Pontifícia Universidade Católica do Rio de Janeiro

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Sectoral Price Salience and Price Flexibility: Three Essays on Households' Inflation Expectations

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Economia.

Advisor: Prof. Carlos Viana de Carvalho

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To my mother, Mari Lima, for her resilience
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Abstract

Mesquita, Gabriel; Carvalho, Carlos (Advisor). **Sectoral Price Salience and Price Flexibility: Three Essays on Households' Inflation Expectations**. Rio de Janeiro, 2025. 239p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Households experience inflation directly when they buy groceries or fuel their cars, not through abstract indices. This dissertation studies how salient price changes shape inflation expectations, macroeconomic dynamics, and monetary policy. The first chapter links U.S. sector-level CPI data with survey forecasts and shows that the frequency of price changes, rather than expenditure share or volatility, drives household expectations. A one percentage point rise in a sector's reset frequency increases its correlation with 1-year inflation expectations by about 0.44 percentage points. The second chapter introduces a diagnostic salience parameter into a fifteen-sector New Keynesian model. Bayesian estimation on U.S. data from 1983Q1 to 2019Q4 favors this behavioral framework over the rational expectations benchmark. Welfare analysis, however, still points to core inflation stabilization. The third chapter develops a two-sector adaptive-learning model with heterogeneous price stickiness. It defines anchored expectations formally and shows how shocks in flexible-price sectors, amplified by biased attention, can unsettle long-run beliefs. Together, the essays identify which prices matter most for households and quantify their macroeconomic effects. The findings suggest that central banks should weigh credibility risks when shocks hit salient prices, especially food and fuel, while focusing on stabilizing stickier sectors when expectations remain anchored.

Keywords

Inflation expectations; Price salience; Multi-sector models; Adaptive learning; Monetary policy.

Resumo

Mesquita, Gabriel; Carvalho, Carlos. **Saliência de Preços Setoriais e Flexibilidade de Preços: Três Ensaios sobre as Expectativas de Inflação das Famílias**. Rio de Janeiro, 2025. 239p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

As famílias vivenciam a inflação diretamente ao fazer compras no supermercado ou abastecer o carro, e não por meio de índices abstratos. Esta tese estuda como mudanças salientes de preços moldam as expectativas de inflação, a dinâmica macroeconômica e a política monetária. O primeiro capítulo relaciona dados do CPI setorial dos EUA com previsões de pesquisas e mostra que a frequência dos reajustes, mais do que a participação no orçamento ou a volatilidade, é o principal fator que explica as expectativas das famílias. Um aumento de 1 p.p. na frequência de reajustes de um setor eleva sua correlação com expectativas de inflação para o ano seguinte em cerca de 0,44 p.p. O segundo capítulo introduz um parâmetro de saliência diagnóstica em um modelo Novo Keynesiano de quinze setores. Estimações Bayesianas com dados dos EUA (1983T1–2019T4) favorecem esse modelo comportamental em relação ao de expectativas racionais. A análise de bem-estar, no entanto, continua a apontar para a estabilização do núcleo da inflação. O terceiro capítulo desenvolve um modelo de aprendizado adaptativo com dois setores e diferentes graus de rigidez de preços. Ele define formalmente o conceito de expectativas ancoradas e mostra como choques em setores de preços flexíveis, amplificados pela atenção enviesada, podem desestabilizar crenças de longo prazo. Em conjunto, os ensaios identificam quais preços mais importam para as famílias e quantificam seus efeitos macroeconômicos. Os resultados sugerem que os bancos centrais devem ponderar os riscos de credibilidade quando choques atingem preços salientes, especialmente alimentos e combustíveis, ao mesmo tempo em que mantêm o foco na estabilização de setores mais rígidos quando as expectativas estão ancoradas.

Palavras-chave

Expectativas de inflação; Saliência de preço; Modelos Multisetoriais; Aprendizado adaptativo; Política monetária.

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1
Introduction

Households experience inflation at grocery stores and gas stations, not in chain-weighted indices. The success of inflation targeting depends on how people interpret those everyday price changes. Over the past fifty years, research has moved beyond the view that household expectations are rational reflections of expert forecasts. Expectations are social. They form around the prices people see, remember, and talk about. This thesis takes that fact seriously and asks what it means for the measurement, modeling, and management of household inflation expectations.

Expectations can shift quickly. In early 2025, during the U.S. tariff escalation, the University of Michigan's 5-year inflation expectation rose from 3.2 percent in January to 4.2 percent in May, well before tariffs raised store prices.[1] The Federal Reserve responded aggressively, and Chair Jerome Powell emphasized that expectations lie "at the very heart of our framework." Earlier, the Volcker disinflation showed that re-anchoring expectations can break an entrenched inflation regime.[2]

Anchoring, defined as the stability of long-run expectations in the face of temporary shocks, underpins credible monetary policy. When long-run beliefs hold steady, central banks can manage near-term tradeoffs without fueling price spirals. But anchoring assumes households discount volatile prices. Recent evidence challenges that assumption.

Measurement explains part of the gap. Professional surveys reference indices such as the CPI, while household surveys ask about "prices in general." Consumers rely on salient local prices, so their expectations often exceed central bank targets across horizons. Long-run beliefs comove with short-run beliefs, and both show right-skewed distributions.[3]

These differences matter for policy. After the pandemic and during the Russian invasion of Ukraine, grocery and fuel prices spiked. Household expectations rose, while many central banks–focused on broader measures–saw little change in medium-term forecasts. If policy reacts only to core inflation while households track headline prices, systematic errors follow. As ECB President Christine Lagarde noted, consumers react strongly to food and

[1] Media coverage of expected price increases and heightened uncertainty likely drove the jump; see Reiche and Meyler (2022) and Carroll (2003).

[2] See Binder and Kamdar (2022).

[3] See D'Acunto et al. (2024).

other frequently purchased goods, and recognizing this sensitivity helps avoid self-fulfilling dynamics.[4]

Even so, anchors remain. In 2022–2023, euro-area households reported downward-sloping term structures of inflation expectations, suggesting the ECB's target still shaped views about the distant future. Disagreement also narrowed at longer horizons, consistent with a common anchor tied to policy.

This context reframes classic results on optimal policy in multisector settings. Conventional wisdom holds that stabilizing sticky-price sectors, such as services, improves welfare, while aggressive responses to volatile sectors, such as gasoline, backfire. But if households overweight volatile sectors–an insight reinforced by Dietrich (2024)–then headline inflation becomes the more relevant target. When consumers focus on non-core components, stabilizing headline inflation may yield welfare gains.

This thesis links these behavioral insights to macroeconomic modeling and asks three questions. First, which prices most influence household inflation expectations? Second, how do salient prices interact with nominal rigidities and other frictions to shape dynamics and welfare? Third, under what conditions can shocks in frequently changing sectors unsettle long-run expectations?

