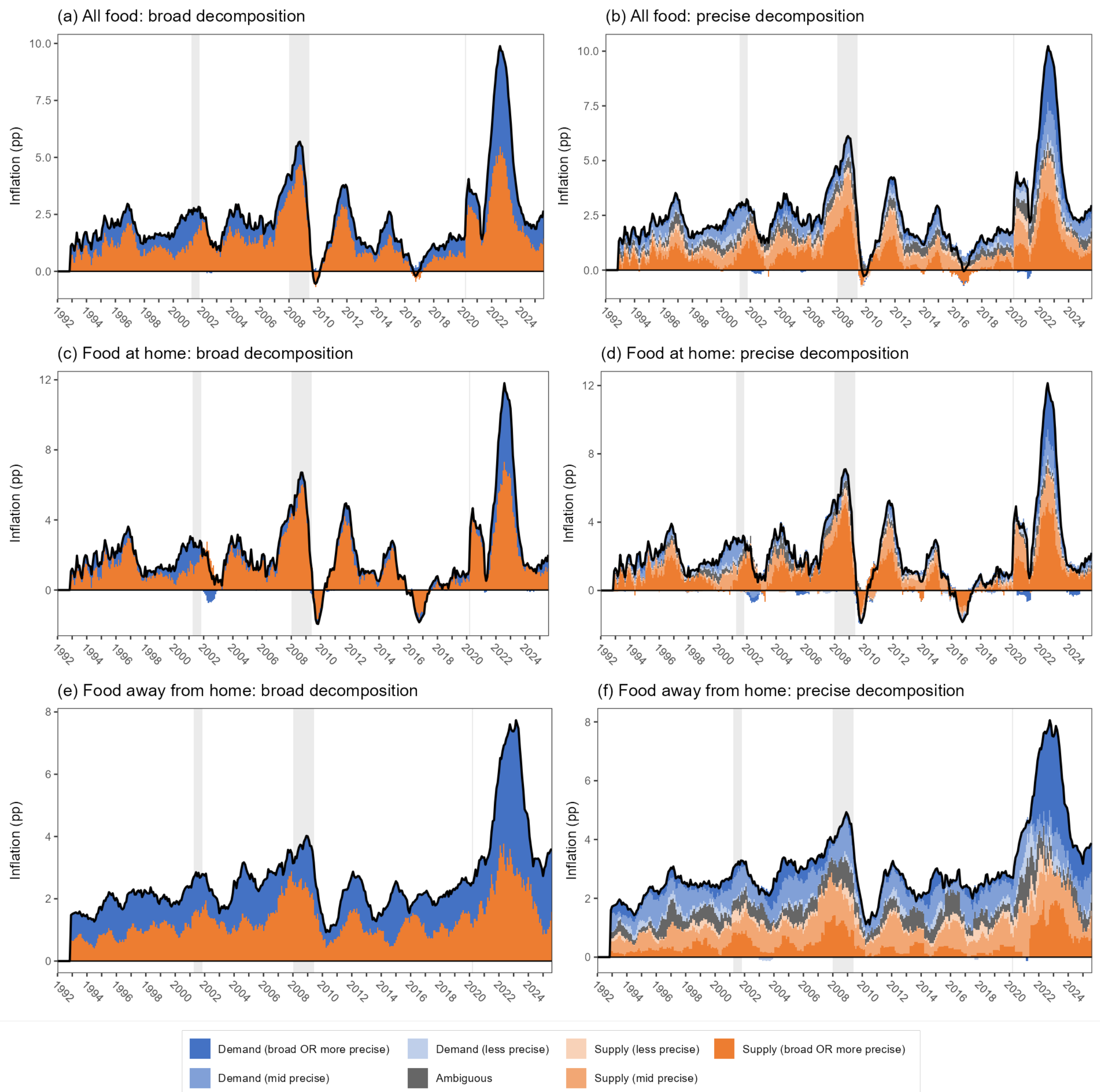

Figure 1. Contributions of supply and demand to U.S. food price inflation, year-over-year. Panels show all food, food at home (FAH), and food away from home (FAFH), with and without precision labeling. Supply-driven contributions are shown in orange; demand-driven contributions in blue. Darker colors are measured more precisely; light gray represents ambiguous contributions. Recession periods (NBER) are shaded in gray. The vertical sum of supply and demand contributions equals observed total food price inflation, by construction.
Source: Authors' calculations based on BEA data.

The supply side: from commodity pass-through to logistics bottlenecks

Our supply-side Shapley decomposition in figure 2 attributes inflation driven by supply shocks to four channels: farm input costs, energy costs, supply chain pressure, and sectoral wage costs (see Methods for channel definitions and theoretical motivation); we present the statistical significance of those Shapley attributions in figure 3. During the GFC, we find that FAH inflation was mostly explained by commodity pass-through—consistent with the prevailing interpretation in the literature[16]. Farm input and energy costs were the two dominant channels during 2008, contributing roughly equally (and significantly). Over the following decade both channels reversed as commodity supplies corrected. Logistics bottlenecks and sectoral wages were generally negligible, and the unexplained residual at times played an outsize role—suggesting that our four supply channels do not fully capture that era's supply-side dynamics. For FAH therefore, the GFC supply-side episode was a commodity-led boom and bust. Not so for FAFH: commodity channels played a far smaller part; instead, sectoral wages were the largest identifiable (and significant) channel, though even they were modest and the residual was substantial. This is consistent with restaurants' labor-intensive cost structure; for them, agricultural and energy commodity prices pass through only indirectly.

Pandemic-era supply side inflation was structurally different. For FAH, supply-side pressures emerged in early 2020, well before demand. The model identifies sectoral wages as the channel most associated with the initial supply surge, reflecting labor scarcity from lockdowns and processing plant closures (wages here are sector-specific and represent a cost input). It surged to over a full percentage point by mid-year. Supply chain pressure followed by mid-2020 as transportation bottlenecks mounted. Energy costs pulled in the opposite direction as the oil price collapsed through demand destruction. The pandemic food price surge began as a pure supply shock, with labor scarcity leading the way.

By mid-2021, farm and energy costs began to pressure FAH prices higher as well. The Ukraine invasion in early 2022 likely served as a catalyst for both channels, disrupting expected wheat, fertilizer, and energy commodity availability[17,18]. At the August 2022 peak, all four supply channels' attributions are statistically significant, and supply chain pressure alone exceeded the contribution of *any single channel* to FAH prices during the average GFC month. For FAFH, sectoral wages and supply chain pressure contributed roughly equally, with commodity inputs negligible—again con-

Figure 2. Shapley value decomposition of supply-side food price inflation, year-over-year. The left panel reports food at home (FAH) and the right panel reports food away from home (FAFH). Channels include farm input costs, energy costs, supply chain pressure, and sectoral wage costs (grocery/retail for FAH; hospitality for FAFH). The dashed red line shows total supply-side inflation. *Source:* Authors' calculations using BEA, FRED (Federal Reserve Bank of St. Louis), Federal Reserve Bank of New York, and BLS data.

