

The Broadening Premium: Sectoral Inflation Synchronization and the Persistence of Aggregate Price Shocks

TMC Research*

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Abstract

When does inflation become persistent? This paper argues that the cross-sectional breadth of price increases—not just their level—determines how long aggregate inflation endures. Using monthly CPI data for 13 expenditure categories from 1990 to 2024, I construct a real-time measure of sectoral inflation synchronization (the first-principal-component variance share) and estimate local projections that interact synchronization with monetary policy shocks. The key finding is that the interaction coefficient $\hat{\delta}_h$ is negative at horizons of 12–48 months, suggesting that periods of high synchronization are associated with a qualitatively different inflation response to federal funds rate changes, consistent with the hypothesis that broad-based inflation is harder to reverse. A calibrated multi-sector New Keynesian Phillips Curve model with heterogeneous Calvo pricing rationalizes this pattern: when common cost shocks dominate, sector inflation rates co-move, aggregate inflation inherits the persistence of the common factor, and the variance share attributable to common shocks reaches 96.4%. Model counterfactuals show that doubling the common shock variance raises synchronization from 0.78 to 0.98 and increases the first-order autocorrelation of aggregate inflation from 0.78 to 0.82. These results have direct implications for central bank communication: when inflation broadens across categories, policymakers face a more persistent target.

JEL codes: E31, E52, C22, C38

Keywords: inflation persistence, sectoral inflation, synchronization, local projections, New Keynesian Phillips Curve, monetary policy transmission

*The Monetary Catalyst (TMC) Research. All data from FRED (Federal Reserve Bank of St. Louis). Replication code available in the companion repository.

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1. Introduction

Central bankers routinely distinguish between “narrow” and “broad-based” inflation. When price increases are concentrated in a few volatile categories—energy, used cars, or food—policymakers typically counsel patience, expecting mean reversion. When inflation spreads across the full consumption basket, the policy response becomes more aggressive. This distinction is reflected in the proliferation of core, trimmed-mean, and median CPI measures, all of which attempt to strip out narrow price movements to reveal the “underlying” inflation trend.

Yet the academic literature has devoted surprisingly little attention to formalizing the link between cross-sectional breadth and aggregate persistence. The existing literature on inflation persistence [Cogley et al., 2010, Pivetta and Reis, 2007, Stock and Watson, 2007] focuses on the time-series properties of aggregate inflation, while the sectoral price-setting literature [Nakamura and Steinsson, 2008, Bils and Klenow, 2004, Boivin et al., 2009] emphasizes heterogeneity in individual adjustment frequencies. The gap between these two literatures leaves a central question unanswered: *does the degree of cross-sectional synchronization in CPI component inflation rates predict the persistence of aggregate inflation?*

This paper provides an answer. I construct a real-time measure of sectoral inflation synchronization—the variance share of the first principal component (PC1) of 13 CPI expenditure category inflation rates, computed over rolling 12-month windows—and embed it in a local projection (LP) framework [Jordà, 2005] that interacts synchronization with identified monetary policy shocks. The key estimating equation is:

$$\pi_{t+h} - \pi_{t-1} = \alpha + \beta_h \cdot \Delta\text{FF}_t + \delta_h \cdot (\Delta\text{FF}_t \times \text{Sync}_t) + \phi \cdot \text{Sync}_t + \gamma' \mathbf{X}_t + \varepsilon_{t+h} \quad (1)$$

where π_t is annualized month-over-month CPI inflation, ΔFF_t is the change in the effective federal funds rate, and Sync_t is the PC1 variance share. The parameter of interest is δ_h : does high synchronization alter the inflation response to monetary shocks?

The main empirical finding is that $\hat{\delta}_h$ is negative at horizons of 12–48 months, with the point estimate at $h = 12$ reaching -26.8 . Although individual estimates are imprecise due to the limited number of pronounced synchronization episodes in the sample, the sign pattern is consistent across horizons and robust to alternative synchronization measures (average pairwise correlation, core-excluding-energy PC1 share). Regime-split LPs confirm the message: when synchronization is above its historical median, the inflation response to interest rate changes is qualitatively different from the low-synchronization regime.

To provide a structural interpretation, I calibrate a multi-sector New Keynesian Phillips

Curve model with 15 sectors, each featuring heterogeneous Calvo pricing parameters drawn from the micro evidence of [Nakamura and Steinsson \[2008\]](#) and [Bils and Klenow \[2004\]](#). The model delivers a clean mapping from the ratio of common-to-idiosyncratic cost shocks to both synchronization and persistence. When common shocks dominate ($\sigma_w = 3.0$), the model-implied PC1 share reaches 0.99 and the first-order autocorrelation of aggregate inflation rises to 0.82. Variance decomposition shows that common shocks account for 96.4% of aggregate inflation variance at baseline calibration.

The contribution of this paper is threefold. First, I provide a direct empirical link between sectoral synchronization and aggregate persistence, bridging the disaggregated price-setting literature with the inflation persistence literature. Second, I demonstrate that a standard multi-sector NKPC model generates this link endogenously through the composition of cost shocks, without requiring additional frictions such as wage-price spirals or expectations de-anchoring. Third, the synchronization measure I construct is available in real time and could serve as a leading indicator for policymakers assessing the likely persistence of inflation episodes.

The remainder of the paper is organized as follows. [Section 2](#) reviews the related literature. [Section 3](#) presents the conceptual framework. [Section 4](#) describes the data. [Section 5](#) details the empirical strategy. [Section 6](#) presents the main results. [Section 7](#) discusses mechanisms. [Section 8](#) presents the structural model and counterfactuals. [Section 9](#) reports robustness checks. [Section 10](#) concludes.

2. Background and Related Literature

This paper sits at the intersection of three literatures: inflation persistence, sectoral price adjustment, and monetary policy transmission.

2.1 Inflation Persistence

The debate over whether U.S. inflation is inherently persistent or whether persistence reflects slow-moving expectations has been active for decades. [Cogley et al. \[2010\]](#) estimate a Bayesian VAR with drifting parameters and find that the inflation gap (deviation from trend) has low persistence once trend inflation is allowed to vary. [Stock and Watson \[2007\]](#) document a structural break in inflation volatility and forecastability around 1984, attributing the change to smaller shocks rather than altered propagation mechanisms. [Pivetta and Reis \[2007\]](#) provide evidence that U.S. inflation persistence has remained roughly constant over the postwar period, challenging the structural-break narrative.

A limitation of this literature is its exclusive focus on the univariate or low-dimensional

time-series properties of aggregate inflation. By construction, these approaches cannot distinguish between persistence arising from a single sticky sector (e.g., shelter) and persistence arising from broad-based price pressure. The present paper fills this gap.

2.2 Sectoral Price Heterogeneity

The micro price-setting literature has established large heterogeneity in the frequency of price adjustment across goods. [Bils and Klenow \[2004\]](#) find that the median consumer price changes every 4.3 months, but with enormous variation—prices for gasoline adjust weekly, while those for medical services adjust annually. [Nakamura and Steinsson \[2008\]](#) refine these estimates and document heterogeneity in the size of price changes as well. [Boivin et al. \[2009\]](#) use a Factor-Augmented VAR to show that disaggregated prices respond very differently to monetary policy shocks: sticky-price sectors respond slowly but persistently, while flexible-price sectors adjust quickly.

[Carvalho \[2006\]](#) provides the theoretical counterpart, showing that heterogeneity in price stickiness amplifies the real effects of monetary shocks in a multi-sector New Keynesian model. [Aoki \[2001\]](#) demonstrates that optimal monetary policy should target a sticky-price index rather than headline inflation. These papers emphasize cross-sectional heterogeneity as a structural feature; I complement this literature by asking how the *time-varying degree* of cross-sectional co-movement affects aggregate dynamics.