The dissertation proceeds as follows. Chapter 2 links sector-specific CPI data to household expectations, showing that sectors with frequent price changes explain more variation in beliefs than expenditure weights or volatility. Chapter 3 embeds these facts in a fifteen-sector New Keynesian DSGE model, where bias toward flexible prices improves fit without overturning standard policy prescriptions. Chapter 4 introduces adaptive learning in a two-sector framework and shows how large shocks in flexible-price sectors can destabilize long-run expectations. The conclusion summarizes the main findings and outlines directions for future research.

[4]See Lagarde (2023).

2
Signals in the Basket: Does Price Flexibility Shape Inflation Expectations?

2.1
Introduction

Household inflation expectations often diverge from realized price dynamics, even when monetary policy is credible. We ask which features of sectoral prices explain cross-sectional variation in short- and medium-term expectations. Our focus is comovement: which CPI categories track survey beliefs most closely across groups and horizons. We show that sectors with higher price adjustment frequencies have stronger belief-price comovement.

Earlier work finds that consumers use simple rules and salient price signals when forming expectations (Ranyard et al., 2008; Bruin; Klaauw; Topa, 2011). They give extra weight to frequent, visible, and volatile purchases (D'Acunto et al., 2021; Dietrich, 2024; Georganas; Healy; Li, 2014). Cognition, information frictions, and demographics also matter (Jonung, 1981; D'Acunto et al., 2019; Weber et al., 2022). Two gaps remain. First, most evidence examines only a small set of CPI categories instead of the full basket. Second, the role of price adjustment frequency, separate from volatility, has not been measured directly.[1]

We estimate pooled OLS regressions using matched sectoral CPI data and survey expectations by demographic cell. The dependent variable is the Fisher z transform of the correlation between sectoral inflation and median 1-year ahead expectations. Regressors include expenditure shares, purchase frequency, price change frequency, and volatility. In regional specifications, a one standard deviation increase in purchase frequency ($\Delta f_{ik} = 0.24$) raises sector-belief comovement by about 0.10 on the z scale. A one standard deviation increase in price change frequency ($\Delta \alpha_k = 0.20$) raises it by about 0.09. Because $z = \tanh^{-1}(\rho)$ is unbounded (in our data $|z| \leq 1.33$), these magnitudes imply similar changes in ρ for typical correlations. Results extend to 3-year expectations, replicate in Michigan data including 5-year horizons, and remain robust when we proxy belief news with forecast revisions.

Section 2.2 defines variables and presents descriptive facts, with full data construction in Appendix A.1. Section 2.3 reports the main regressions. Section 2.3.3 provides robustness checks, including regional versus national CPI

[1] Dietrich (2024) link attention to price adjustment frequency, largely as a proxy for volatility. We treat frequency itself as an attention margin.

and revision-based measures. Section 2.4 interprets the findings and relates them to the literature. Section 2.5 concludes.

2.2 Measuring Comovement and Salience

This section defines the objects we take to the data and explains why each matters for our tests. Full source descriptions, concordances, cleaning rules, imputation formulas, weighting, and measurement caveats appear in Appendix A.1. Here we: (i) define the outcome, which is a Fisher z transform of the correlation between sectoral inflation and group-specific expected inflation; (ii) describe the explanatory margins, which include expenditure share, purchase frequency, price change frequency, and volatility; and (iii) preview two descriptive facts that motivate the specification. Figure 2.1 shows a comparative snapshot of these ingredients across sectors and motivates the specifications that follow.

2.2.1 Variables and Measurement

Outcome variable. For each demographic cell i (for example households with income below \$50,000, aged 40–60, with high school education, living in the Midwest)[2] and each CPI sector k, we compute the Pearson correlation

$$\mathrm{z}_{ik} \equiv z(corr(\pi_{ik,t}, \pi^e_{i,t})) \tag{2-1}$$

where $\pi_{ik,t}$ is the 12-month inflation rate for sector k in region i, and $\pi^e_{i,t}$ is the median 12-month ahead inflation expectation for the same group. The Fisher z transform yields an approximately normal outcome on $[-\infty, \infty]$ with variance that depends only on the sample size.[3] A larger z_{ik} means prices in sector k move more closely with that group's beliefs.

We use the scale-invariant correlation (on the z scale) rather than covariances or simple-regression betas. Because $\mathrm{cov}(\pi_{ik}, \pi^e_i) = \rho_{ik}\,\sigma(\pi_{ik})\,\sigma(\pi^e_i)$ and $\beta_{ik} = \rho_{ik}\,\sigma(\pi_{ik})/\sigma(\pi^e_i)$, those alternatives load mechanically on sectoral volatility and price flexibility, precisely the regressors we study. The correlation isolates comovement (salience) from amplitude.

[2]Demographic definitions follow the household reference person. See Section A.1.1 for NYFED survey details.

[3]See Hotelling (1953) on transforms of the correlation and Li (2002) for a related z scale application.

Expenditure salience. The budget share

$$n_{ik} = \frac{\text{average spending in sector } k}{\text{average spending}}$$

captures how prominent sector k is in group i's basket. Following Dhamija, Nunes and Tara (2023), larger items (housing, transport) can loom larger in expectation formation, though our results below show salience margins matter beyond shares.

Likewise the comovement, a sector k's expenditure share can vary by consumer group i, reflecting differences in consumption patterns across regions, income and age brackets, and education levels.

Purchase frequency. We proxy the visibility of price changes with

$$f_{ik} \equiv \frac{\#\text{ days with positive expending in k}}{14} \tag{2-2}$$