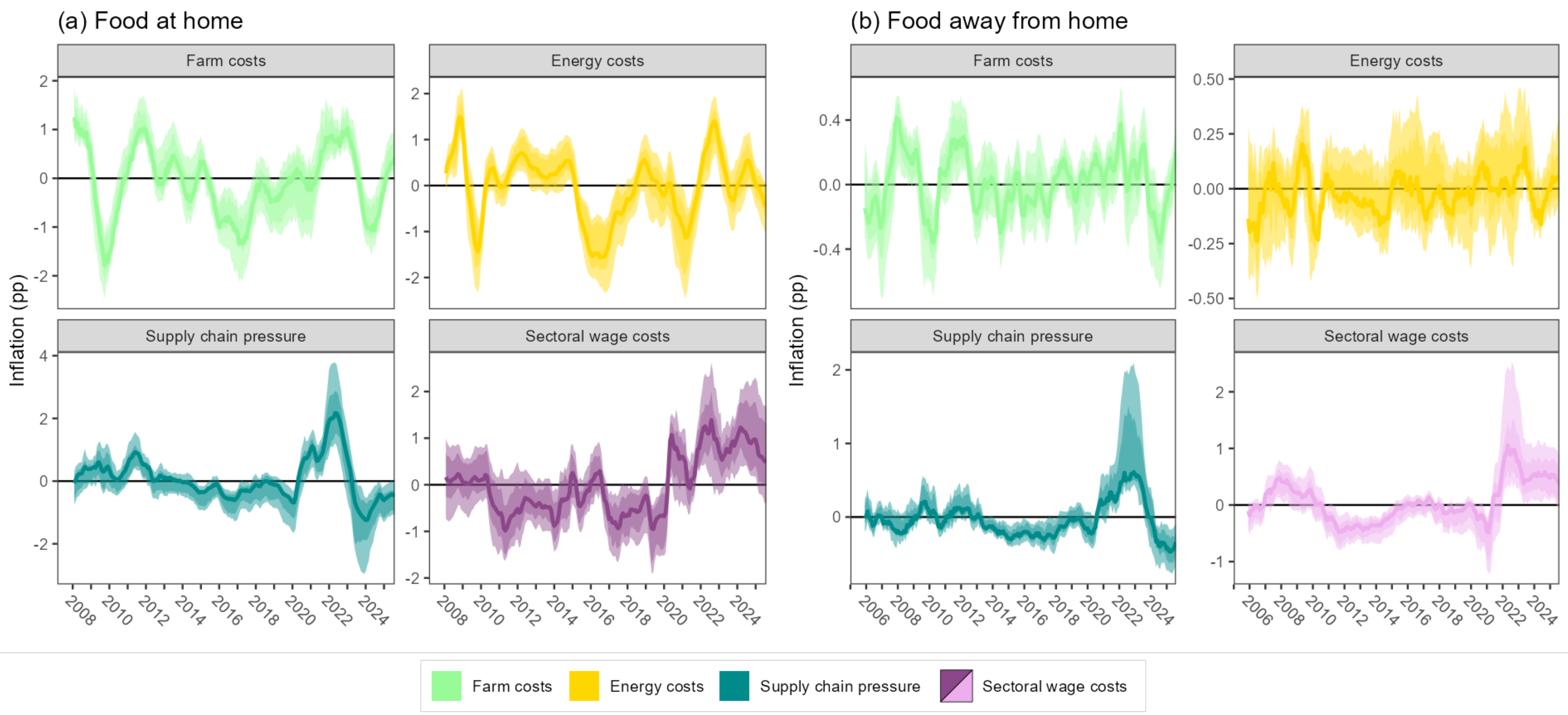

Figure 3. Bootstrapped Shapley value decomposition of supply-side food price inflation, year-over-year. The left set of panels reports food at home (FAH) and the right set reports food away from home (FAFH). In each panel, the line shows the estimated channel contribution. Dark shading denotes the 68% confidence interval and light shading denotes the 90% confidence interval. Intervals are based on 1,000 12-month moving-block bootstrap replications with 500 Monte Carlo draws each.
Source: Authors' calculations using BEA, FRED (Federal Reserve Bank of St. Louis), Federal Reserve Bank of New York, and BLS data.

sistent with restaurants' labor-intensive cost structure. The pandemic supply shock was therefore structurally novel; it was not primarily a commodity price phenomenon, but a disruption to the physical capacity of the food supply chain—port congestion, container shortages, processing plant closures, reduced availability of truck drivers[19],compounded by labor scarcity. By 2024, supply chains adjusted and farm input costs reversed. The sole remaining positive supply-side forces were sectoral wage and energy costs.

The demand side: sparked by stimulus, sustained by income growth

Our Shapley attribution of the demand component in figure 4 includes four channels: global real economic activity[20], financial stress (the Chicago Fed's adjusted National Financial Conditions Index, or NFCI[21]), fiscal stimulus, and economy-wide wage growth; figure 5 displays the bootstrapped confidence bands. During the GFC, the overall demand component was small. Global real economic activity was the largest demand-side channel for both FAH and FAFH—and the only one consistently significant. Notably, despite the severity of the financial crisis we find no substantive role for financial stress in food price inflation. Across the entire sample demand for FAH and FAFH is responsive to actual household cash flow but appears *not* to respond strongly to credit availability, asset prices, or financial market conditions (see Supplementary Note A4 for additional detail on financial stress attribution under alternative specifications), at least directly.

Breaking with several decades of precedent, the demand side was central to food price inflation during the pandemic; it unfolded in two phases. Fiscal stimulus pressure grew steadily more positive from mid-2021 to nearly a full percentage point by late 2021 before peaking close to 2 percentage points in early 2022, and remained the dominant demand-side force through mid-2022. FAFH followed the same pattern with similar timing and magnitude. Confidence bands confirm that the FAH stimulus attribution is statistically robust during the pandemic; FAFH bands are wider, though Supplementary Note A4 shows that fiscal attribution still excludes zero at the 68% confidence level in roughly two-thirds of pandemic months under the most-precise specification. As transfers expired and households spent them down, wage growth emerged as the leading demand channel by mid-2022, consistent with the temporary nature of transfer programs versus the persistence of income rises. By 2023, FAFH demand pressure and its income attribution remained elevated and substantially larger than for FAH. This may reflect a structural difference between

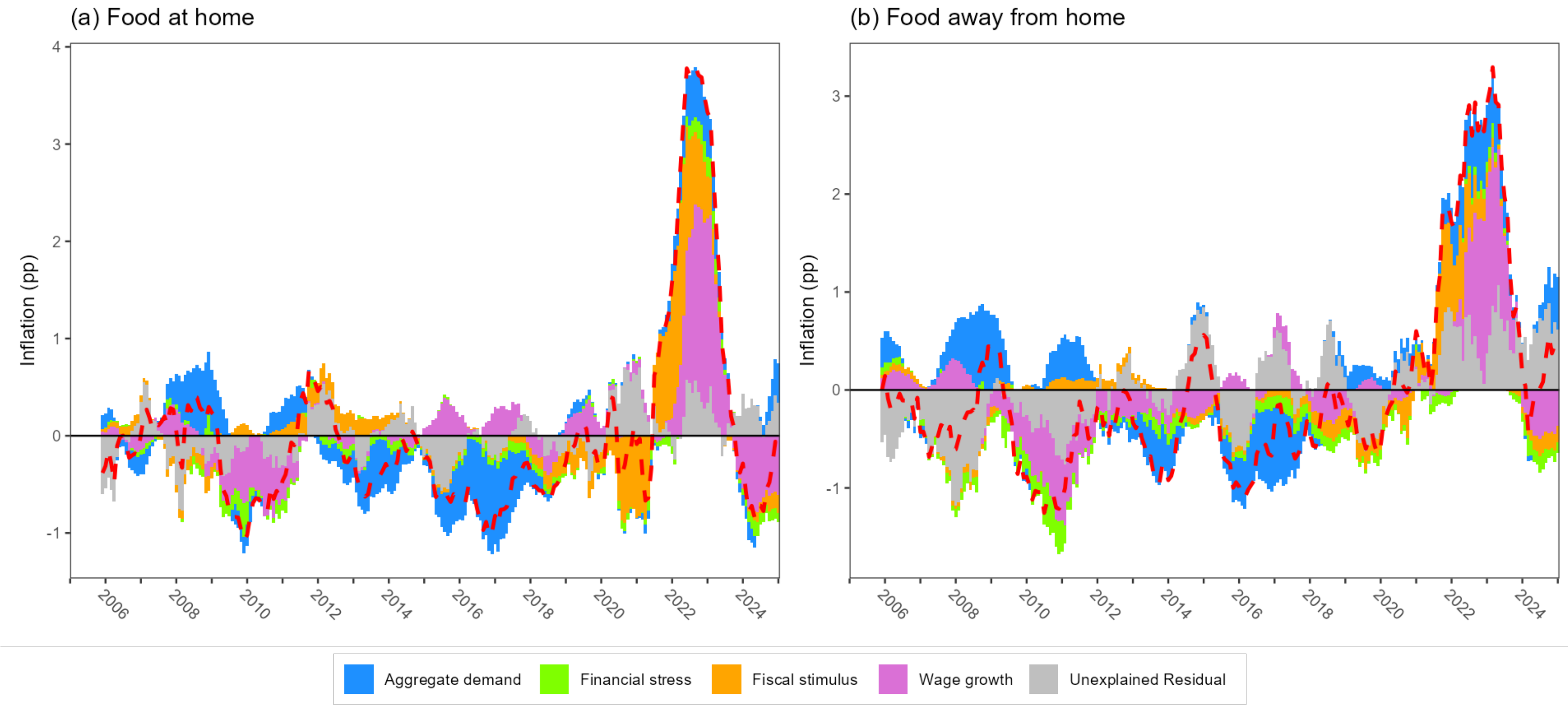

Figure 4. Shapley value decomposition of demand-side food price inflation, year-over-year. The left panel reports food at home (FAH) and the right panel reports food away from home (FAFH). Channels include aggregate demand, financial stress, fiscal stimulus, and wage growth. The dashed red line shows total demand-side inflation.
Source: Authors' calculations using BEA, FRED (Federal Reserve Bank of St. Louis), Federal Reserve Bank of New York, and BLS data.