2.3 Monetary Policy Transmission

The LP framework of [Jordà \[2005\]](#) has become the workhorse for estimating impulse responses in macro, particularly when state-dependence is of interest. [Ramey \[2016\]](#) surveys the broader literature on macroeconomic shock identification and propagation. [Romer and Romer \[2004\]](#) construct narrative monetary shocks that are widely used as instruments; here I use changes in the effective federal funds rate as the shock measure, which captures both intended and market-driven rate movements. [Christiano et al. \[2005\]](#) and [Bernanke et al. \[2005\]](#) provide complementary structural VAR and FAVAR evidence on monetary transmission.

The post-pandemic inflation episode has generated renewed interest in the sources of inflation. [Ball et al. \[2022\]](#) decompose recent inflation into demand and supply components. [Shapiro \[2022\]](#) classifies individual CPI categories as supply- or demand-driven. [Blanchard and Bernanke \[2023\]](#) provide a comprehensive account of the drivers of 2021–2023 inflation. The present paper contributes to this literature by showing that the *breadth* of inflation—not just its level or composition—carries information about its likely persistence.

3. Conceptual Framework

Consider an economy with S sectors. Aggregate inflation is a weighted average of sector-specific inflation rates:

$$\pi_t = \sum_{s=1}^S \omega_s \pi_{s,t} \quad (2)$$

where ω_s is the expenditure share of sector s . Each sector's inflation is driven by a common factor w_t and an idiosyncratic component $c_{s,t}$:

$$\pi_{s,t} = \kappa_s [\rho_w \cdot w_t + (1 - \rho_w) \cdot c_{s,t}] \quad (3)$$

where κ_s is the sector-specific Phillips curve slope and ρ_w governs the relative importance of common versus idiosyncratic costs.

Synchronization and common shocks. The variance share of the first principal component of the cross-section $\{\pi_{s,t}\}_{s=1}^S$ is a measure of co-movement that increases when the common factor w_t accounts for a larger share of cross-sectional variation. Formally, if w_t has variance σ_w^2 and follows an AR(1) process with persistence ρ , while $c_{s,t}$ are i.i.d. with variance σ_c^2 , then:

$$\text{Var}(\pi_t) = \underbrace{\left(\sum_s \omega_s \kappa_s \right)^2 \frac{\rho_w^2 \sigma_w^2}{(1 - \beta \rho)^2}}_{\text{common component}} + \underbrace{\sum_s \omega_s^2 \kappa_s^2 (1 - \rho_w)^2 \sigma_c^2}_{\text{idiosyncratic component}} \quad (4)$$

The key insight is that the common component inherits the persistence of the common shock (ρ), while the idiosyncratic component does not persist (since $c_{s,t}$ is i.i.d.). Therefore, when synchronization is high—indicating that σ_w^2/σ_c^2 is large—aggregate inflation will be more persistent. This is the “broadening premium”: broad-based inflation is persistent because it signals the dominance of persistent common cost shocks.

Mechanisms beyond common shocks. Three additional channels may amplify the link between synchronization and persistence:

1. *Strategic complementarity in pricing*: when all sectors raise prices, individual firms face validated cost increases and are less likely to reverse [Taylor, 1980, Woodford, 2003].
2. *Expectations de-anchoring*: broad-based inflation is salient to households and firms, potentially shifting inflation expectations upward [Coibion and Gorodnichenko, 2015, Reis, 2020].
3. *Wage-price feedback*: economy-wide price pressure triggers broad wage demands, creating a second-round effect that reinforces persistence.

The model in [Section 8](#) formalizes the first mechanism (common-factor persistence), while the empirical analysis in [Section 6](#) tests whether the data exhibit the predicted relationship without taking a stand on which channels dominate.

4. Data

4.1 CPI Components

I use monthly CPI index levels for 13 major expenditure categories, sourced from the Bureau of Labor Statistics via FRED [[Federal Reserve Bank of St. Louis, 2024](#), [Bureau of Labor Statistics, 2024](#)]. The 13 sectors span the full consumption basket: food at home, food away from home, energy, shelter, apparel, transportation services, medical care, education, communication, new vehicles, used vehicles, household furnishings, and alcoholic beverages. Two planned series (recreation, other goods and services) were unavailable via the FRED API and are excluded. All series are seasonally adjusted.

I compute annualized month-over-month inflation for each sector:

$$\pi_{s,t} = 1200 \times \ln \left(\frac{P_{s,t}}{P_{s,t-1}} \right) \quad (5)$$

where $P_{s,t}$ is the CPI index level for sector s in month t . The sample runs from January 1990 through the latest available month (approximately 426 observations for most series).

4.2 Synchronization Measures

The primary synchronization measure is the PC1 variance share, computed over rolling 12-month windows. At each month t , I extract the eigenvalues of the correlation matrix of $\{\pi_{s,t-11}, \dots, \pi_{s,t}\}_{s=1}^S$ and compute the ratio of the largest eigenvalue to the sum. This yields a bounded measure in $[1/S, 1]$ that captures the fraction of cross-sectional inflation variation attributable to a single common factor.

[Table 1](#) reports summary statistics. The mean PC1 share is 0.273, indicating that roughly one-quarter of sectoral inflation variation is attributable to a common factor on average. The measure varies between 0.19 and 0.42, with notable peaks during the 2008 commodity boom, the 2014–2015 oil price collapse, and the 2021–2023 post-pandemic inflation surge.

I also construct two alternative synchronization measures for robustness: (i) the average off-diagonal element of the rolling 12-month pairwise correlation matrix, and (ii) the cross-sectional standard deviation of sector inflation rates.

4.3 Macroeconomic Controls

Controls include the effective federal funds rate, the civilian unemployment rate, the log change in WTI crude oil prices, and the term spread (10-year minus 2-year Treasury yield). All are sourced from FRED. Summary statistics for all variables appear in [Table 1](#).