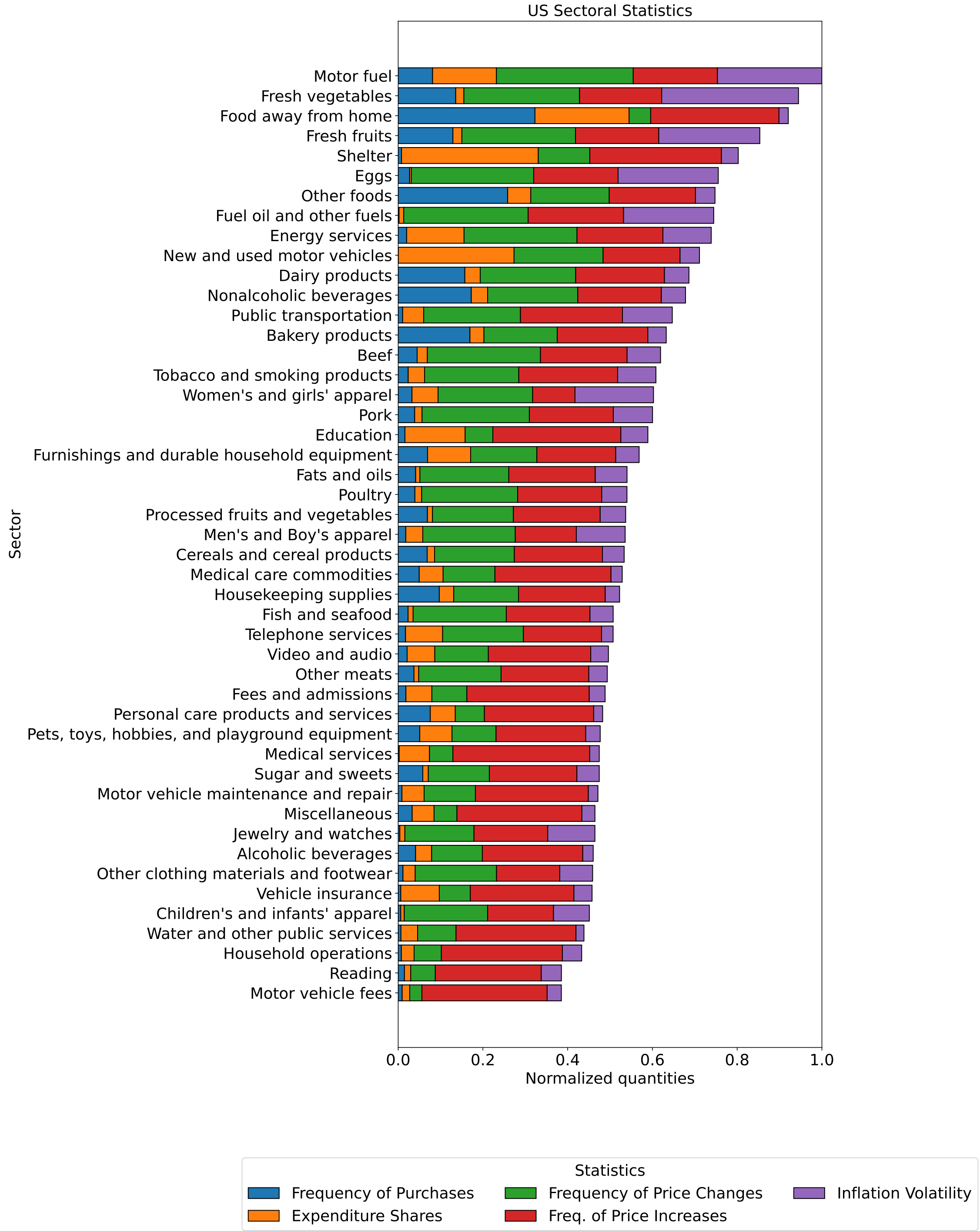
computed from the *Diary Survey*, which records daily outlays over a two-week window. The ratio is bounded in $[0, 1]$ and rises with the regularity of transactions, thereby with opportunities to observe price moves. All results are robust to counting transactions rather than days; see Figures 2.1–A.8.

The first definition offers a more precise measure of price salience. An additional expenditure on the same good on the same day likely reflects the same price, while separate expenditures on different days increase the likelihood of encountering price change information.

Price-setting statistics. On the producer side, we use the frequency of price changes for posted prices, α_k, and the share of increases, α_k^+, taken from Nakamura and Steinsson (2008). More frequent changes produce more price "news" and may tighten the link between realized and expected inflation.

Price volatility. We measure $\text{volatility}_{ik} \equiv \text{sd}(\pi_{ik,t})$. Volatile sectors (e.g., energy) exhibit larger swings that are easier to notice. Including volatility helps separate structural salience from transitory sector-specific shocks.

Figure 2.1: Normalized sectoral statistics across U.S. consumption categories. Expenditure shares and purchase frequencies come from the Consumer Expenditure Surveys (BLS), CPI inflation volatility from the BLS, and frequencies of price changes and price increases from Nakamura and Steinsson (2008). Each statistic was normalized by dividing sector values by the maximum within the statistic. We then scaled the sector totals by the maximum across sectors to allow comparison.



2.2.2 Sectoral Comovement with Inflation Beliefs

Two regularities guide our specification. (i) Frequent-purchase, flexible-price staples dominate short horizons. The Food and Beverages division shows the strongest link with beliefs at the 1-year horizon (average correlation about 0.27), and several of its sectors fall in the top quintile of the perceived inflation distribution. The Transportation division, also frequent in purchases and flexible in prices, ranks second for 1-year expectations. (ii) Persistent services shape longer horizons. For 5-year expectations, the strongest sectoral correlation is Alcoholic Beverages Away from Home (0.48). At the division level, Food and Beverages ranks second (0.30) and Other Goods and Services third (0.24).

Input linkages and pass-through. CPI categories move together because common inputs transmit shocks across sectors. Food is a standard case: restaurants rely on grocery inputs, so a supermarket price shock passes through to Food Away from Home with a short delay. Figure A.13 shows food-at-home inflation leading dining-out inflation by one to three months.[4] Energy is another case: Public Transportation fares move with fuel costs, while Airline Fares track jet fuel prices more closely because fuel has a higher cost share. Wheat drives both Cereals and Cereal Products and Bakery Products. Common textile inputs align prices in Men's and Boys' Apparel and Women's and Girls' Apparel.

Adjustment speed: goods vs services. Retail goods adjust faster than services. Restaurants delay menu changes and transit agencies face regulatory or contractual frictions, so services absorb input shocks more slowly. This timing gap explains the horizon pattern: flexible goods drive short-run comovement, while stickier services can matter for longer horizons.

Why linkages matter for beliefs. Shared inputs are not spurious. They are the channel through which common shocks become salient. After a wheat shock, flexible goods such as Cereals and Bakery Products move quickly, shifting short-term beliefs. Slower adjustments in Food Away from Home then reinforce the signal at longer horizons. Oil shocks pass contemporaneously to Motor Fuel and with lags to transportation services. These dynamics show

[4] The y axis reports the correlation coefficient. The x axis is the lag applied to the food CPI.

how flexible and sticky sectors transmit the same information across the expectations term structure.

Frequency of increases. The share of upward changes, α_k^+, captures another margin of salience. Consumers often miss discounts, but they notice hikes. Empirically α_k^+ is negatively correlated with overall change frequency α_k. Sticky sectors such as rents and medical services change rarely and mostly upward. Very flexible sectors such as gasoline change often with many decreases. In the regressions we use both α_k (news frequency) and α_k^+ (directional asymmetry) to separate these channels.

Figure 2.2: Sectoral correlations with perceived inflation (2016Q1–2019Q4) and with 1-year and 5-year ahead inflation expectations (2000M1–2019M12) from the University of Michigan Survey of Consumers.