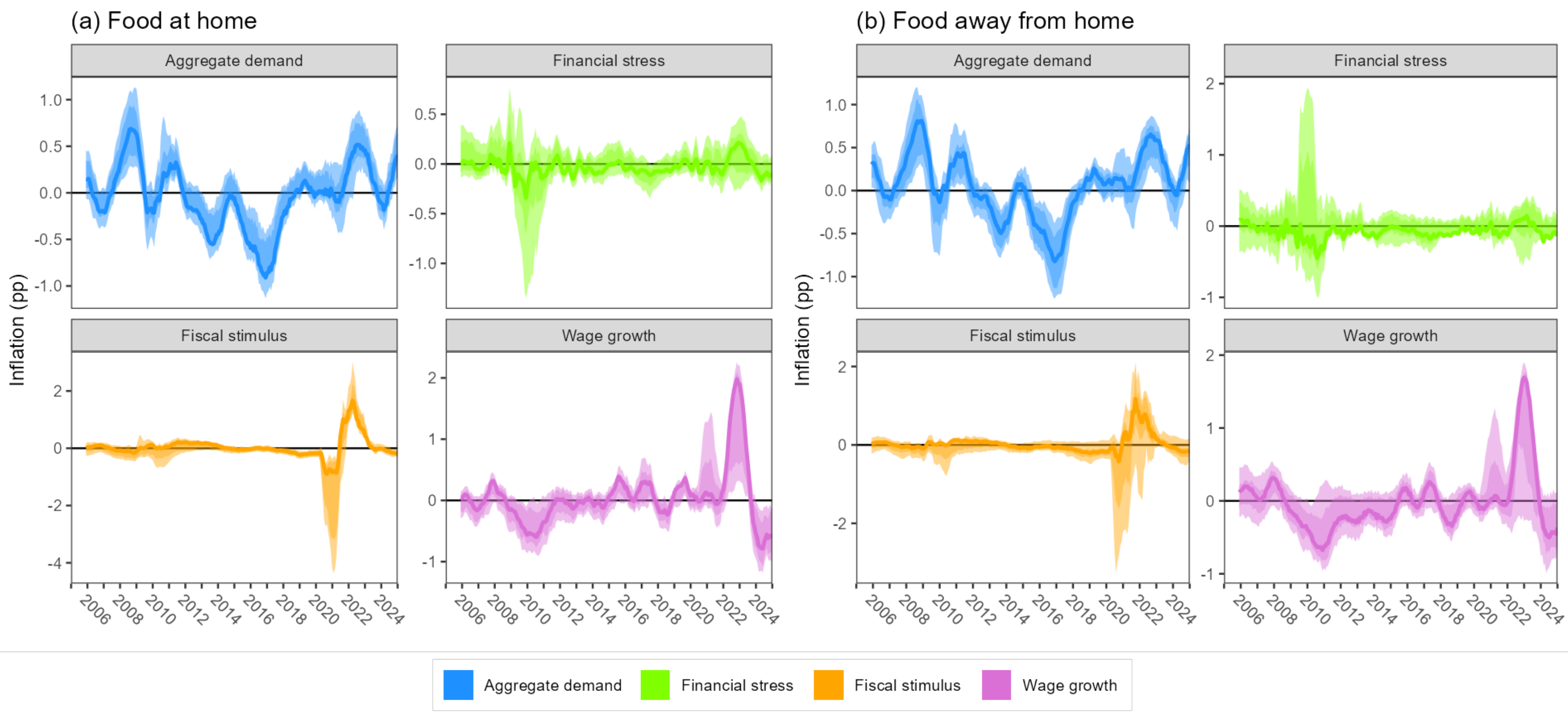

Figure 5. Bootstrapped Shapley value decomposition of demand-side food price inflation, year-over-year. The left set of panels reports food at home (FAH) and the right set reports food away from home (FAFH). In each panel, the line shows the estimated channel contribution. Dark shading denotes the 68% confidence interval and light shading denotes the 90% confidence interval. Intervals are based on 1,000 12-month moving-block bootstrap replications with 500 Monte Carlo draws each.

Source: Authors' calculations using BEA, FRED (Federal Reserve Bank of St. Louis), Federal Reserve Bank of New York, and BLS data.

grocery and restaurant spending, since recurring discretionary expenditure depends on sustained income rather than lump-sum transfers. Both demand-side channels also flowed disproportionately through lower-income households—fiscal transfers by design, and pandemic-era wage gains because they were concentrated at the bottom of the income distribution[22]. The households that ultimately bore the largest food-price burden were therefore also a primary source of the demand-side pressure on those prices, with significant distributional consequences.

The unexplained residual is more prominent in FAFH's demand side than FAH throughout the sample. This likely reflects the fact that restaurant spending is shaped by behavioral factors our macroeconomic channels are not designed to capture, like the evolving mix of limited- and full-service formats and other idiosyncratic drivers of discretionary food spending. Pandemic-specific effects—pent-up demand for dining out after lockdowns, shifts to takeout and delivery, changes in tipping behavior—likely contributed to the residual, too.

Comparing the two inflation episodes

By 2023, fiscal stimulus zeroed out, supply chain pressure on food prices reversed, and commodity prices moderated. Yet food price inflation in figure 1 remained elevated for both FAH and FAFH. Our Shapley decomposition attributes the persistence of elevated inflation primarily to wage growth on *both* sides of the ledger, simultaneously boosting food prices through higher labor costs and greater purchasing power. For FAFH these effects were larger from both sides of the market, which is intuitive because restaurant prices are doubly wage-sensitive: labor is both a key cost input and a critical determinant of consumer decision making when it comes to dining out. This dual-channel wage exposure distinguishes the pandemic episode from the earlier food price spike in our sample.

During the GFC, food price inflation was predominantly on the supply-side and commodity driven, so relief occurred once those markets adjusted—that is, once high prices led producers to respond. During the pandemic, every non-wage channel also eventually self-corrected: bottlenecks cleared, farm input costs reversed, and fiscal stimulus expired on its own timeline. But wage growth persisted on both sides of the market. Pandemic-era frictions like mandatory lockdowns, coupled with historic levels of fiscal and monetary stimulus, fueled unprecedented levels of excess savings[23], far more than following the fiscal stimulus associated with the financial crisis. The resulting labor market tightness sustained food price increases through both the demand and supply channels simultaneously. By 2024, as the labor market cooled, wage contributions declined and food inflation moderated accordingly, confirming that labor market conditions were the key swing factor for food price persistence.

Discussion

Rising food costs distress all households but especially low-income ones, whose budgets are dominated by food spending[1]; they also have political salience, with voters expecting policy makers to act[24]. Our analysis reveals that the post-pandemic food price surge was not just larger than historical food inflation generally, and the GFC spike in particular; it was structurally different, a compound shock operating through novel channels. Our Shapiro decomposition shows that standard supply-side forces cannot fully explain recent food price inflation. And rather than typical commodity-oriented input costs, our Shapley analysis attributes its origin to labor scarcity and supply chain pressure on the supply side, fiscal stimulus on the demand side, and then a persistent wage-dominated regime operating through both sides of the market: labor costs and income. This pattern suggests that future compound food price shocks—those involving both demand and supply—may have similarly large and prolonged food price effects, and that the appropriate policy response depends on which side of the market is generating the pressure and which specific forces are at work.