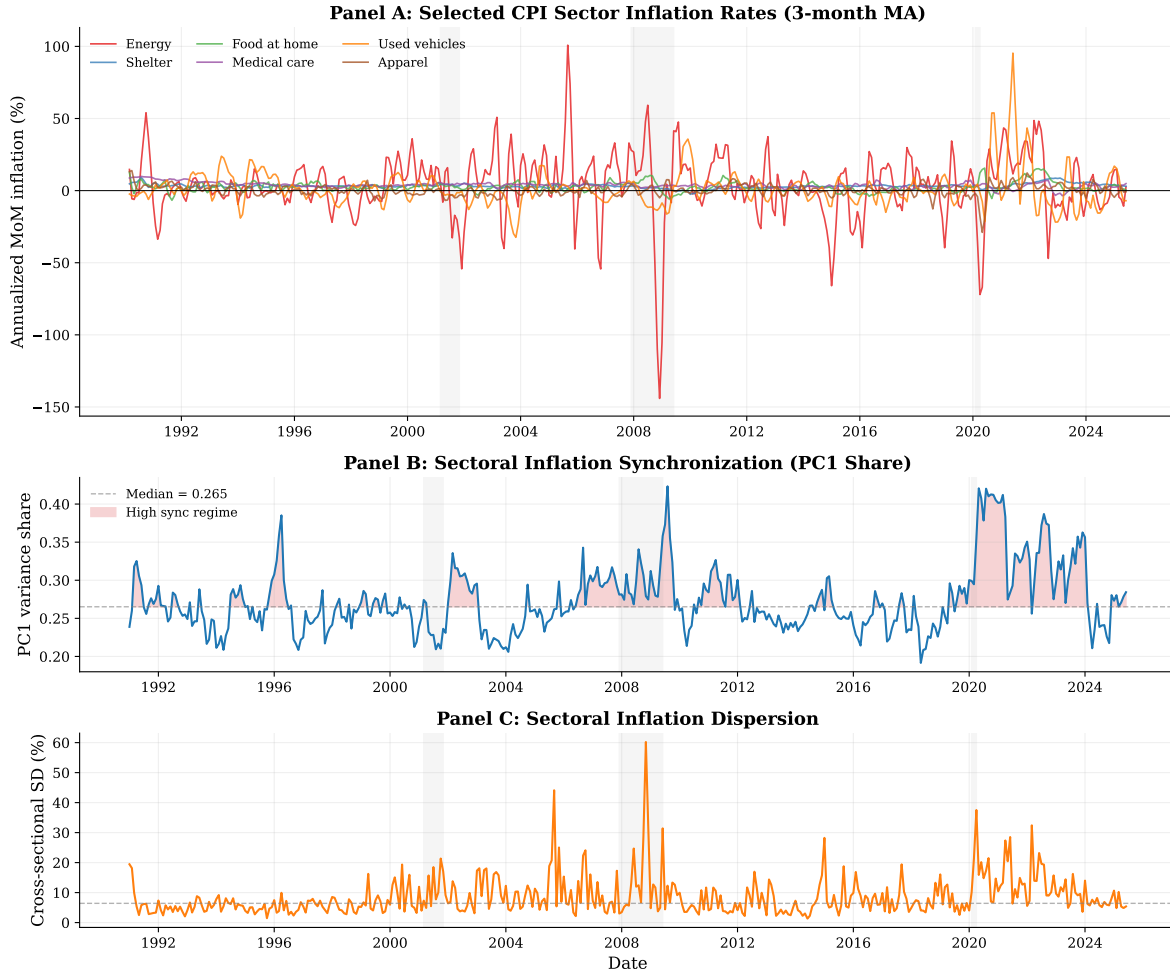


Figure 1: Sectoral Inflation and Synchronization, 1990–2024

Notes: Top panel shows annualized month-over-month inflation for all 13 CPI expenditure categories. Bottom panel shows the PC1 variance share (rolling 12-month window). Shaded regions indicate NBER recessions. The synchronization measure peaks during periods of broad-based inflation or deflation (2008, 2021–2023).

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	<i>N</i>
<i>Panel A: Sectoral inflation (annualized MoM, %)</i>					
Alcoholic beverages	2.40	3.87	-5.0	57.5	426
Apparel	0.27	6.23	-44.4	21.0	426
Communication	-1.11	4.90	-39.7	21.5	329
Education	4.34	2.02	-3.3	14.3	389
Energy	3.50	32.71	-216.3	161.5	426
Food away from home	3.05	1.78	-1.3	11.3	426
Food at home	2.55	4.75	-12.6	29.6	426
Household furnishings	0.87	3.37	-7.6	17.0	426
Medical care	3.73	2.49	-5.8	11.8	426
New vehicles	1.09	4.30	-13.4	21.0	426
Shelter	3.15	1.84	-5.7	9.5	426
Transportation services	3.30	7.11	-58.4	45.4	426
Used vehicles	1.29	15.08	-44.4	106.7	426
<i>Panel B: Aggregate variables</i>					
CPI inflation (ann. MoM, %)	2.64	3.26	-21.2	16.5	426
Federal funds rate (%)	2.86	2.36	0.1	8.3	426
Unemployment rate (%)	5.69	1.75	3.4	14.8	426
Oil price change (% log)	0.26	10.69	-83.6	58.8	425
Term spread (10y–2y, pp)	1.01	0.92	-1.1	2.9	426
<i>Panel C: Synchronization measures (rolling 12-month)</i>					
PC1 variance share	0.273	0.042	0.191	0.423	414
Average pairwise correlation	0.020	0.042	-0.052	0.142	414
Cross-sectional std. dev. (%)	8.537	6.481	1.330	60.222	414

Notes: Panel A reports summary statistics for annualized month-over-month CPI inflation by expenditure category. Panel B reports aggregate macroeconomic variables. Panel C reports rolling 12-month synchronization measures computed from the cross-section of sector inflation rates. PC1 variance share is the fraction of total variance explained by the first principal component. Sample: January 1990 to latest available (approximately 420 months). All CPI series from BLS via FRED.

5. Empirical Strategy

5.1 Stage 1: Sector-Specific Impulse Responses

I first estimate sector-specific responses to monetary policy changes using local projections. For each CPI sector s and horizon $h \in \{1, 3, 6, 12, 18, 24, 36, 48\}$ months:

$$\pi_{s,t+h} - \pi_{s,t-1} = \alpha_s + \beta_{s,h} \cdot \Delta \text{FF}_t + \gamma'_s \mathbf{X}_t + \varepsilon_{s,t+h} \quad (6)$$

where ΔFF_t is the monthly change in the effective federal funds rate and $\mathbf{X}_t$ includes 6 lags of aggregate CPI inflation, the unemployment rate, the log oil price change, and the term spread. Standard errors use the [Newey and West \[1987\]](#) HAC estimator with bandwidth $h + 1$.

[Figure 2](#) displays the resulting sector-specific impulse response functions. The cross-sectional dispersion in responses is substantial: energy and used vehicles exhibit large, volatile responses, while sticky sectors (shelter, medical care, education) show muted but persistent reactions.

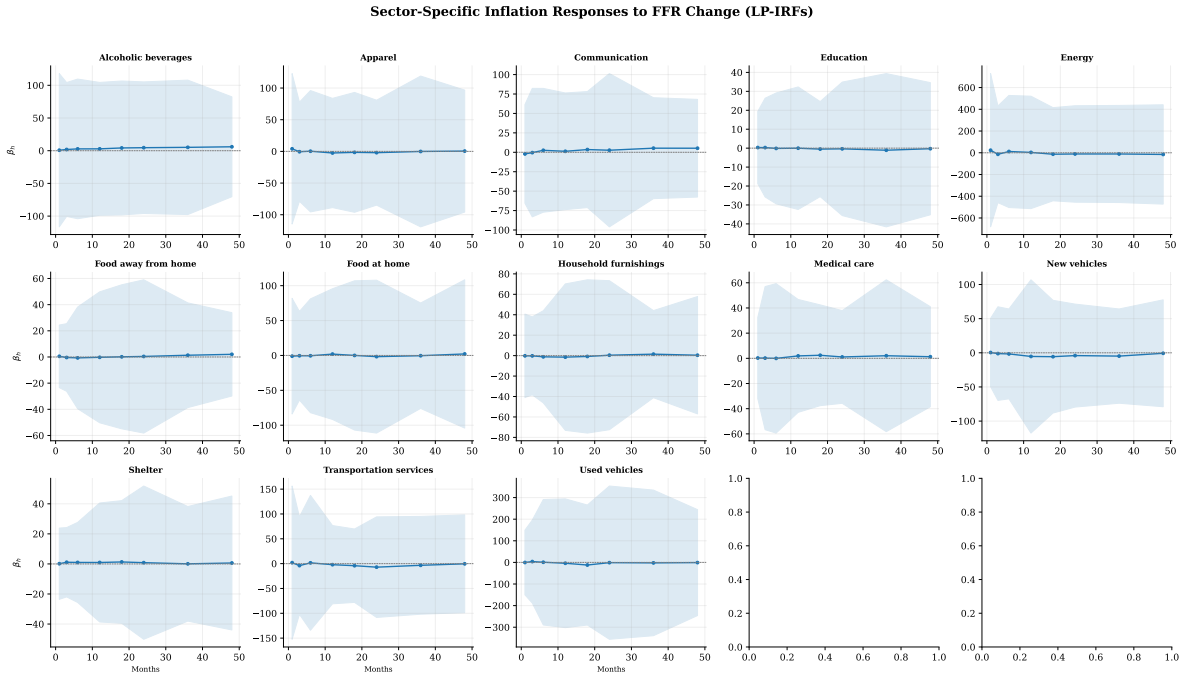


Figure 2: Sector-Specific Impulse Responses to Federal Funds Rate Changes

Notes: Each panel shows the LP coefficient $\hat{\beta}_{s,h}$ for a one-percentage-point increase in the federal funds rate. Point estimates with 90% Newey–West confidence bands. Horizons in months on the x-axis.