2.3 The Role of Purchase Frequency and Price Flexibility

To measure how salient price signals shape household inflation beliefs, we estimate pooled OLS panel regressions of the form

$$z_{ik} = \beta_0 + \beta_1 n_{ik} + \beta_2 f_{ik} + \beta_3 \text{volatility}_{ik} + \beta_4 \alpha_k + \beta_5 \alpha_k^+ + \eta_i + \epsilon_{ik}, \qquad (2\text{-}3)$$

where z_{ik} is the Fisher z transform of $\text{corr}(\pi_{ik,t}, \pi^e_{i,t})$ (Section 2.2). n_{ik} is the expenditure share. f_{ik} is purchase frequency. $\text{volatility}_{ik} \equiv \text{sd}(\pi_{ik,t})$ is sectoral CPI volatility for group i. α_k is the frequency of price changes. α_k^+ is the share of price increases. The vector η_i collects fixed effects.

We estimate two sets of specifications. The first includes separate age, income, education, and region fixed effects. The second uses consumer group fixed effects. Standard errors are two-way clustered by sector and consumer group.

2.3.1 Results: One-Year Ahead Expectations

Table 2.1 reports the baseline estimates using regional CPI series.[5] Three results stand out.

(1) Purchase frequency strongly predicts comovement. Adding f_{ik} raises explanatory power. R^2 rises from 0.07 to 0.09 with separate fixed effects and from 0.13 to 0.15 with group fixed effects. Coefficients on f_{ik} lie between 0.41 and 0.43 (columns ii, iii, v, vi) and are significant at the 5 percent level. On the natural $[0, 1]$ scale, a 0.1 increase in purchase frequency is associated with a 0.041-0.043 rise in z_{ik}.

(2) Price-change frequency (news arrival) matters independently. Coefficients on α_k range from 0.44 to 0.48 and are highly significant in all columns, including those controlling for f_{ik}. A 0.1 increase in α_k predicts a 0.044-0.048 increase in z_{ik}. The stability of β_4 after adding f_{ik} shows that purchase frequency and price change frequency capture distinct salience margins rather than serving as proxies for one another.

[5] Low R^2 values are common in survey-based expectations research and do not imply that the estimated effects lack economic relevance (see D'Acunto et al. (2021)).

Table 2.1: This table shows panel regressions where the dependent variable is the Fisher-z transformed correlation between median 1-Yr ahead inflation expectations across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and sectoral inflation over the past year. Regressors include the frequency of price changes, median size of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (1-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.27	-1.84**	-1.79**	-0.27	-1.85**	-1.81**
	(0.36)	(0.71)	(0.73)	(0.36)	(0.71)	(0.74)
Freq. of Price Changes	0.45***	0.48***	0.44**	0.45***	0.48***	0.44**
	(0.13)	(0.13)	(0.19)	(0.14)	(0.13)	(0.19)
Regional Volatility	-0.19**	-0.16**	-0.15	-0.19**	-0.16**	-0.15
	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.09)
Purchase Frequency		0.42**	0.41**		0.43**	0.41**
		(0.18)	(0.19)		(0.18)	(0.19)
Freq. of Price Increases			-0.04			-0.04
			(0.14)			(0.14)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.07	0.09	0.09	0.13	0.15	0.15
Within R^2	0.06	0.08	0.08	0.06	0.08	0.09

Notes: Standard errors are clustered by sector and consumer group.

(3) Volatility turns negative once salience margins are controlled. Regional volatility loads between –0.16 and –0.19, often with significance. Conditional on exposure (f_{ik}) and news arrival (α_k), residual volatility likely reflects transitory noise that lowers the signal-to-noise ratio in the correlation measure.[6]

Two additional points stand out. First, the share of increases α_k^+ is small and insignificant (about -0.04) once α_k is included, consistent with their strong negative correlation. Directional asymmetry adds little beyond overall change frequency. Second, expenditure shares become more negative and significant when f_{ik} is included, suggesting that large-budget categories do not dominate the belief link once salience is accounted for.

2.3.2 Medium-term Inflation Beliefs and the Role of Regional CPI

Medium-term inflation beliefs. Table A.2 reports results for 3-year ahead expectations using regional CPI series. The patterns mirror the 1-year horizon. The purchase frequency coefficient is positive and significant (0.38-0.39). A 0.1 increase in f_{ik} is associated with a 0.038-0.039 rise in z_{ik}. The frequency of price changes remains a strong predictor (0.43-0.45), implying about 0.043-0.045 per 0.1 increase in α_k. Regional CPI volatility loads negatively (-0.17 to -0.19), consistent with noise weakening the signal once salience margins are controlled.

Why regional CPI matters. Replications with national CPI (Tables A.4, A.5) show the cost of geographic mismatch. At the three year horizon, the purchase frequency coefficient turns negative and significant (–0.27 to –0.36 in Table A.5), while it is positive with regional CPI (Table A.2). At the one year horizon, the national specification yields a positive coefficient on f_{ik}, but other results differ. Volatility loads more negatively, and α_k^+ turns strongly negative. These changes suggest that aggregation blends heterogeneous local price dynamics. The regional design produces sign stable and horizon consistent salience effects, and more interpretable loadings on volatility and asymmetry. The tradeoff is narrower sectoral coverage.[7]

[6] Once exposure and news arrival are held fixed, extra regional volatility mainly reflects idiosyncratic noise that raises variance without adding informative covariance. See Appendix A.2 for a simple decomposition.

[7] Using regional CPI reduces sector coverage (Appendix Tables A.20–A.21) but better matches the geography of prices to respondents' shopping environment.

2.3.3 Robustness

Michigan data. Reestimating with the Michigan Survey of Consumers (2000–2019) confirms the main results across demographic splits by income, age, education, and region. The longer sample and the availability of five year expectations allow us to study medium and long horizons. In the one year regressions, purchase frequency is positive and significant for age and region splits (Tables A.7, A.9). It is positive but less precise in income and education splits (Tables A.6, A.8). At the five year horizon, purchase frequency is positive and significant across all splits. Expenditure shares load negatively and more strongly at five years than at one year. This is consistent with large service heavy categories diluting the signal once salience margins are held fixed. The frequency of price changes α_k remains a robust positive predictor. Volatility is more negative at five years than at one year, consistent with medium horizon smoothing of high frequency noise.

Share of price increases vs. frequency of changes. In the regional SCE regressions (Tables 2.1, A.2), the total change frequency α_k is the key predictor. Once α_k is included, the share of increases α_k^+ is small and insignificant. In the national specifications (Tables A.4, A.5), α_k^+ turns negative and significant. This is likely an aggregation artifact, so we treat those estimates with caution. In the Michigan five year regressions (Tables A.6-A.9), α_k^+ becomes positive and significant alongside α_k. This is consistent with households interpreting frequent upward revisions in stickier sectors as persistent inflationary pressure.