The model identifies logistics disruptions as the dominant supply-side driver of FAH inflation, coinciding with recent evidence highlighting how U.S. agri-food distribution depends on interlocking waterways, highways, railways, and logistics hubs[25–27]. Through the Infrastructure Investment and Jobs Act, the federal government invested significantly in transportation network resilience: roughly \$1.9 billion in port development awards since FY2022[28–32], \$17.1 billion in Army Corps navigation funding[33], USDA's \$400 million Resilient Food Systems Infrastructure program for middle-of-the-supply-chain capacity[34], and USDOT freight programs addressing surface and intermodal bottlenecks[35–37]. Regulatory reform could also help, since even well-intended regulations add substantial costs to food production[38]. During the pandemic the FDA temporarily permitted food originally prepared for restaurants to be diverted to grocery stores[39]; though later withdrawn[40], the episode suggests distribution channel barriers can be relaxed without compromising food safety. Our results also show that labor scarcity was the *first* supply channel to activate in 2020, suggesting that policies affecting labor availability in food sectors—worker safety regulations, visa policy, minimum wage levels in retail and hospitality—likewise affect supply-side pressure on food prices[41,42].

Policy makers have also focused on industrial organization within the supply chain, proposing bans on price gouging and restrictions on digital shelf labels and data-driven individualized pricing[43,44], and using antitrust enforcement to block mergers[45,46]. If oligopolistic retailers use pricing technologies as coordination mechanisms[47], they may maintain or increase margins as supply pressures decrease; on the other hand, price ceilings could generate shortages if they prevent prices from permitting suppliers to meet demand[48]. (Our decomposition does not include a markup channel and cannot directly evaluate these claims; exploring that question likely requires firm-level margin data.) Other policy makers have pursued direct intervention: thirteen states have supported independent grocery stores in low-income areas[49], and several have proposed a "public option" for retail food[50–52]. Whether publicly-run grocery stores can lower food prices depends on their efficiency of operation, a clear challenge since they do not have access to the same logistics networks, experience, and expertise of large retailers.

Tariffs may introduce new supply-side pressure if they raise landed costs for imported foods and agricultural inputs. Evidence from the 2018–2019 trade war shows near-complete pass-through to import prices but smaller and more gradual effects at the retail level[53–56]. The magnitude and duration of tariff price effects depends on the capacity of markets to adjust[57].

On the demand side, our finding that financial stress has negligible explanatory power implies that monetary policy has limited *direct* effect on food demand, although it may operate indirectly through other channels. The demand-side channels that matter are fiscal transfers and wages: U.S. policy makers injected trillions of dollars into the economy at a time of lockdowns[8,58], raising Americans' savings[23]—which our Shapley attribution associates with demand-driven food price increases. The initial demand-side food price inflation was, in this sense, an unintended outcome of fiscal policy. Our findings cannot speak to what caused wages to cool, but they do identify the wage channel as the key inflationary transmission channel on both sides of the market.

Recent legislative action speaks directly to these demand channels. The 2025 reconciliation law reduces projected SNAP outlays[59,60] and imposes new responsibilities on states[61]. While our decomposition does not directly measure SNAP's contribution to food demand, fiscal channel results suggest that policies reducing household cash flow can lower demand-side pressure on food prices, although perhaps at the cost of disproportionately burdening the very households most vulnerable to food price increases.

A common thread runs through several other prominent post-pandemic policy responses: increasing funding for agricultural researchers and USDA's Agricultural Research Service to improve crop resilience and boost yields[62], supporting domestic energy production to reduce input costs, adjusting tariffs on imported agricultural inputs, and limiting food waste[63]. Each of these targets commodity availability or producer costs, beneficial to be sure especially if future inflationary episodes resemble the commodity-led pattern of 2008. However, focusing on the supply side alone would be an incomplete response to the post-pandemic episode and leave the households who bore its largest welfare consequences without targeted relief. Effective response for low-income consumers calls for policies that also address logistics resilience, labor capacity in food sectors, and the fiscal-and-income channels our analysis associates with the recent inflation episode.

Our findings have broader implications that extend well beyond food markets. Compound inflation shocks operating simultaneously through fiscal, supply-chain, and labor channels may become more common under climate, geopolitical, and epidemiological disruption. As a result, modern food-system resilience is as vulnerable to logistics and labor capacity as it is to commodity availability, reframing how infrastructure and workforce policy can be directed to effectively reduce the constraints that lead to food price volatility. And the same households that bear the largest welfare consequences of food inflation are also a principal source of demand-side pressure during recovery episodes, so the design of fiscal stimulus and safety-net programs has direct distributional consequences for food affordability. Diagnosing which side of the market is responsible, and which specific forces are at work within it, is a first step toward responses that fit the specific inflation episode at hand.

Methods

Stage 1: Supply–demand decomposition

We adopt Shapiro's[12] decomposition approach to analyze food price inflation, using category-level regressions on personal consumption expenditure (PCE) data. This allows us to identify supply- and demand-side shocks by examining monthly changes in price and quantity indices for various food categories. While recent studies on U.S. food price inflation apply conventional time series methods that rely on strong assumptions[8–11], applying Shapiro's model offers a more robust and intuitive analysis of economic shocks' impact on food prices. Our general approach is to estimate a time series model of price and quantity at the food category level; residuals to the model represent unexpected changes in the price or quantity of food over time. We categorize the latter as demand-driven when the price and quantity residuals move in the same direction, and supply-driven when the residuals are opposite-signed[64]. (Supplementary Note A1 provides the conceptual framework linking these reduced-form residuals to underlying supply and demand shocks.) By weighting each category according to its share of total U.S. expenditures on food, we then aggregate to estimate the overall contributions of demand and supply shocks to food price inflation.

Specifically, for each of the 30 PCE food subcategories tracked by BEA, we estimate bivariate vector autoregressions (VARs) in log prices and log quantities:

$$\Delta \ln q_{i,t} = \sum_{j=1}^{12} \gamma_j^{qp} \, \Delta \ln p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{qq} \, \Delta \ln q_{i,t-j} + c + u_{i,t}^{q} \tag{1}$$

$$\Delta \ln p_{i,t} = \sum_{j=1}^{12} \gamma_j^{pp} \, \Delta \ln p_{i,t-j} + \sum_{j=1}^{12} \gamma_j^{pq} \, \Delta \ln q_{i,t-j} + c + u_{i,t}^{p} \tag{2}$$

Regressions 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 (60-month) window, permitting parameters to vary with time.

Same-sign price and quantity residuals ($u_{i,t}^{p}$ and $u_{i,t}^{q}$) indicate a net demand shock; opposite-sign residuals indicate a net supply shock. These are "net" shocks in the sense that they set-identify the dominant side of the market: being assigned a net demand shock means the category experienced at least a demand shock, though a simultaneous supply shock could co-exist (see Supplementary Note A2 for the formal proof). Category-level contributions are aggregated using contemporaneous expenditure weights $\omega_{i,t-1}$:

$$\pi_t = \underbrace{\sum_i \mathbb{1}^{\text{sup}}_{i,t}\, \omega_{i,t-1}\, \pi_{i,t}}_{\text{supply}} + \underbrace{\sum_i \mathbb{1}^{\text{dem}}_{i,t}\, \omega_{i,t-1}\, \pi_{i,t}}_{\text{demand}}. \tag{3}$$

where $\pi_{i,t}$ is the month-over-month price change for category i. Year-over-year contributions are computed as twelve-month running products, since inflation rates are multiplicative.

PCE 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. While the CPI represents only urban residents, the PCE data include expenditures of both urban and rural Americans. The two broad categories relevant to food purchases are "food and beverages purchased for off-premises consumption" (FAH) and "food services" (FAFH). We use the lowest level of aggregation available for analysis, yielding thirty food subcategories in total. For each subcategory, BEA provides price and quantity indices, as well as total expenditure levels at the monthly frequency. While most subcategories have complete observations from January 1959, three food service subcategories (meals at limited-service eating places, meals at other eating places, and meals at drinking places) are only available from January 1987. We use the first five years of available data to establish a baseline for model estimation.