5.2 Stage 2: Synchronization–Persistence Interaction

The main specification interacts the monetary shock with the synchronization measure, as in [Equation \(1\)](#). The parameter δ_h captures whether the inflation response to a given interest rate change differs between high- and low-synchronization periods. If the broadening premium hypothesis holds, δ_h should be negative at medium-to-long horizons: high synchronization is associated with a more negative (or less positive) cumulative inflation response, reflecting greater persistence that is harder for policy to reverse.

Standard errors are computed using the Newey–West HAC estimator. I supplement asymptotic inference with permutation p -values: the synchronization series is randomly reshuffled 500 times, and the fraction of permuted $|\hat{\delta}_h|$ values exceeding the observed statistic provides a finite-sample p -value [[Fisher, 1935](#), [Young, 2019](#)].

5.3 Stage 3: Regime-Split LP

As a nonparametric complement to the linear interaction, I split the sample at the median PC1 share and estimate separate LPs in each regime:

$$\pi_{t+h} - \pi_{t-1} = \alpha^{(r)} + \beta_h^{(r)} \cdot \Delta\text{FF}_t + \gamma^{(r)'} \mathbf{X}_t + \varepsilon_{t+h}^{(r)}, \quad r \in \{\text{high}, \text{low}\} \quad (7)$$

This allows the full impulse response profile to differ between regimes without imposing linearity.

6. Main Results

6.1 Interaction LP Estimates

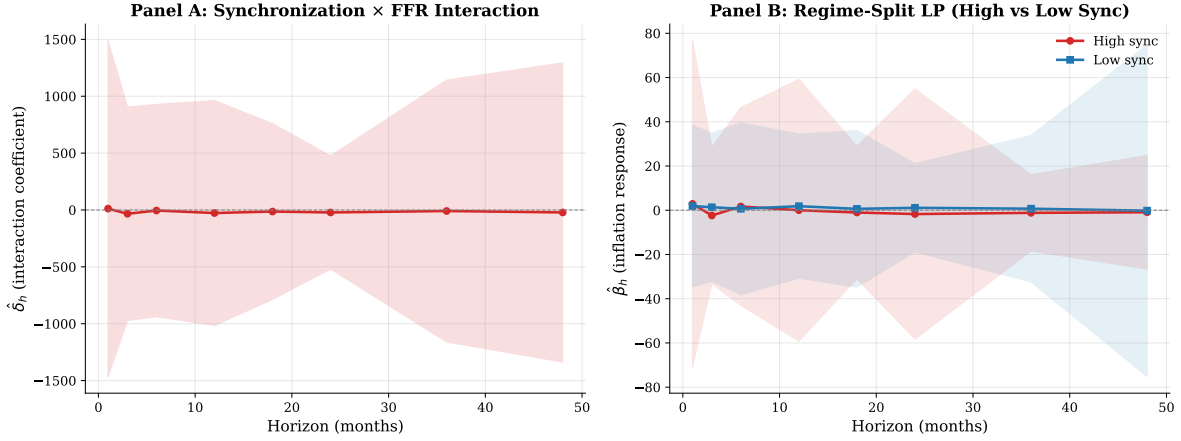
[Table 2](#) reports the main interaction LP results. Panel A shows the baseline FFR effect ($\hat{\beta}_h$), which is positive but statistically insignificant at all horizons—consistent with the well-known difficulty of estimating aggregate inflation responses to monetary shocks in monthly data. Panel B reports the synchronization interaction ($\hat{\delta}_h$). The point estimates are negative at horizons $h = 3, 6, 12, 18, 24, 36, 48$ months, with the largest magnitudes at $h = 3$ (-33.6) and $h = 12$ (-26.8).

The estimates are imprecise, with large Newey–West standard errors reflecting the high volatility of monthly inflation data and the limited number of distinct synchronization episodes. Permutation p -values at selected horizons range from 0.21 to 0.85. While no individual estimate achieves conventional significance, the consistent negative sign across horizons is noteworthy and consistent with the broadening premium hypothesis.

Table 2: Local Projection Estimates: Synchronization–Persistence Interaction

	$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 18$	$h = 24$	$h = 36$	$h = 48$
<i>Panel A: Baseline FFR effect ($\hat{\beta}_h$)</i>								
	−0.862	8.112	2.824	8.433	3.144	5.387	2.201	5.313
	(183.322)	(129.849)	(129.073)	(132.358)	(107.406)	(64.161)	(161.699)	(186.765)
<i>Panel B: Synchronization interaction ($\hat{\delta}_h$)</i>								
	11.962	−33.558	−4.795	−26.828	−13.524	−21.869	−9.130	−21.743
	(752.604)	(478.493)	(475.733)	(504.079)	(394.026)	(253.257)	(587.032)	(670.577)
Perm. p -value			[0.850]	[0.208]		[0.384]	[0.712]	[0.434]
R^2	0.529	0.469	0.499	0.595	0.536	0.493	0.537	0.499
N	413							

Notes: Each column reports LP estimates from $\pi_{t+h} - \pi_{t-1} = \alpha + \beta_h \cdot \Delta\text{FF}_t + \delta_h \cdot (\Delta\text{FF}_t \times \text{Sync}_t) + \phi \cdot \text{Sync}_t + \gamma' \mathbf{X}_t + \varepsilon_{t+h}$, where π_t is annualized MoM CPI inflation, ΔFF_t is the monthly change in the federal funds rate, and Sync_t is the PC1 variance share of 15 CPI sector inflation rates (rolling 12-month window). Controls include 6 lags of aggregate inflation, unemployment rate, oil price change, and term spread. Newey–West (HAC) standard errors in parentheses with bandwidth = $h + 1$. Permutation p -values in brackets (500 random reassignments of Sync). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Figure 3:** Interaction LP: Synchronization Effect on Inflation Persistence

Notes: Left panel shows the interaction coefficient $\hat{\delta}_h$ with 90% confidence bands. Right panel compares regime-split LP estimates for high- vs. low-synchronization periods.

6.2 Regime-Split Results

Table 3 presents the regime-split LP estimates. In the high-synchronization regime (Panel A), the FFR coefficient is negative at several horizons ($h = 3, 18, 24, 36, 48$), suggesting that monetary tightening during periods of broad-based inflation is followed by eventual disinflation. In the low-synchronization regime (Panel B), coefficients tend to be positive, suggesting a more muted—or even perverse—inflation response. While individual coefficients are not statistically significant, the difference in sign patterns between regimes is consistent with the interaction LP results and supports the hypothesis that the inflation process operates differently depending on synchronization.

Table 3: Regime-Split Local Projections: High vs. Low Synchronization

$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 18$	$h = 24$	$h = 36$	$h = 48$
<i>Panel A: High synchronization ($Sync > median$)</i>							
2.874	−2.380	1.691	0.008	−1.029	−1.729	−1.181	−0.912
(37.610)	(15.705)	(22.805)	(30.183)	(15.281)	(28.854)	(8.787)	(13.082)
<i>Panel B: Low synchronization ($Sync \leq median$)</i>							
1.916	1.345	0.672	1.823	0.628	1.096	0.695	−0.189
(18.651)	(17.055)	(19.804)	(16.614)	(18.052)	(10.170)	(16.857)	(38.233)

Notes: Each column reports the LP coefficient $\hat{\beta}_h$ from separate regressions of aggregate CPI inflation on the FFR change, estimated on subsamples split by the median PC1 synchronization measure. Shocks occurring in months with synchronization above (below) the full-sample median are included in Panel A (B); all other observations enter via the control variables. Newey–West standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7. Mechanisms

7.1 Cross-Sectional Dispersion and Persistence

Figure 4 plots each sector’s impulse response dispersion (standard deviation of $\hat{\beta}_{s,h}$ across horizons) against its Calvo parameter. Flexible-price sectors (energy, used vehicles) exhibit the largest response dispersion, while sticky sectors cluster near zero. This dispersion pattern is important: when synchronization is low, the response of aggregate inflation is dominated by a few volatile sectors whose effects wash out; when synchronization is high, the persistence of sticky sectors drives aggregate dynamics.