Price flexibility and forecast revisions. As a stricter test of salience, we replace level comovement (one year expected inflation vs twelve month sectoral inflation) with a "belief news" measure. This is the Fisher z correlation between monthly revisions in expected inflation and contemporaneous sectoral inflation by region. Using revisions is standard in the information rigidity literature. In sticky or noisy information models, forecast revisions are a sufficient statistic for news, and the revision coefficient maps one for one into rigidity.[8]

At the one year horizon, signs and magnitudes align with the baseline. In the regional regressions (Table A.10), purchase frequency is positive and precise (0.07-0.09). Price change frequency is positive (0.07-0.10). Expenditure shares are modestly negative. Volatility is small. Using national CPI (Table A.14) preserves the positive role of price change frequency (0.13-0.15) but weakens

[8] See Coibion and Gorodnichenko (2012) and Coibion and Gorodnichenko (2015).

purchase frequency (about zero). This again shows the value of regional matching. At the three year horizon, monthly revisions are noisier. With regional CPI (Table A.12), coefficients shrink toward zero. With national CPI (Table A.15), only price change frequency remains positive (0.04-0.05). This suggests that monthly sectoral news moves short run beliefs but provides less signal for three year expectations, where revisions are infrequent and low variance.

Survey of Professional Forecasters. As a further robustness check, we repeat the sector and belief comovement analysis using the Survey of Professional Forecasters (SPF) and compare the results with those from the Michigan survey discussed above. We continue to measure comovement on the Fisher z scale, defined as the correlation between sectoral inflation and median expectations, and estimate cross-sectional regressions across 47 CPI sectors. The standardized regressors capture basket weight, frequency of price changes, inflation volatility, purchase frequency, and the frequency of price increases (Tables A.17–A.18).

At the one-year horizon, SPF comovement is most strongly associated with CPI weights (around 0.07, $p < 0.05$), while price flexibility plays a smaller and statistically weaker role. This pattern contrasts sharply with the Michigan results, where more frequent repricing predicts stronger comovement. At the five-year horizon, the contrast becomes even clearer. For Michigan, sectoral characteristics explain little beyond a positive intercept, consistent with stable long-run beliefs. For SPF, price flexibility enters with a negative and significant coefficient (around –0.12, $p < 0.05$), while basket weights remain modestly positive.

Together, these findings support our interpretation that households respond mainly to visible and frequently changing prices in forming short-run beliefs, whereas professionals focus on the structure of the CPI and filter out temporary sectoral movements, especially at longer horizons.

Sectoral Inflation Persistence. One potential concern is that sector–belief comovement could appear mechanically stronger in sectors with more persistent inflation, regardless of salience. Persistent price series generate greater low-frequency variation, which naturally aligns more closely with the slow-moving component of household expectations. Because persistence may also correlate with price flexibility and volatility, omitting it could bias the estimated coefficients on these salience measures.

To assess this, we construct a measure of regional sectoral inflation persistence and include it as an additional regressor. Columns (iii) and (vi) of Table A.16 show that the persistence coefficient is small and statistically insignificant, while the coefficients on purchase frequency and the frequency of price changes remain virtually unchanged. These results indicate that the main patterns are not driven by differences in sectoral persistence but rather by the distinct roles of exposure and news arrival in shaping belief–price comovement.

2.4 Discussion

Why do some CPI categories matter more than their expenditure shares in shaping household beliefs? Our evidence shows that two factors explain much of the difference. The first is how often consumers encounter a price. The second is how often firms reset it. Together these two margins explain about two thirds of the cross sector variation in belief-price comovement between the 25th and 75th percentiles.

Interpreting magnitudes. The dependent variable is the Fisher z transform of the sector belief correlation, $z = \tanh^{-1}(\rho)$, which is unbounded unlike $\rho \in [-1, 1]$. In our data, $|z|$ never exceeds 1.33. In the baseline regional one year specification, a one standard deviation increase in purchase frequency ($\Delta f_{ik} = 0.24$) raises z by about $0.42 \times 0.24 \approx 0.10$. A one standard deviation increase in price change frequency ($\Delta \alpha_k = 0.20$) raises z by about $0.45 \times 0.20 \approx 0.09$. Changes in the raw correlation ρ are of similar order.

Mechanisms and links to prior work. The results align with the frequency bias experiments of Georganas, Healy and Li (2014) and the scanner data evidence of D'Acunto et al. (2021), which show that consumers overweight prices they see often. Our aggregate regressions extend this bias to the population level and show that it applies to the full CPI basket. The prominence of α_k also echoes the sectoral heterogeneity documented by Carvalho (2006) and Nakamura and Steinsson (2008). Sticky price sectors leave weaker imprints on beliefs because they generate fewer news events.

Other evidence shows that households shape expectations to the prices they pay. Using scanner data, Kaplan and Schulhofer-Wohl (2017) document wide dispersion in household specific inflation rates driven mainly by relative price variation within identical goods. Those micro price paths shape future expectations according to Huber, Minina and Schmidt (2023). Cavallo, Cruces and Perez-Truglia (2017) show that in low inflation environments individuals rely on salient grocery prices when priors are weak, even when they have accurate aggregate statistics. Our finding that high purchase and high flexibility sectors carry the most weight in aggregate beliefs provides a macro level counterpart. The same goods that dominate individual price diaries also dominate the collective expectations statistic.

Dietrich (2024) show that households' attention to volatile non core items makes headline inflation a more welfare relevant target than core measures. Our results caution against taking this prescription literally. Sectors that are both volatile and frequently reprice disproportionately shape one and three year expectations.

Robustness and alternative explanations. The main coefficients hold under several checks. These include alternative clustering schemes, controls for sector-specific inflation volatility, comparisons between Michigan and NY Fed expectations, and horizons of one, three, and five years. We also control for sectoral inflation persistence, which addresses the concern that more persistent series might mechanically comove more with expectations because they load more heavily on low-frequency movements. Including persistence barely changes the coefficients on purchase frequency and price-change frequency, and the persistence term itself is small and insignificant. This suggests that our salience margins capture more than the simple time-series properties of sectoral inflation.

A comparison with the Survey of Professional Forecasters reinforces this interpretation. When we repeat the sector–belief comovement analysis using SPF data, price flexibility plays only a modest role at the one-year horizon and becomes negatively associated with comovement at five years, while CPI weights remain the main predictor. In contrast, household expectations comove more strongly with sectors that reprice often and are purchased frequently. This divergence is consistent with professionals filtering out high-frequency sectoral noise and focusing on the structure of the CPI, whereas households overweight salient, fast-moving prices.

Policy relevance. Because price signals from high frequency, flexible price sectors such as food and fuel quickly feed into one year expectations, communication that stresses the temporary nature of shocks in these categories may help prevent wage-price spirals. Evidence that these signals shape longer term expectations is weaker in our monthly revision tests. At the three year horizon, monthly forecast revisions are infrequent and low variance, and none of the sectoral statistics significantly explains them (Tables A.12–A.15). This pattern is consistent with anchored expectations over 2000-2024. Small, noisy monthly updates occur around a stable anchor rather than reflecting an absence of salience.