Precision thresholds

In our baseline results, all unexpected price and quantity shifts are classified as either supply- or demand-driven. To guard against the possibility that the model misidentifies shocks when residuals are small, we also define an "ambiguous" category for cases in which at least one residual is within 0.025 food category-specific standard deviations of zero, and we report less precise, mid precise, and more precise classifications using thresholds of 0.025, 0.05, and 0.25 food category-specific standard deviations, respectively. See Supplementary Note A1 for the conceptual framework and

Supplementary Note A4 for a robustness illustration.

Stage 2: Shapley value attribution

Stage 1 tells us *how much* food price inflation at each date is supply- versus demand-driven. Stage 2 asks a different question: *which observable macroeconomic channels help explain each component?* Our goal in stage 2 is to provide a transparent accounting of which channels line up most closely with the time variation in each stage-1 component using Shapley decomposition[13,14].

We regress each stage-1 component on four macroeconomic channel groups for each food type and each side of the market. Let y_t denote the stage-1 component at month t. Each channel enters as a regressor group consisting of its current value plus 12 monthly lags (13 regressors: $X_{k,t}, X_{k,t-1}, \ldots, X_{k,t-12}$). The regression yields a fitted value $\hat{y}_t$: the portion of the stage-1 component explained by the channels.

Because channels move together and no single ordering of them is natural, we use Shapley's approach to allocate $\hat{y}_t$: each channel's marginal contribution is averaged across all $4! = 24$ possible entry orders (see Supplementary Note A3 for the intuition behind this approach). This delivers an accounting identity at every date:

$$\hat{y}_t = \bar{y} + \sum_{k=1}^{4} \phi_k(t), \tag{4}$$

where $\bar{y}$ is the sample mean of the stage-1 component (its normal level) and $\phi_k(t)$ is the Shapley contribution of channel k at month t. We report the difference between the observed component and its fitted value as an unexplained residual, $r_t = y_t - \hat{y}_t$, so that:

$$y_t = \bar{y} + \sum_{k=1}^{4} \phi_k(t) + r_t. \tag{5}$$

A channel receives a large attribution in a given month if its recent behavior helps explain why the supply- (or demand-) driven component is unusually high (or low) relative to its baseline, expected level. A channel can therefore receive a negative attribution if it is associated with pulling inflation *below* its normal level on that side of the market. Likewise, a channel can be statistically important in the regression sense but still have a small Shapley contribution in a particular episode if its movements during that episode are unremarkable.

Because channels are correlated, the marginal contribution of a channel depends on what is already in the model. We therefore compute the conditional expectations needed for the Shapley values under a Gaussian copula approximation to the joint distribution of channels[14]. We use 5,000 Monte Carlo draws to evaluate these conditional expectations (results are insensitive to the draw count; see Supplementary Note A4).

Finally, we note that the Shapley attribution is associational rather than causal: it identifies which channels co-move most strongly with each stage-1 component, not which channels caused it. The advantage is transparency and completeness. We quantify how much of the modeled supply- or demand-driven inflation aligns with each channel at each date, while allowing the data to assign the remainder to an unexplained residual.

Supply-side channels

We include four supply-side channels chosen to capture the major cost and capacity constraints that shift food supply curves over time. Farm input costs are measured by the Bureau of Labor Statistics (BLS) PPI for farm products, which captures upstream agricultural cost pressures that pass through most directly to FAH (rather than FAFH). Energy costs are measured by the BLS PPI for energy, reflecting production inputs, transportation, processing, and packaging costs that matter for both FAH and FAFH. Supply chain pressure is measured by the NY Fed's Global Supply Chain Pressure Index (GSCPI)[65]; it summarizes disruptions such as bottlenecks, delivery delays, and scarcity of critical inputs—including pandemic-era transportation frictions like reduced availability of truck drivers[19]. Finally, we include sector-specific wage costs (average hourly earnings) to capture labor inputs: for FAH we use BLS series for grocery and food retail wages (series CEU4244500003), and for FAFH we use leisure and hospitality wages (series CES7000000008). This distinction reflects production technology: in restaurants, labor accounts for roughly 30% of operating costs, but labor is also an important cost component throughout the food distribution and retail network[66–68].

Demand-side channels

On the demand side, we include four channels intended to capture broad macroeconomic forces that can shift willingness to pay for food, while separating global conditions, credit conditions, and household cash flow. Global real economic activity is measured by Kilian's index constructed from dry cargo shipping rates[20]; it captures the international business cycle and commodity-demand environment. Financial stress is measured by the GDP-adjusted National Financial Conditions Index from the Chicago Fed, which isolates credit availability and financial market stress from the business cycle; without it, credit booms and busts could be absorbed by aggregate demand or income measures. Fiscal stimulus is measured as the first principal component of three pandemic-era income support programs—excess unemployment insurance benefits relative to a 2015–2019 baseline, economic impact payments, and the expanded child tax credit—all expressed per capita; this channel is meant to represent temporary, policy-driven cash inflows to household budgets.

To capture the income channel for both FAH and FAFH, we use the Atlanta Fed's median wage growth tracker[69]. Unlike average hourly earnings, the median wage tracker is constructed from micro data for continuously employed workers and is designed to measure underlying wage growth with less sensitivity to compositional shifts in employment and hours. This makes it a cleaner proxy for broad household income growth, the mechanism relevant for demand pressure in both grocery and restaurant spending.

All channel variables are standardized as described above. Wages therefore appear on both sides of the decomposition, but they represent different mechanisms: wage growth proxies household income on the demand side, while sectoral wages proxy labor costs on the supply side. This is not double-counting. Stage 1 has already separated demand- and supply-driven components, so we focus on how labor market shocks operate through income and cost channels on different sides of the market.

Bootstrap inference

We quantify the precision of Shapley attributions using a moving block bootstrap[70]. We draw 1,000 replications with a block length of 12 months, chosen to preserve the serial correlation structure of the monthly data. Each replication re-samples contiguous blocks from the original time series, re-estimates the OLS regression on the pseudo-sample, re-computes grouped Shapley values (with 500 Monte Carlo draws per replication, sufficient for stable replication-level estimates given the smoothing across 1,000 replications), and records the resulting channel attributions. We extract the 16th/84th percentiles (68% confidence bands, analogous to ± 1 standard error) and the 5th/95th percentiles (90% confidence bands) at each date. These bands reflect sampling uncertainty in both the regression coefficients and the Shapley conditional expectations, but do not incorporate first-stage estimation error from the Shapiro VAR.

Data availability

All data used in this study are publicly available from the sources described in Methods. Processed datasets and replication code will be deposited in a public repository upon publication.

Code availability

All code is available from the corresponding author upon request and will be deposited in a public repository upon publication.

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Figure Legends

Fig. 1 | Contributions of supply and demand to U.S. food price inflation, year-over-year. Panels show all food (**a**, **b**), food at home (FAH; **c**, **d**), and food away from home (FAFH; **e**, **f**), with and without precision labeling. Supply-driven contributions are shown in orange; demand-driven contributions in blue. Darker colors are measured more precisely; light gray represents ambiguous contributions. Recession periods (NBER) are shaded. The vertical sum of supply and demand contributions equals observed total food price inflation, by construction. **Fig. 2 | Shapley value decomposition of supply-side food price inflation, year-over-year.** **a**, FAH. **b**, FAFH. Channels: farm input costs, energy costs, supply chain pressure, and sectoral wage costs (grocery/retail for FAH; hospitality for FAFH). The dashed red line shows total supply-side inflation. **Fig. 3 | Bootstrapped Shapley value decomposition of supply-side food price inflation, year-over-year.** **a**, FAH. **b**, FAFH. Lines show estimated channel contributions. Dark shading denotes the 68% confidence interval; light shading denotes the 90% confidence interval. Intervals are based on 1,000 12-month moving-block bootstrap replications with 500 Monte Carlo draws each. **Fig. 4 | Shapley value decomposition of demand-side food price inflation, year-over-year.** **a**, FAH. **b**, FAFH. Channels: aggregate demand (Kilian's REA), financial stress (GDP-adjusted NFCI), fiscal stimulus (PC1 of pandemic-era transfers), and wage growth. The dashed red line shows total demand-side inflation. **Fig. 5 | Bootstrapped Shapley value decomposition of demand-side food price inflation, year-over-year.** **a**, FAH. **b**, FAFH. Lines show estimated channel contributions. Dark shading denotes the 68% confidence interval; light shading denotes the 90% confidence interval. Intervals are based on 1,000 12-month moving-block bootstrap replications with 500 Monte Carlo draws each.