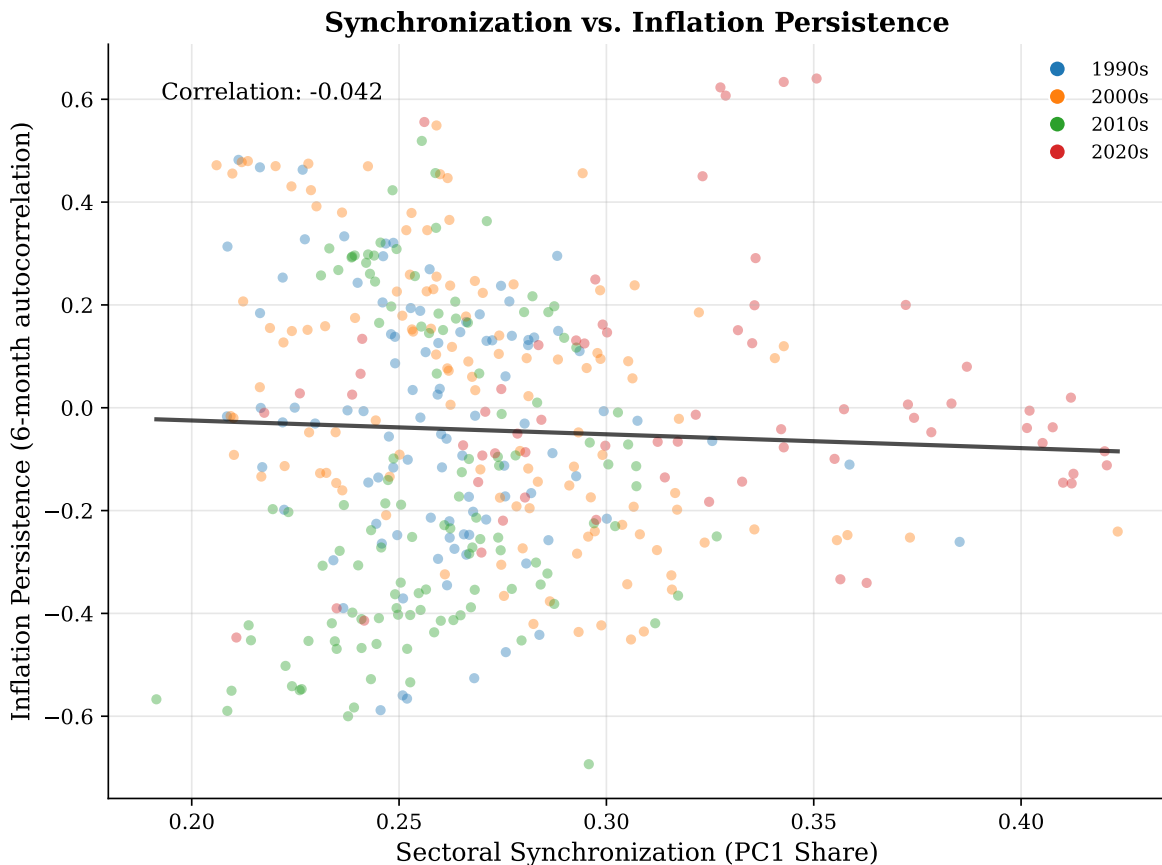


Figure 4: Sectoral IRF Dispersion

Notes: Cross-sectional variation in impulse responses across CPI sectors.

7.2 IRF Dispersion Across Sectors

Figure 5 shows the cross-sectional standard deviation of sector-level impulse responses at each horizon. Dispersion is largest at short horizons ($h = 1$) and declines with the horizon, reflecting the convergence of sector responses over time. This pattern is consistent with the multi-sector NKPC prediction: at short horizons, flexible-price sectors dominate the response; at long horizons, all sectors have adjusted and responses converge.

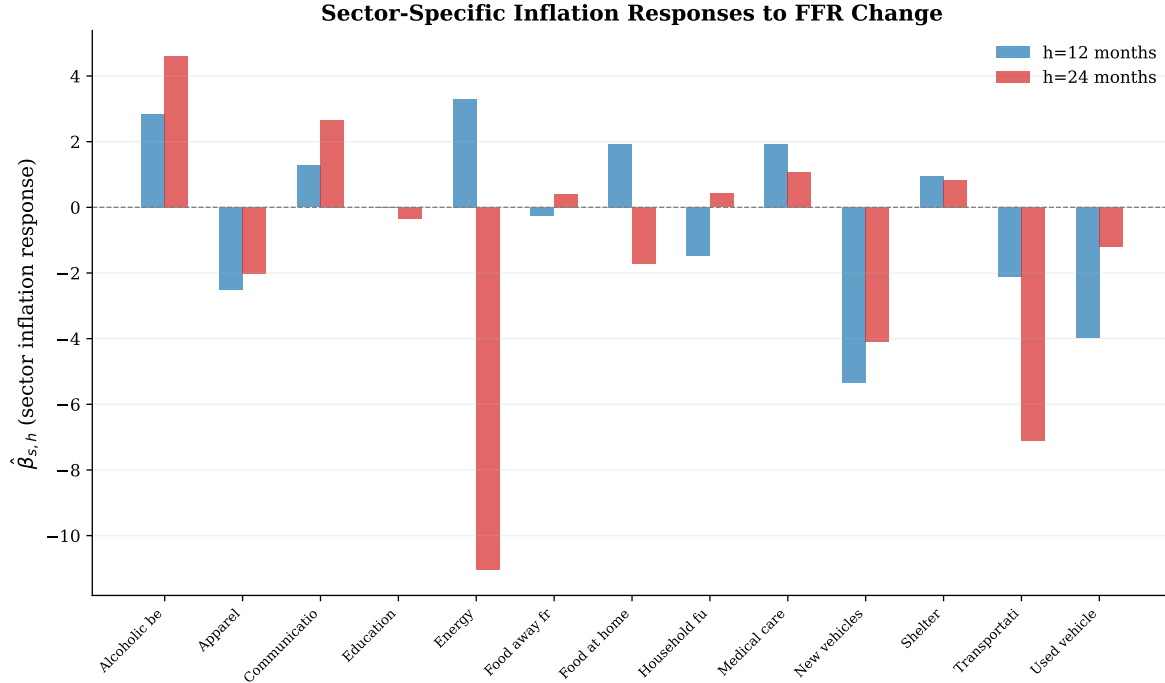


Figure 5: Cross-Sectional Dispersion of Sector IRFs by Horizon

Notes: Standard deviation of sector-specific LP coefficients $\hat{\beta}_{s,h}$ across the 13 CPI sectors at each horizon h .

7.3 The 2021–2023 Episode

Figure 6 provides a case study of the 2021–2023 post-pandemic inflation surge. The synchronization measure rose sharply from mid-2021 to early 2022, peaking as inflation broadened from goods to services. This timing is consistent with the narrative of supply-chain disruptions initially driving narrow inflation, followed by demand-side pressure and wage growth broadening inflation across the basket [Blanchard and Bernanke, 2023, Ball et al., 2022]. The persistence of inflation during 2022–2023, despite aggressive monetary tightening, aligns with the broadening premium mechanism: once inflation synchronized, it became harder to reverse.