When we move from monthly revisions to 12 month inflation rates, the three year results are strong and mirror the one year patterns. This raises a natural question: are month to month sectoral rates the right signal for medium term updates? If households aggregate information over longer windows, monthly rates may understate salience at three years. Aggregating sectoral inflation over three months or longer could yield different conclusions and speaks directly to memory. How far back do households look when updating longer run beliefs? They may require persistent multi month movements to adjust medium term expectations. Exploring alternative aggregation windows is a direction for future research.

Still, the one year results are clear. With monthly sectoral inflation, the revision regressions are significant and confirm the central role of high frequency, flexible price signals in short run expectation formation.

Limitations. First, sectoral price setting statistics come from Nakamura and Steinsson (2008). Updated data could refine α_k. Second, the purchase frequency metric is limited to a two week Diary window and misses stockpiling behavior. Third, we lack a clean instrument for price setting frequency, so we cannot rule out reverse causality if firms adjust prices more often because consumers monitor them closely. Finally, the analysis cannot control for media coverage due to data constraints. Chahrour, Shapiro and Wilson (2025) show that news about higher prices raises inflation expectations.

Purchase frequency and its determinants. There is an important interplay between purchase frequency behavior and firms' price setting strategies.[9] Firms in some sectors may adjust prices strategically in response to demand from consumers who purchase frequently. Conversely, consumers may adapt their purchasing patterns to sector specific price characteristics, adopting behaviors such as stockpiling or timing purchases around predictable cycles. These dynamics reflect structural features of the economy that shape beliefs about inflation and point to a promising direction for future research.

[9] In Appendix A.10, we use detailed microdata to examine the relationship between purchase frequency and expenditure shares across sectors, alongside demographic characteristics and sectoral price setting statistics.

2.5 Conclusion

Households do not track the largest items in their basket. They track the most flexible ones. Sectors that people purchase often and that firms reprice often comove more tightly with one, three, and five year inflation expectations, even after controlling for expenditure shares and volatility. Quantitatively, a one standard deviation increase in either salience margin raises the sector-belief correlation by about 0.09 to 0.10.

Some headline components, often dismissed as noise, are closer to what households actually see and remember. Emphasizing these salient items in policy communication can help anchor expectations, especially when food or fuel drive the news, even if policy continues to target core measures for stabilization.

The patterns are robust across clustering schemes, volatility and persistence controls, NY Fed versus Michigan surveys, horizons from one to five years, and a revision-based definition of belief news. They also appear specific to households: for professional forecasters, sectoral comovement is tied more closely to CPI weights and, at longer horizons, even negatively related to price flexibility. A simple organizing principle summarizes the evidence. Attention and news arrival, captured by purchase frequency and price flexibility, are the key margins linking sectoral prices to household inflation expectations in the data we study.

3
Sectoral Price Salience: A Stereotype-Based Perceived Inflation Model

3.1
Introduction

This chapter builds a tractable fifteen sector New Keynesian model in which households overweight prices that change often. We ask two questions. First, does this model fit the data well? Second, does attention to flexible prices overturn the classic stickiness principle that places policy focus on the most rigid prices? We show that a single diagnosticity parameter linking observed price reset frequencies to perceived weights improves the fit to belief data without changing primitives. The optimal target remains core inflation, not headline or perceived inflation.

The motivation is empirical. Chapter 2 shows that households recall salient and frequently adjusted prices such as food and gasoline. We discipline price perception with data: observable sectoral reset frequencies f_k and the basket average $\bar{f}$. The framework preserves conventional preferences, technology, and policy. Any departure from a rational benchmark comes only from how agents aggregate prices.

We formalize two cognitive shortcuts, sampling and representativeness, into stereotype weights $\tilde{n}_k$. Agents ignore unchanged prices and exaggerate the frequency of above average adjustments, producing $\tilde{n}_k \propto n_k f_k (f_k/\bar{f})^{\theta}$ up to normalization, with $\theta \geq 0$ governing diagnosticity. Both households and firms build a perceived price index $\tilde{P}_t$ with $\tilde{n}_k$ and behave rationally given that index. This replaces P_t with $\tilde{P}_t$ in two places that matter for dynamics: the Euler equation (through $\tilde{\pi}_{t+1}$) and the sectoral demand wedge $(\pi_{k,t} - \tilde{\pi}_t)$. Pricing follows Calvo with sectoral stickiness and indexation. Production retains input-output linkages and segmented labor markets.

We estimate three variants, Rational, Stereotypes, and Arbitrary Weights, on US quarterly data from 1983Q1 to 2019Q4 using full information Bayesian methods. With belief data included, the Stereotypes model clearly dominates the rational benchmark. It gains more than 40 log marginal likelihood points and better tracks spikes in one year expected inflation while adding only one parameter θ. A data driven weight model can raise the likelihood further but does so with fifteen additional parameters and unstable posterior weights. Without belief data, fit differences are smaller, but the salience specification still improves belief price moments directly.

We then connect to the optimal target literature. In quadratic multi sector welfare, the stickiness principle of Aoki (2001) survives salience. Across values of θ and robustness checks that shut down indexation, labor segmentation, and input output links, targeting core inflation minimizes welfare losses.

The remainder is organized as follows. Section 3.2 lays out the environment and equilibrium. Section 3.3 describes estimation and model comparison. Section 3.4 presents policy experiments. Section 3.5 interprets mechanisms and limitations. Section 3.6 concludes. An Online Appendix contains derivations and additional results.

3.2 The model

We build on Carvalho, Lee and Park (2021) and Bordalo et al. (2016) by introducing sector specific salience distortions into a standard New Keynesian multisector environment. Preferences and technology remain conventional. The innovation is a cognitive assumption: when agents aggregate prices, they overweight sectors that adjust more often by forming price stereotypes.

Sectors. The economy has K sectors, each with a Calvo stickiness parameter α_k (the probability of not resetting in a period) and an indexation rate ν_k. Heterogeneity in (α_k, ν_k) generates persistent cross sector dispersion in inflation, which the model uses to match observed PCE moments. Each sector also receives idiosyncratic productivity shocks $A_{k,t}$ and relative demand shocks $D_{k,t}$.

Technology. Production uses a roundabout input output structure and sector specific labor markets. Firms combine sector specific labor with a Dixit-Stiglitz composite of intermediates from all sectors. A common parameter $\delta \in (0, 1)$ governs the share of intermediates in gross output. The substitution elasticity η across sectoral inputs determines how relative price changes reallocate demand.

Households. A representative household consumes a CES bundle of sectoral goods, supplies differentiated labor, and trades Arrow securities. Utility is log consumption and separable in labor with a constant Frisch elasticity φ. Households form expectations using a salience distorted price index. Instead of the true expenditure weights n_k, they recall stereotype weights $\tilde{n}_k$ that give more weight to sectors with frequent price changes. This distortion enters all aggregations, including real interest rates, intertemporal consumption, and labor supply.