Supplementary Notes

A1 Conceptual Model: Identifying Supply and Demand Shocks

Following Shapiro[12], with quantity and price data for food category i, and facing supply curve slope β^s and demand curve slope β^d, running the vector autoregression (VAR) model:

$$\begin{bmatrix} \Delta \ln p_{it} \\ \Delta \ln q_{it} \end{bmatrix} = \sum_{j=1}^{J} A_{ij} \begin{bmatrix} \Delta \ln p_{i,t-j} \\ \Delta \ln q_{i,t-j} \end{bmatrix} + \begin{bmatrix} u_{it}^p \\ u_{it}^q \end{bmatrix} \tag{A1}$$

where p_{it} and q_{it} denote the price and quantity indices, and J lags produces reduced-form residuals u_{it}^p and u_{it}^q. These residuals can be transformed to recover the structural supply and demand shocks ε_{it}^s, ε_{it}^d, where:

$$\varepsilon_{it}^s = u_{it}^q - \beta^d u_{it}^p, \tag{A2}$$

$$\varepsilon_{it}^d = u_{it}^q - \beta^s u_{it}^p, \tag{A3}$$

according to:

$$\begin{bmatrix} u_{it}^p \\ u_{it}^q \end{bmatrix} = \frac{1}{\beta^s - \beta^d} \begin{bmatrix} 1 & -1 \\ \beta^s & -\beta^d \end{bmatrix} \begin{bmatrix} \varepsilon_{it}^d \\ \varepsilon_{it}^s \end{bmatrix}. \tag{A4}$$

Restrictions on the sign of the supply and demand slopes specified in (A4) (consistent with basic economic theory) imply restrictions on both the signs of the reduced-form residuals and structural shocks[64]. That is, the relationship in equation (A4) 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. We categorize them as follows:

$$\text{Positive Supply Shock:} \quad u_{it}^p < 0,\ u_{it}^q > 0 \tag{A5}$$

$$\text{Negative Supply Shock:} \quad u_{it}^p > 0,\ u_{it}^q < 0 \tag{A6}$$

$$\text{Positive Demand Shock:} \quad u_{it}^p > 0,\ u_{it}^q > 0 \tag{A7}$$

$$\text{Negative Demand Shock:} \quad u_{it}^p < 0,\ u_{it}^q < 0 \tag{A8}$$

For a given food category i at time t, same-sign price and quantity residuals from equation (A1) 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. However, because the supply and demand curves can move simultaneously, using unexpected price and quantity changes in equations (A5)–(A8) 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, as shown in Supplementary Note A2. In the case of simultaneous demand and supply curve shifts, the net shock reveals their combined influence.

A1.1 Determining contributions to food price inflation

Once time t shocks for each food category are segregated into net supply and demand shocks, they can be used to decompose observed food price inflation into the portion driven by each broad side of the market. Following Shapiro[12], we specify indicator functions:

$$\mathbb{1}^s_{it} = \begin{cases} 1 & \text{if } \operatorname{sign}(u^p_{it}) \neq \operatorname{sign}(u^q_{it}) \\ 0 & \text{otherwise} \end{cases}, \quad \mathbb{1}^d_{it} = \begin{cases} 1 & \text{if } \operatorname{sign}(u^p_{it}) = \operatorname{sign}(u^q_{it}) \\ 0 & \text{otherwise} \end{cases}. \tag{A9}$$

Then observed price inflation between $t-1$ and t can be decomposed into supply-driven (π^s_t) and demand-driven (π^d_t) components, each of which represents sums of category-level inflation—classified by type of shock—and weighted by their share of the overall consumption basket:

$$\pi_t = \pi^s_t + \pi^d_t, \quad \text{where} \quad \pi^k_t = \sum_i w_{i,t-1} \cdot \Delta p_{it} \cdot \mathbb{1}^k_{it}, \quad k \in \{s, d\}. \tag{A10}$$

In this equation, $w_{i,t-1}$ represents the share of time $t-1$ expenditures on category i, while Δp_{it} is the percent change in price for category i between $t-1$ and t. If the data are monthly, then the contributions to year-over-year inflation are their twelve-month running product, since inflation rates are multiplicative:

$$\Pi^k_{12,t} = \prod_{j=0}^{11} \left(1 + \pi^k_{t-j}\right) - 1, \quad k \in \{s, d\}. \tag{A11}$$

A1.2 Precision thresholds

In the baseline results, our estimates leave no space for uncertainty; all unexpected price and quantity shifts are classified as either a supply or demand shock. 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. Small reduced-form residuals increase the risk of a mislabeling, so like Shapiro[12] we re-interpret a given food category's contribution to inflation as ambiguous if at least one of the residuals 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. As shown in Fig. 1, 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 classifications. The darkest demand shading is most apparent in the food price rises observed 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[23]. At the same time, more precisely-measured supply shocks became more important, as fertilizer prices increased ahead of (and then in response to) Russia's invasion of Ukraine.

A2 Net Shocks Are Set Identified

Net supply or demand shocks in this article 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 show that the existence of a net shock requires an underlying structural shock of that type, we begin with the model in equations (A1)–(A4), 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:

$$u^p = \frac{\varepsilon^d - \varepsilon^s}{\beta^s - \beta^d}, \qquad u^q = \frac{\beta^s \varepsilon^d - \beta^d \varepsilon^s}{\beta^s - \beta^d}. \tag{A12}$$

Inverting this system yields:

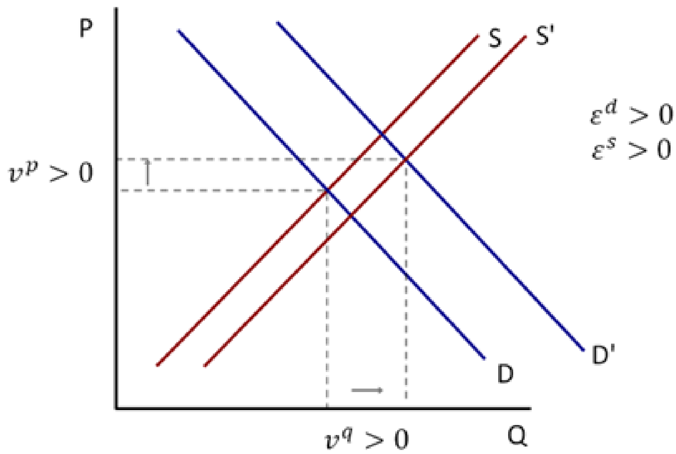
$$\varepsilon^d = u^q - \beta^d u^p, \qquad \varepsilon^s = u^q - \beta^s u^p. \tag{A13}$$

A positive net demand shock is assigned when $u^p > 0$ and $u^q > 0$. Because $\beta^d < 0$, this implies $\varepsilon^d = u^q - \beta^d u^p > 0$; that is, a positive net demand classification guarantees an underlying positive structural demand shock. However, the accompanying structural supply shock $\varepsilon^s = u^q - \beta^s u^p$ may be positive or negative depending on magnitudes. Likewise, a negative net demand shock with $u^p < 0$ and $u^q < 0$ implies $\varepsilon^d < 0$, while still permitting ε^s of either sign. Turning to the other side of the market, a positive net supply shock is assigned when $u^p < 0$ and $u^q > 0$. Because $\beta^s > 0$, this implies $\varepsilon^s = u^q - \beta^s u^p > 0$, but permits a demand shock of either sign. Similarly, a negative net supply shock ($u^p > 0$, $u^q < 0$) implies $\varepsilon^s < 0$ while allowing ε^d to be positive or negative. Figure A1 illustrates the point graphically: both panels generate the same net demand shock, even though one accompanies a positive structural supply shock and the other a negative one. The key result is that set identification guarantees the presence (and sign) of the labeled shock type, even though it cannot rule out simultaneous shocks on the other side of the market.