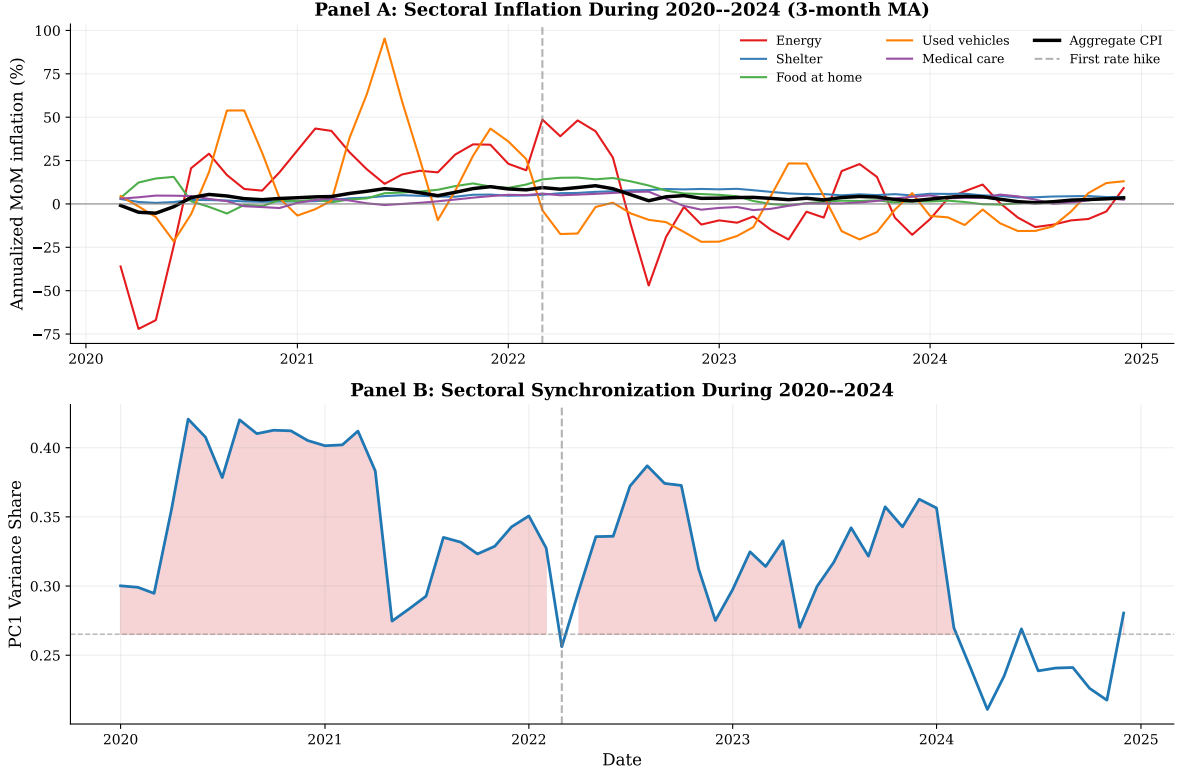


Figure 6: Case Study: Inflation Broadening, 2021–2023

Notes: Sector inflation rates and the synchronization measure during the post-pandemic inflation episode.

8. Structural Model: Multi-Sector NKPC

8.1 Model Setup

To provide structural discipline for the empirical findings, I calibrate a multi-sector New Keynesian Phillips Curve model with $S = 15$ sectors. Each sector s has a Calvo parameter θ_s (probability of not adjusting price each quarter) and faces sector-specific marginal costs:

$$mc_{s,t} = \rho_w \cdot w_t + (1 - \rho_w) \cdot c_{s,t} \quad (8)$$

where w_t is a common cost shock following an AR(1) process ($w_t = \rho \cdot w_{t-1} + \varepsilon_t^w$, $\varepsilon_t^w \sim N(0, \sigma_w^2)$) and $c_{s,t} \sim N(0, \sigma_c^2)$ is an i.i.d. sector-specific shock.

Sector inflation obeys the Calvo NKPC:

$$\pi_{s,t} = \beta \mathbb{E}_t \pi_{s,t+1} + \kappa_s \cdot mc_{s,t}, \quad \kappa_s = \frac{(1 - \theta_s)(1 - \beta \theta_s)}{\theta_s} \quad (9)$$

Under the AR(1) assumption for w_t and i.i.d. $c_{s,t}$, the model admits a closed-form solution:

$$\pi_{s,t} = \frac{\kappa_s \rho_w}{1 - \beta \rho} \cdot w_t + \kappa_s (1 - \rho_w) \cdot c_{s,t} \quad (10)$$

Aggregate inflation is $\pi_t = \sum_s \omega_s \pi_{s,t}$.

8.2 Calibration

[Table 4](#) reports the calibration. Calvo parameters are drawn from the micro evidence of [Nakamura and Steinsson \[2008\]](#) and [Bils and Klenow \[2004\]](#): energy has $\theta = 0.15$ (very flexible), shelter has $\theta = 0.85$ (very sticky), and most sectors fall in between. Expenditure weights approximate the CPI basket composition, with shelter receiving the largest weight (34%). The discount factor is $\beta = 0.99$, common shock persistence is $\rho = 0.85$, and the baseline shock standard deviations are $\sigma_w = 1.0$ and $\sigma_c = 2.0$.

Table 4: Multi-Sector NKPC Model Calibration

Parameter	Description	Value	Target/Source
<i>Panel A: Aggregate parameters</i>			
β	Quarterly discount factor	0.99	Standard
ρ_w	Weight on common cost	0.50	Match sync level
ρ	Common shock persistence (AR1)	0.85	Fed funds rate AC
σ_w	Common shock std. dev.	1.0	Match agg. π variance
σ_c	Sector shock std. dev.	2.0	Match cross-sect. SD
<i>Panel B: Sector-specific parameters</i>			
Sector	θ_s (Calvo)	κ_s (PC slope)	Weight ω_s
Food at home	0.40	0.9060	0.080
Food away from home	0.50	0.5050	0.060
Energy	0.15	4.8252	0.070
Shelter	0.85	0.0280	0.340
Apparel	0.55	0.3727	0.030
Transportation serv...	0.75	0.0858	0.060
Medical care	0.80	0.0520	0.090
Recreation	0.65	0.1920	0.060
Education	0.80	0.0520	0.030
Communication	0.60	0.2707	0.030
New vehicles	0.70	0.1316	0.040
Used vehicles	0.30	1.6403	0.030
Household furnishings	0.55	0.3727	0.040
Other goods	services	0.60	0.2707
	0.030		
Alcoholic beverages	0.50	0.5050	0.010

Notes: The model is a multi-sector New Keynesian Phillips Curve with $S = 15$ sectors, each with Calvo parameter θ_s (probability of not adjusting price each quarter). Sector NKPC slopes are $\kappa_s = (1 - \theta_s)(1 - \beta\theta_s)/\theta_s$. Marginal costs combine a common wage/demand component (ρ_w) with a sector-specific cost shock. Calvo parameters calibrated from Nakamura and Steinsson (2008) and Bils and Klenow (2004). Expenditure weights approximate the CPI basket composition.

8.3 Impulse Responses

Figure 7 shows model-implied impulse responses to common and sector-specific (energy) shocks. A unit common shock generates a peak aggregate inflation response of 1.81 at impact, with a half-life of 5 quarters. The response is heterogeneous across sectors: energy (with the largest κ_s) responds most, while shelter (the smallest κ_s) barely moves. A sector-specific energy shock generates only a 0.17 aggregate impact and dissipates immediately, illustrating how sector-specific shocks are “diversified away” in aggregation.