Firms. In each sector, a continuum of monopolistically competitive firms draw prices from Calvo lotteries and index non resets at rate ν_k. Managers share the salience bias and evaluate markups, marginal costs, and real wages using $\tilde{P}_t$ instead of P_t. Their perceived aggregate price index is

$$\tilde{P}_t = \left(\sum_{k=1}^{K} (\tilde{n}_k D_{k,t}) P_{k,t}^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

This systematically deviates from the true cost of living index P_t. Here $D_{k,t}$ is a relative demand shifter normalized so that $\sum_k n_k D_{k,t} = 1$, and η is the elasticity of substitution across sectoral bundles. Agents are rational given their distorted information. They forecast all endogenous variables correctly but feed $\tilde{P}_t$ instead of P_t into every aggregation. Appendix B gives full derivations and shows how sampling and representativeness biases pin down the stereotype weights $\tilde{n}_k$.

3.2.1 Stereotypes-based weights

Decision makers face a prediction task: estimating an aggregate price index $p_t = \sum_{k=1}^{K} n_k p_{k,t}$, where $n_1, \ldots, n_K$ are sectoral expenditure shares. Our premise is that salience follows information arrivals. People attend to jumps (price resets) because they contain new information about costs and markups, and they mostly ignore drifts (indexation) because these inherit the past and add little information.

Sampling bias. Consider a K sector Calvo economy with sector share n_k and reset probability $1 - \alpha_k$. In period t, the expected mass of firms in sector k that reset is

$$n_k(1 - \alpha_k), \tag{3-1}$$

If perceived importance is proportional to how often a sector supplies news bearing jumps, then effective weights satisfy

$$\frac{n_k(1 - \alpha_k)}{\sum_{k'=1}^{K} n_{k'}(1 - \alpha_{k'})}. \tag{3-2}$$

The intuition is that sectors that reoptimize more often release more information and therefore loom larger in perceived inflation. This mirrors the availability heuristic of Tversky and Kahneman (1973), where people judge importance by what comes easily to mind.

Evidence supports this jump focused attention. Daily survey data show that non core items, especially food and energy, disproportionately shape headline expectations. This is consistent with households tracking volatile categories more closely (Dietrich, 2024). Similar patterns appear outside the United States. U.K. households react more to food price shocks than to core goods moves (Anesti; Esady; Naylor, 2024). Jo and Klopack (2025) provides causal evidence on the link between gas prices and household inflation expectations.

These facts motivate our implementation. Weighting sectors by $n_k(1-\alpha_k)$ captures the observed gradient of attention and improves the fit to inflation expectations data (Section 3.3).

Representativeness bias. Prices in the Calvo indexation setup take two forms: (i) actively reset prices and (ii) mechanically indexed trend prices. Agents see both and form stereotypes[1] about each sector's reset frequency

$$f_k \;=\; 1 - \alpha_k \tag{3-3}$$

and the basket average

$$\bar{f} = \sum_{j=1}^{K} n_j\, f_j \quad \Longrightarrow \quad \bar{\alpha} = 1 - \bar{f}. \tag{3-4}$$

Define representativeness ratios

$$R_k = \frac{f_k}{\bar{f}}, \qquad R'_k = \frac{\alpha_k}{\bar{\alpha}}, \tag{3-5}$$

which measure how often sector k contributes an adjustment relative to the basket.[2] Following Bordalo et al. (2016), distorted probabilities take the form

$$\hat{f}_k = f_k \frac{h(R_k)}{f_k h(R_k) + \alpha_k h(R'_k)}, \tag{3-6}$$

where $h(\cdot)$ is a weakly increasing function.[3] We denote the pair $(\hat{f}_k, \hat{\alpha}_k)$ as the stereotype for sector k. Sectors with higher true adjustment frequencies f_k receive proportionally larger distorted weights, and the curvature of $h(\cdot)$ governs how sharply representativeness amplifies those differences.

Two forces therefore compound. First, sampling: people aggregate using the expenditures they see changing. Second, representativeness: they overstate

[1]Hilton and Hippel (1996) define stereotypes as mental representations of real differences between groups that allow easier and more efficient processing of information.

[2]In CPI microdata, food adjusts in 65.2 percent of quotes versus 36.9 percent for the basket, so $R_{\text{food}} = 0.652/0.369 \approx 1.77$.

[3]Full derivations appear in Appendix B.1.6.

change frequencies for above average movers. Together these forces push perceived inflation toward highly flexible sectors.

Combining the two yields perceived weights

$$\tilde{n}_k = \frac{\frac{f_k\left(\frac{f_k}{\bar{f}}\right)^{\theta}}{\alpha_k\left(\frac{\alpha_k}{\bar{\alpha}}\right)^{\theta}+f_k\left(\frac{f_k}{\bar{f}}\right)^{\theta}}}{\sum_{k'=1}^{K} n_{k'}\frac{f_{k'}\left(\frac{f_{k'}}{\bar{f}}\right)^{\theta}}{\alpha_{k'}\left(\frac{\alpha_{k'}}{\bar{\alpha}}\right)^{\theta}+f_{k'}\left(\frac{f_{k'}}{\bar{f}}\right)^{\theta}}} n_k, \tag{3-7}$$

where $\theta \geq 0$ indexes the strength of representativeness.

We are not invoking rare event stereotypes (such as "Republicans are wealthy"). Here the focal trait, frequent resets, is common. This is probability weighting. As f_k rises, so does $h(R_k)$, and the sector gains influence in perceived inflation. The reference point matters. The bias is relative to $\bar{f}$. When the economy becomes more flexible[4] and $\bar{f}$ rises, all R_k fall and the bias fades mechanically. Alternative frames with time varying $\bar{f}_t$ are possible but lie beyond our scope.

In short, sampling and representativeness map objective reset frequencies into amplified perceived weights $\tilde{n}_k$. This mechanism, paired with a standard New Keynesian structure, matches how households form inflation beliefs while keeping preferences, technologies, and policy rules conventional.

3.2.2 Households

Distorted inflation beliefs matter through three channels. First, they tilt spending across sectors because households price bundles with the perceived relative price $P_{k,t}/\tilde{P}_t$. Second, they shift intertemporal choices because the Euler equation discounts with expected salience adjusted inflation $\tilde{\pi}_{t+1}$. Third, they affect labor supply because hours are chosen from the perceived real wage $W_{k,t}/\tilde{P}_t$. In each case, $\tilde{P}_t$ and $\tilde{\pi}_{t+1}$ replace the true aggregates, transmitting cognition into real outcomes.