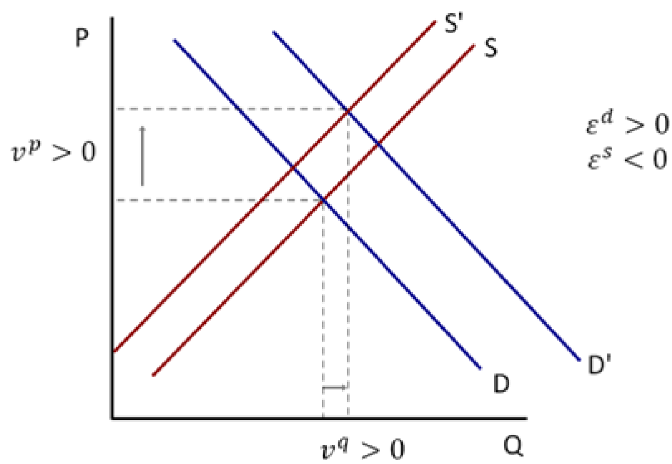
A3 Shapley value attribution: intuition

We use Shapley's value decomposition[13,14] to allocate the fitted value $\hat{y}_t$ across correlated macroeconomic channels. During the pandemic, for example, wages, aggregate demand, and supply chain pressure all shifted sharply, and in an ordinary regression there is no single, natural way to decide how much of $\hat{y}_t$ should be "credited" to each channel when predictors are correlated. Incremental exercises (like adding one channel at a time and tracking ΔR^2) are inherently order-dependent.

A Shapley approach addresses this directly. Fix a month t. Start from the baseline prediction for that month, which is the sample mean $\bar{y}$ of the stage-1 component (that is, the normal level of inflation). Now consider adding the four channels to the model one at a time. Each ordering is one possible way in which the channels enter. Because the channels are correlated, the incremental change in the fitted value when (say) wages enter will generally depend on whether fiscal stimulus or aggregate demand has already entered. Shapley resolves this by repeating the exercise for *every*



(a) A net demand shock with $\varepsilon^d > 0$ and $\varepsilon^s > 0$.



(b) A net demand shock with $\varepsilon^d > 0$ and $\varepsilon^s < 0$.

Figure A1. Net shocks are set identified. Both panels generate $u^p > 0$ and $u^q > 0$ (a net demand shock), but each case permits a latent underlying supply shock of either sign.
Source: Authors' illustration.

possible entry order (with four channels, there are $4! = 24$), recording the incremental change in the fitted value when each channel enters, and then averaging that increment across orders. That average is the Shapley contribution of the channel at month t. The decomposition therefore assigns each channel a share of the fitted component, with shares summing exactly (plus the residual), rather than relying on order-dependent measures like incremental ΔR^2 or partial correlations.

A4 Robustness of Shapley Attributions

A4.1 Channel rankings

Because small residuals increase the risk of mislabeling a shock, we evaluate the robustness of our results by comparing the baseline model against two increasingly strict filters: a "No Ambiguity" specification that removes marginal classifications, and a "Most Precise" specification that retains only the strongest inflationary pressure from each side of the market. If our core findings are robust, the relative importance of the macroeconomic channels should remain stable even as we filter the underlying data for shock precision.

Table A1 confirms that they are. Each cell reports a channel's share of total absolute Shapley attribution on that side of the market during the pandemic (2020–2023). Our attribution rankings do not change very much when we use more precisely-measured inflation shocks. On the supply side, sectoral wages and supply chain pressure account for roughly 70% of FAH attribution across all three specifications, with farm costs a stable third. For FAFH the same two channels dominate, though in reverse order: supply chain pressure leads, consistent with the different cost structures of grocery retail versus food service. Energy costs rank towards the bottom for both food types regardless of the filter applied.

For the demand side, wage growth is the leading channel for both FAH and FAFH across all specifications, absorbing 31–36% of attribution. Fiscal stimulus is the next-largest identifiable channel: it ranks second under the baseline specification (24% for FAH, 27% for FAFH) and third under the stricter specifications, where the unexplained residual edges ahead of it. Aggregate demand is consistently fourth across all specifications, reflecting that the global business cycle was a secondary force during this episode. Although wage growth is the largest channel over the full pandemic window, our timing analysis (figure 4) shows that fiscal transfers were the dominant force

Table A1: **Robustness of Shapley channel rankings across stage 1 specifications (pandemic 2020–2023).**

Market	Rank	Baseline	No ambiguity	Most precise
Supply FAH				
	1st	Sec. wages (37%)	Sec. wages (38%)	Sec. wages (40%)
	2nd	Supply chain pressure (32%)	Supply chain pressure (32%)	Supply chain pressure (30%)
	3rd	Farm costs (22%)	Farm costs (21%)	Farm costs (24%)
	4th	Residual (5%)	Residual (5%)	Energy costs (5%)
	5th	Energy costs (4%)	Energy costs (4%)	Residual (1%)
Demand FAH				
	1st	Wage growth (34%)	Wage growth (33%)	Wage growth (36%)
	2nd	Fiscal (24%)	Residual (25%)	Residual (26%)
	3rd	Residual (23%)	Fiscal (23%)	Fiscal (23%)
	4th	Agg. demand (15%)	Agg. demand (14%)	Agg. demand (11%)
	5th	Fin. stress (4%)	Fin. stress (5%)	Fin. stress (4%)
Supply FAFH				
	1st	Supply chain pressure (37%)	Supply chain pressure (42%)	Supply chain pressure (43%)
	2nd	Sec. wages (29%)	Sec. wages (34%)	Sec. wages (38%)
	3rd	Residual (14%)	Farm costs (13%)	Farm costs (13%)
	4th	Farm costs (13%)	Residual (6%)	Residual (6%)
	5th	Energy costs (6%)	Energy costs (6%)	Energy costs (0%)
Demand FAFH				
	1st	Wage growth (31%)	Wage growth (32%)	Wage growth (32%)
	2nd	Fiscal (27%)	Residual (30%)	Residual (31%)
	3rd	Residual (25%)	Fiscal (19%)	Fiscal (20%)
	4th	Agg. demand (13%)	Agg. demand (13%)	Agg. demand (12%)
	5th	Fin. stress (4%)	Fin. stress (5%)	Fin. stress (5%)

Notes: Values in parentheses represent the channel's percentage share of the total absolute inflation contribution on that side of the market for the specified 12-lag model.
Source: Authors' calculations using BEA, FRED (Federal Reserve Bank of St. Louis), Federal Reserve Bank of New York, and BLS data.

in the early phase (2021–mid-2022) before income persistence took over through 2023. Financial stress ranks last in nearly every model and specification, confirming that food demand is more responsive to household cash flow than credit conditions. The demand-side residual is notably larger for FAFH (25–31%) than for FAH (23–26%), consistent with the main text's observation that restaurant spending is shaped by difficult-to-capture behavioral factors.

A4.2 Bootstrap confidence levels

Table A2 reports the percentage of pandemic months (2020–2023) in which each channel's bootstrap confidence interval excludes zero, across the three stage 1 specifications, at both the 68% and 90% confidence levels. Three broad patterns stand out.

First, attributions are estimated more precisely for the supply side than the demand side–their CIs include zero less often. This is intuitive: our supply channels include farm costs, energy costs, and supply chain pressure are measured by producer price indices and logistics indicators; they connect directly to production costs, leaving less room for omitted behavioral variation. On the demand side, the link between macroeconomic conditions and consumers' willingness to pay for food is noisier—shaped by savings behavior, expectations, and idiosyncratic spending decisions that our four channels cannot capture as smoothly. The larger demand-side residual (see Table A1) reflects this, and wider confidence bands follow naturally. Even so, fiscal stimulus—the most directly measurable demand channel, constructed from observed per-capita transfer payments—excludes zero at the 68% level in roughly four out of every five pandemic months for FAH (79–83% across specifications) and at the 90% level in 35–58% of months. This is the strongest demand-side result in the table, and consistent with the fact that transfers are concrete, measurable cash infusions (relative to a baseline) rather than an indirect proxy for purchasing power. Second, FAFH attributions are less precise than FAH attributions on both sides of the market. Restaurant spending is inherently discretionary, more sensitive to local conditions, and more shaped by behavioral forces (format mix, tipping norms, delivery platform adoption) than grocery store buying. Those factors are more difficult to capture with our macroeconomic channels, so their attributions are as a result less precise. For FAFH supply, sectoral wages are the exception: they exclude zero at the 90% level in 67–79% of months regardless of specification, consistent with labor being the single largest and most directly observable cost input for restaurants. Supply chain pressure is also reliably significant under the baseline and no-ambiguity specifications. For FAFH demand, fiscal stimulus excludes zero at the 68% level in 38–65% of months across specifications, and wage growth in 35–40%—each consistent with the channel rankings above—but neither excludes zero at the 90% level in any meaningful share of months, likely because unexplained variation in restaurant demand widens the bands around every channel in the model.