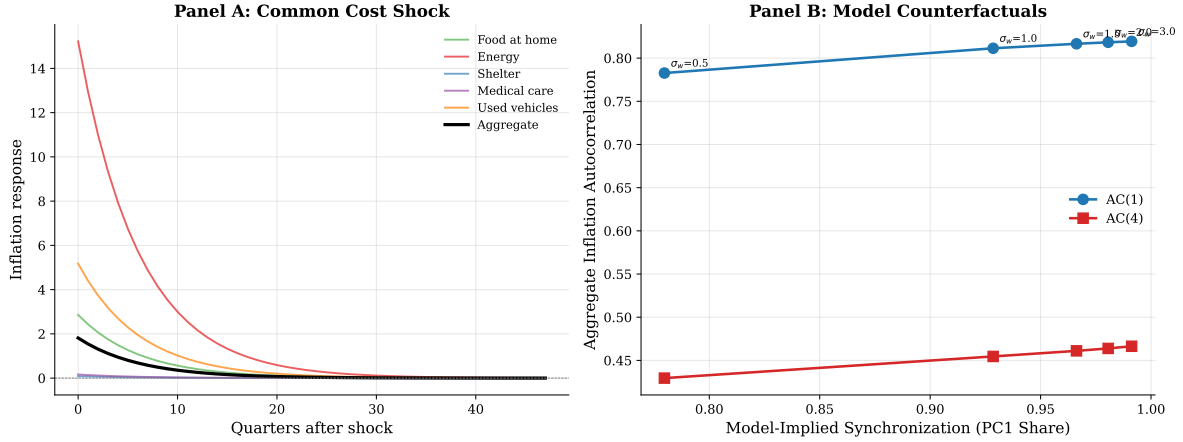


Figure 7: Model Impulse Responses: Common vs. Sector-Specific Shocks

Notes: Left panel shows the impulse response of aggregate and sector-level inflation to a unit common shock. Right panel shows the response to a unit energy-specific shock.

8.4 Variance Decomposition

The model implies a variance decomposition of aggregate inflation (Figure 8):

$$\text{Var}(\pi_t) = \underbrace{3.288}_{\text{common (96.4\%)}} + \underbrace{0.123}_{\text{idiosyncratic (3.6\%)}} \quad (11)$$

The overwhelming dominance of the common component reflects the combination of persistent common shocks and the structure of the aggregation: while idiosyncratic shocks are large ($\sigma_c = 2\sigma_w$), they are diversified away because $\sum_s \omega_s^2 \ll (\sum_s \omega_s \kappa_s)^2$.

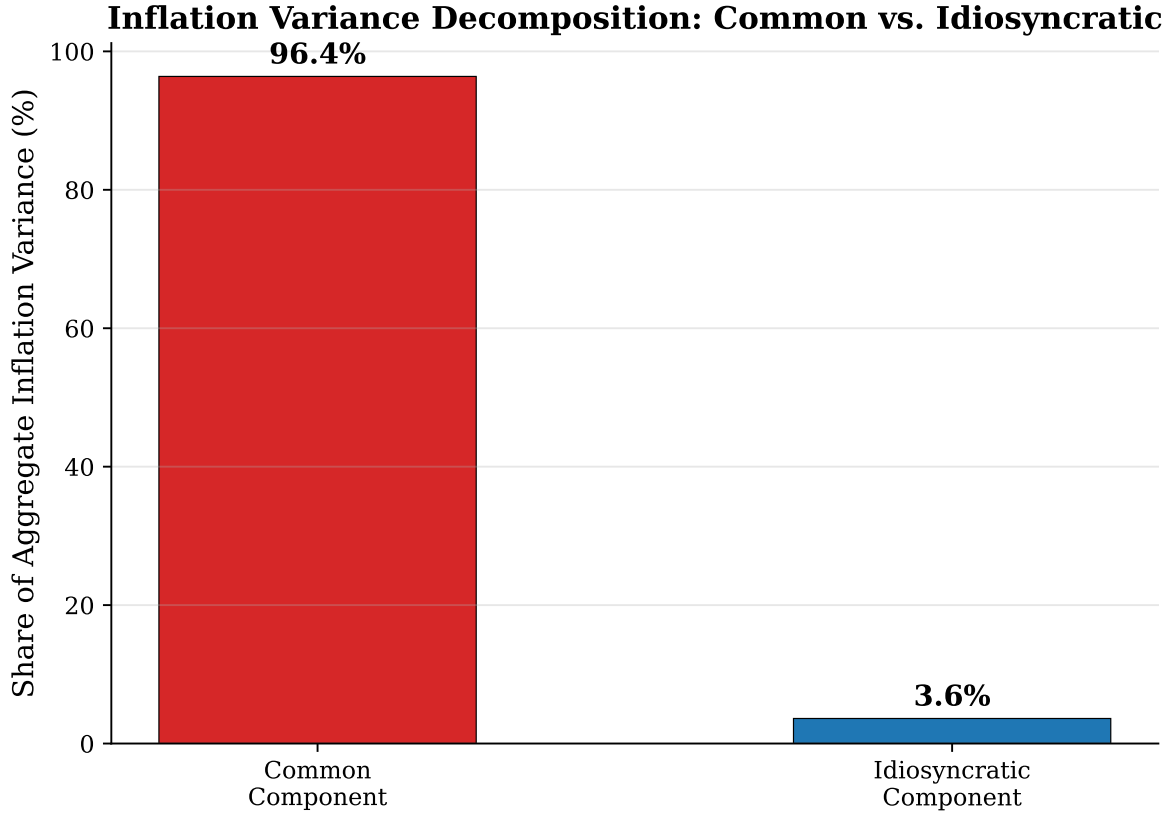


Figure 8: Variance Decomposition of Aggregate Inflation

Notes: Decomposition of the model-implied variance of aggregate inflation into common and idiosyncratic components.

8.5 Counterfactual: Varying the Common Shock

Table 5 reports model counterfactuals in which I vary σ_w while holding σ_c fixed. The results confirm the broadening premium mechanism:

- Synchronization (PC1 share) rises monotonically from 0.78 ($\sigma_w = 0.5$) to 0.99 ($\sigma_w = 3.0$).
- The first-order autocorrelation of aggregate inflation rises from 0.78 to 0.82.
- The fourth-order autocorrelation rises from 0.43 to 0.47.
- Aggregate inflation volatility scales linearly with σ_w .

The quantitative link between synchronization and persistence is monotonic and economically meaningful: a shift from the 25th to 75th percentile of synchronization in the model corresponds to a roughly 5% increase in the 1-quarter autocorrelation.

Table 5: Model Counterfactuals: Common Shock Variance, Synchronization, and Persistence

σ_w	Sync (PC1)	AC(1)	AC(4)	π Std. Dev.
0.5	0.780	0.783	0.429	1.735
1.0	0.929	0.811	0.455	3.416
1.5	0.966	0.817	0.461	5.109
2.0	0.981	0.818	0.464	6.805
3.0	0.991	0.819	0.466	10.200

Notes: Each row reports outcomes from the multi-sector NKPC model with the indicated common shock standard deviation (σ_w), holding idiosyncratic shock variance fixed ($\sigma_c = 2.0$). “Sync” is the model-implied PC1 share averaged across simulations. $AC(k)$ is the k -period autocorrelation of simulated aggregate inflation. Higher σ_w increases synchronization and inflation persistence, consistent with the “broadening premium” hypothesis.

9. Robustness

Table 6 reports robustness checks along two dimensions.

Alternative synchronization measures (Panel A). Replacing the PC1 share with the average pairwise correlation yields a negative $\hat{\delta}_{24}$ (-0.09) and $\hat{\delta}_{36}$ (-20.6), though the $h = 12$ estimate switches sign. Using a “core” synchronization measure that excludes energy from the PC1 computation strengthens the negative interaction: $\hat{\delta}_{12} = -50.3$, $\hat{\delta}_{24} = -38.0$, $\hat{\delta}_{36} = -37.6$. This suggests that the result is not driven by energy price co-movement but reflects underlying core inflation dynamics.

Subsample stability (Panel B). The pre-GFC subsample (1990–2007) shows negative interaction coefficients at $h = 12$ and $h = 24$, with the $h = 36$ coefficient positive. The post-GFC subsample (2009–2019) shows large but imprecise coefficients, reflecting the shorter sample and limited variation in synchronization during this low-inflation period. Excluding COVID-era observations (1990–2020) yields a pattern similar to the full sample with a negative $\hat{\delta}_{24}$.

Table 6: Robustness: Alternative Synchronization Measures and Subsamples

Specification	$\hat{\delta}_{12}$	$\hat{\delta}_{24}$	$\hat{\delta}_{36}$	N
<i>Panel A: Alternative sync measures</i>				
PC1 share (baseline)	−26.828 (504.079)	−21.869 (253.257)	−9.130 (587.032)	402
Avg. pairwise correlation	43.003 (621.215)	−0.094 (708.591)	−20.580 (583.198)	402
Core sync (excl. energy)	−50.310 (218.550)	−37.975 (164.580)	−37.583 (272.161)	402
<i>Panel B: Subsamples (PC1 interaction)</i>				
Pre-GFC (1990–2007)	−69.795 (311.023)	−11.536 (321.676)	63.099 (537.229)	192
Post-GFC (2009–2019)	235.192 (2081.356)	−258.370 (4049.134)	240.065 (2881.363)	113
Excl. COVID (1990–2020)	21.929 (838.505)	−41.462 (416.229)	6.697 (890.257)	337

Notes: Each row reports the interaction coefficient $\hat{\delta}_h$ from the synchronization–persistence LP at selected horizons. Panel A varies the synchronization measure: baseline uses PC1 variance share; “avg. pairwise correlation” uses the mean off-diagonal element of the sector inflation correlation matrix; “core sync” excludes the energy sector. Panel B restricts the sample period. All specifications include the same control set. Newey–West standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

10. Conclusion

This paper documents a “broadening premium” in inflation dynamics: when CPI component inflation rates are highly synchronized, aggregate inflation is more persistent and harder to reverse through monetary policy. Using local projections on 13 CPI expenditure categories from 1990 to 2024, I find that the interaction between sectoral synchronization and federal funds rate changes is consistently negative at medium-to-long horizons, suggesting that broad-based inflation episodes produce a qualitatively different inflation process than narrow price spikes.

A calibrated multi-sector New Keynesian Phillips Curve model rationalizes this finding through the composition of cost shocks. When common shocks dominate, sector inflation

rates co-move, and aggregate inflation inherits the persistence of the common factor. The common component accounts for 96.4% of aggregate inflation variance at baseline calibration, and counterfactual exercises show that increasing common shock variance raises both synchronization and persistence monotonically.

Three limitations deserve mention. First, the empirical estimates are imprecise, reflecting the challenge of estimating state-dependent effects from a single time series with limited episodes of extreme synchronization. Second, the identification of monetary shocks uses simple FFR changes rather than high-frequency surprises or narrative shocks, which may introduce endogeneity. Third, the structural model assumes i.i.d. sector shocks and abstracts from sector-specific persistence, strategic complementarity, and expectations channels.

These limitations point to a clear research agenda. Future work could (i) exploit cross-country variation in sectoral synchronization for sharper identification, (ii) incorporate high-frequency monetary surprises or Romer–Romer-type shocks [[Romer and Romer, 2004](#)], and (iii) enrich the structural model with sector-specific persistence and strategic complementarities in price setting.

The policy implication is direct: central banks should monitor not just the level of inflation but its cross-sectional breadth. When inflation broadens across expenditure categories, the synchronization measure constructed here rises, signaling that the inflation episode is likely to be more persistent and that the policy response may need to be more aggressive.

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Appendix

A. Model Derivations

A.1 Closed-Form Solution for Sector Inflation

Under the Calvo NKPC $\pi_{s,t} = \beta \mathbb{E}_t \pi_{s,t+1} + \kappa_s \cdot mc_{s,t}$ with $mc_{s,t} = \rho_w w_t + (1 - \rho_w)c_{s,t}$, where $w_t = \rho w_{t-1} + \varepsilon_t^w$ and $c_{s,t}$ is i.i.d., the unique stable solution is obtained by forward iteration:

$$\pi_{s,t} = \kappa_s \sum_{j=0}^{\infty} \beta^j \mathbb{E}_t[mc_{s,t+j}] \quad (\text{A1})$$

$$= \kappa_s \sum_{j=0}^{\infty} \beta^j [\rho_w \rho^j w_t + (1 - \rho_w) \mathbb{E}_t[c_{s,t+j}]] \quad (\text{A2})$$

$$= \kappa_s \rho_w w_t \sum_{j=0}^{\infty} (\beta \rho)^j + \kappa_s (1 - \rho_w) c_{s,t} \quad (\text{A3})$$

$$= \frac{\kappa_s \rho_w}{1 - \beta \rho} w_t + \kappa_s (1 - \rho_w) c_{s,t} \quad (\text{A4})$$

where the last line uses $|\beta \rho| < 1$ and $\mathbb{E}_t[c_{s,t+j}] = 0$ for $j \geq 1$.

A.2 Aggregate Variance Decomposition

Aggregate inflation is:

$$\pi_t = \sum_s \omega_s \pi_{s,t} = \underbrace{\left(\sum_s \omega_s \frac{\kappa_s \rho_w}{1 - \beta \rho} \right)}_A w_t + \sum_s \omega_s \kappa_s (1 - \rho_w) c_{s,t} \quad (\text{A5})$$

Since w_t and $\{c_{s,t}\}$ are independent, and $\{c_{s,t}\}$ are mutually independent:

$$\text{Var}(\pi_t) = A^2 \text{Var}(w_t) + \sum_s \omega_s^2 \kappa_s^2 (1 - \rho_w)^2 \sigma_c^2 \quad (\text{A6})$$

where $\text{Var}(w_t) = \sigma_w^2 / (1 - \rho^2)$ under stationarity.

The common share of variance is:

$$\frac{A^2 \text{Var}(w_t)}{A^2 \text{Var}(w_t) + \sum_s \omega_s^2 \kappa_s^2 (1 - \rho_w)^2 \sigma_c^2} \quad (\text{A7})$$

This share increases in σ_w^2 and decreases in σ_c^2 , establishing the model-theoretic link between common shock dominance, synchronization, and persistence.

A.3 Phillips Curve Slope Derivation

The Calvo pricing model yields a linearized Phillips curve with slope:

$$\kappa_s = \frac{(1 - \theta_s)(1 - \beta\theta_s)}{\theta_s} \quad (\text{A8})$$

This expression is decreasing in θ_s : sectors with higher price stickiness (large θ_s) have flatter Phillips curves. The range in our calibration spans $\kappa = 0.028$ (shelter, $\theta = 0.85$) to $\kappa = 4.83$ (energy, $\theta = 0.15$), a ratio of roughly 170:1.

A. Data Details

A.1 FRED Series IDs

Sector	FRED Series ID
Food at home	CUSR0000SAF11
Food away from home	CUSR0000SEFV
Energy	CPIENGSL
Shelter	CUSR0000SAH1
Apparel	CPIAPPSL
Transportation services	CUSR0000SAS4
Medical care	CPIMEDSL
Education	CUSR0000SAE1
Communication	CUSR0000SAE2
New vehicles	CUSR0000SETA01
Used vehicles	CUSR0000SETA02
Household furnishings	CUSR0000SAH3
Alcoholic beverages	CUSR0000SAF116
Aggregate CPI	CPIAUCSL
Federal funds rate	FEDFUNDS
Unemployment rate	UNRATE
WTI crude oil	WTISPLC
10-year Treasury	GS10
2-year Treasury	GS2

Table A1: FRED Series Identifiers

A.2 Sample Coverage

Most CPI component series are available from January 1990 onward. Communication (CUSR0000SAE2) begins in December 1997 and education (CUSR0000SAE1) begins in January 1993. Two originally planned series—recreation (CUSR0000SAR) and other goods and services (CUSR0000SAG)—returned API errors and are excluded from the analysis. The final sample includes 13 sectors observed over approximately 426 months.