Third, financial stress includes zero at the 90% level in nearly all months across all specifications and both food types. Quite apart from imprecision, it is a precisely estimated zero. Once we control for cash flow (through wage growth and fiscal stimulus), our model results indicate that credit conditions, asset prices, and financial market stress do not help explain food demand variation.

Table A2: **Bootstrap significance across stage 1 specifications (percentage of pandemic months, 2020–2023).**

		68% Confidence Interval			90% Confidence Interval		
Market	**Channel**	**Baseline**	**No Amb.**	**Most Prec.**	**Baseline**	**No Amb.**	**Most Prec.**
Supply FAH							
	Farm costs	58%	56%	56%	48%	48%	50%
	Energy costs	65%	62%	67%	46%	46%	56%
	Supply chain pressure	79%	79%	79%	62%	62%	56%
	Sec. wages	81%	77%	73%	46%	44%	58%
Demand FAH							
	Agg. demand	56%	42%	48%	31%	29%	10%
	Fin. stress	19%	19%	35%	0%	2%	0%
	Fiscal	81%	79%	83%	56%	58%	35%
	Wage growth	42%	40%	44%	29%	25%	31%
Supply FAFH							
	Farm costs	25%	29%	50%	4%	10%	4%
	Energy costs	12%	15%	56%	2%	4%	2%
	Supply chain pressure	79%	77%	69%	44%	62%	0%
	Sec. wages	81%	83%	90%	67%	77%	79%
Demand FAFH							
	Agg. demand	56%	48%	46%	25%	23%	0%
	Fin. stress	27%	35%	38%	0%	0%	0%
	Fiscal	54%	38%	65%	0%	0%	2%
	Wage growth	35%	35%	40%	0%	0%	0%

Notes: Values indicate the percentage of pandemic months where that channel's indicated bootstrap confidence interval excludes zero for the baseline, 12-lag model.
Source: Authors' calculations using BEA, FRED (Federal Reserve Bank of St. Louis), Federal Reserve Bank of New York, and BLS data.

A4.3 Lag length in stage 2

Comparing Shapley models using 6, 12 (baseline), and 18 monthly lags offers insight into how quickly different macroeconomic channels transmit food price pressure. Modifying lags this way reveals a clear distinction between fast- and slow-transmitting channels. Channels that transmit quickly will account for a consistent share of attribution even with a short lag window; channels that operate with long delays gain attribution share as the stage 2 lag window expands. Table A3 reports absolute attribution shares during the pandemic under each lag specification, at a monthly frequency, along with a column that indicates the change in share from the shortest to the longest window.

Two channels transmit quickly. Supply chain pressure accounts for half or more of our supply-side attribution at 6 lags for both FAH (54%) and FAFH (50%), and its share declines as the

Table A3: **Lag sensitivity (pandemic 2020–2023).**

Market	**Channel**	**6 lags**	**12 lags**	**18 lags**	**Δ(6→18)**
Supply FAH					
	Farm costs	2%	22%	27%	+25 pp
	Energy costs	4%	4%	9%	+5 pp
	Supply chain pressure	54%	32%	35%	−19 pp
	Sec. wages	33%	37%	26%	−7 pp
	Residual	8%	5%	3%	−5 pp
Demand FAH					
	Agg. demand	13%	15%	19%	+6 pp
	Fin. stress	2%	4%	5%	+3 pp
	Fiscal	10%	24%	29%	+19 pp
	Wage growth	27%	34%	29%	+1 pp
	Residual	47%	23%	19%	−29 pp
Supply FAFH					
	Farm costs	0%	13%	19%	+19 pp
	Energy costs	1%	6%	12%	+11 pp
	Supply chain pressure	50%	37%	38%	−11 pp
	Sec. wages	23%	29%	27%	+4 pp
	Residual	25%	14%	3%	−23 pp
Demand FAFH					
	Agg. demand	12%	13%	16%	+4 pp
	Fin. stress	2%	4%	2%	+0 pp
	Fiscal	19%	27%	31%	+12 pp
	Wage growth	24%	31%	22%	−2 pp
	Residual	43%	25%	28%	−15 pp

Notes: Values represent the average attribution shares of each channel during the pandemic period. The $\Delta(6 \rightarrow 18)$ column displays the percentage point change in attribution when expanding the model's lag window from 6 to 18 months.
Source: Authors' calculations using BEA, FRED (Federal Reserve Bank of St. Louis), Federal Reserve Bank of New York, and BLS data.

window expands—indicating that logistics disruptions pass through to food prices within months. Aggregate demand is similarly stable across lag lengths on the demand side (13–19% for FAH, 12–16% for FAFH), consistent with the global business cycle operating through commodity markets and trade flows that adjust relatively rapidly.

Two channels transmit slowly. Fiscal stimulus accounts for 10% of FAH demand attribution and 19% of FAFH demand attribution at 6 lags but grows to 29% and 31%, respectively, at 18 lags. This is intuitive: households receive transfers, accumulate savings, and draw them down over time—a behavioral process that a 6-month window is too narrow to fully capture. Farm input costs show a strikingly similar pattern on the supply side, rising from 2% to 27% for FAH as the lag window expands, consistent with the delay in agricultural commodity pass-through to retail shelves.

A final point offers a key robustness result: shortening the lag length does not shuffle attribution between the named channels. Instead, it pushes more variation into the unexplained residual. For demand FAH, moving from 6 to 12 to 18 lags reduces the residual attribution from 47%, to 23%, to 19%; the pattern is similar across all four models. The model's explanatory power increases steadily as the lag window rises, confirming that longer transmission horizons capture a more complete picture of the macroeconomic forces associated with food price inflation, without changing which channels matter most.

A4.4 Monte Carlo convergence and bootstrap parameters

Calculating exact Shapley values requires evaluating the model's expected prediction across all possible combinations of predictor variables. When a variable is excluded from a given combination, its effect must be integrated out using its conditional distribution given the included variables. Because these conditional expectations generally lack closed-form solutions, we approximate them using Monte Carlo integration under a Gaussian copula assumption[14].

For our baseline (point-estimate) Shapley attributions, we use 5,000 Monte Carlo draws per observation. To verify that this is sufficient, we compared a 1,000-draw run to the 5,000-draw baseline: the maximum deviation across all channel-period combinations was 0.018 percentage points, confirming full algorithmic convergence. For the bootstrap confidence bands we use 1,000 block-bootstrap replications with 500 Monte Carlo draws per replication. Within each replication 500 draws is sufficient because the bootstrap percentiles aggregate Shapley estimates across 1,000 replications: per-replication Monte Carlo noise averages out, and reducing the per-replication draw count delivers a roughly tenfold reduction in run-time while keeping band widths stable.

A5 Limitations

We take stage 1 VAR supply and demand share results as given rather than estimating them with uncertainty and propagating that uncertainty into the Shapley decomposition. As a result, the bootstrap confidence bands address only second-stage sampling variability. This treatment follows established practice in the supply–demand decomposition literature: Shapiro[12] reports the stage 1 classification as a point estimate without confidence bands, and related applications using the same identification strategy proceed similarly.

Moreover, two features mitigate the consequences of this approach. First, our central conclusions rest on *cross-episode contrasts* (the Global Financial Crisis versus the pandemic) and *cross-channel* relative attributions, both of which are robust to stage 1 sampling uncertainty: the qualitative differences between episodes are large enough to overcome classification noise. Second, our robustness analysis in Supplementary Note A4 confirms that leading channel rankings are stable to varying the stage 1 precision thresholds. Bootstrap bands we report should therefore be interpreted as a lower bound on total uncertainty. Finally, our stage 2 approach naturally omits possible channels that could help explain inflationary pressure; we represent them with a residual. Although not an exhaustive list, candidate omitted factors include consumer sentiment, inflation expectations, pandemic behavioral shifts, and trade policy.