Sectoral consumption choice. Households allocate expenditure across sectoral varieties according to

$$C_{k,t}(i) = D_{k,t}\left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\epsilon}\left(\frac{P_{k,t}}{\tilde{P}_t}\right)^{-\eta} C_t, \tag{3-8}$$

[4] Gautier et al. (2024) show time varying properties of price change frequencies in the Euro area.

where i indexes varieties within sector k, ϵ is the within sector elasticity of substitution, η is the across sector elasticity, C_t is aggregate consumption, $P_{k,t}$ is the sector k composite price, and $\tilde{P}_t$ is the perceived aggregate index. A higher perceived $P_{k,t}/\tilde{P}_t$ lowers demand for sector k.

Euler equation. With segmented beliefs, households discount using the perceived real interest rate:

$$\beta \mathbb{E}_t \left[\frac{\Gamma_{t+1}}{\Gamma_t} \frac{C_t}{C_{t+1}} \frac{R_t}{\tilde{\pi}_{t+1}} \right] = 1 \tag{3-9}$$

where β is the discount factor and R_t is the gross nominal return. A higher expected $\tilde{\pi}_{t+1}$ lowers the perceived real return and raises the incentive to consume today.

Labor supply. Hours equate the perceived real wage to the marginal disutility of work:

$$\frac{W_{k,t}}{\tilde{P}_t} = \omega_k H_{k,t}^{\varphi} C_t \tag{3-10}$$

where $H_{k,t}$ is hours supplied to sector k, $W_{k,t}$ is the sectoral wage, φ is the inverse Frisch elasticity, and ω_k scales the disutility of sector k hours. Aggregating across sectors delivers the economy wide labor supply condition that feeds into marginal costs and then into the Phillips curves.

In short, replacing P_t and π_{t+1} with their salience weighted counterparts $(\tilde{P}_t, \tilde{\pi}_{t+1})$ is the single cognitive twist that carries belief distortions into consumption, saving, and labor decisions.

3.2.3 Firms

Managers tend to follow headline inflation more closely than households because they track rivals, price lists, and pending adjustments. Yet their forecast moments, such as means and variances, look closer to households' than to professional forecasters'. Surveys show managers often rely on media and day to day shopping to gauge prices Kumar et al. (2015), and Binder and Kamdar (2022) argue that consumer expectations are a reasonable proxy for firms' price setting beliefs.

Because in our model consumption goods can also be used as intermediate inputs, and to keep the model tractable and consistent with the data, we assume managers carry the same aggregation bias as households. They misweight the true price index P_t toward salience adjusted shares $\tilde{n}_k$. This keeps the mechanism focused on representativeness and aligns firm beliefs with household beliefs.

Distorted beliefs affect firm decisions in three ways. First, how they source intermediates across sectors. Second, how they split inputs between intermediates and labor. Third, how they set reset prices. In each case, the perceived index $\tilde{P}_t$ replaces P_t, tilting costs, markups, and pass through.

Demand for intermediates. Firm ik's demand for variety i' from sector k' mirrors the household demand system:

$$Z_{k,k',t}(i,i') = D_{k',t} \left(\frac{P_{k',t}(i')}{P_{k',t}} \right)^{-\epsilon} \left(\frac{P_{k',t}}{\tilde{P}_t} \right)^{-\eta} Z_{k,t}(i) \tag{3-11}$$

where $Z_{k,t}(i)$ is total intermediates used by firm ik. Perceived relative prices $P_{k',t}/\tilde{P}_t$ reweight the composite input bundle and feed into the sectoral Phillips curves through the relative price wedge.

Cost-minimizing input mix. Nominal marginal cost under the perceived index is

$$\tilde{MC}_{k,\tau} \equiv \frac{1}{1-\delta} \left(\frac{\delta}{1-\delta} \right)^{-\delta} \left(\frac{W_{k,t}}{\tilde{P}_t} \right)^{1-\delta} \frac{\tilde{P}_t}{A_t A_{k,t}} \tag{3-12}$$

where $\delta \in (0,1)$ is the intermediates share, $W_{k,\tau}$ is the sectoral wage, A_τ is aggregate productivity, and $A_{k,\tau}$ is sectoral productivity. Because $\tilde{P}_\tau$ enters the real wage term, any inflation misperception directly becomes a marginal cost mismeasurement.

Price setting à la Calvo. The optimal reset price $P^*_{k,t}$ solves

$$\mathbb{E}_t \left[\sum_{\tau=t}^{\infty} \alpha_k^{\tau-t} Q_{t,\tau} Y_{k,\tau}(i) \left((1-\tau_{k,\tau}) P^*_{k,t} \prod_{s=1}^{\tau-t} \Pi^{\nu_k}_{k,t+s-1} - \frac{\epsilon}{\epsilon-1} \tilde{MC}_{k,\tau} \right) \right] = 0 \tag{3-13}$$

where $\tau_{k,t}$ is a sector specific subsidy that offsets steady state markups and ν_k governs indexation. With $\nu_k > 0$, the pricing rule blends forward and backward looking components, and $(1-\alpha_k)$ scales the slope with sectoral stickiness. Distorted marginal costs $\tilde{MC}_{k,\tau}$ tilt markups and pass through toward the sectors that loom larger under salience.

3.2.4 Log-linearized equilibrium

We express the equilibrium conditions in log linear form around the stationary equilibrium. Define the aggregate output gap as $x_{c,t} \equiv c_t - c_t^n$ and the sectoral gap as $x_{c_k,t} \equiv c_{k,t} - c^n_{k,t}$, where c_t^n and $c^n_{k,t}$ are value added under flexible prices at the aggregate and sector level. The dynamics of

$$\{x_{c,t}, \pi_t, \tilde{\pi}_t, i_t, c_t^n, \tilde{r}_t^n, \{x_{c_k,t}, \pi_{k,t}\}_{k=1}^K$$

are pinned down by:

Euler equation. Optimal consumption-saving implies

$$x_{c,t} = \mathbb{E}_t[x_{c,t+1}] - (i_t - \mathbb{E}_t[\tilde{\pi}_{t+1}] - \tilde{r}_t^n) + \mathbb{E}_t\gamma_{t+1} - \gamma_t, \tag{3-14}$$

so current activity rises with expected future activity and falls with the perceived real rate gap.

Sectoral Phillips curve. Optimal price setting yields

$$\begin{aligned}\pi_{k,t} &= \frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1} + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}] \\ &+\frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k(1+\beta\nu_k)}\left\{\left[\frac{(1-\delta)\varphi}{1+\delta\varphi}+\frac{1}{\eta}\right]x_{c_k,t}\right. \\ &+\left.\left[\frac{(1-\delta)(1+\delta\varphi(1+\varphi))}{1+\delta\varphi}-\frac{1}{\eta}\right]x_{c,t}\right\},\ \forall k\in\{1,\ldots,K\}\end{aligned} \tag{3-15}$$

Indexation ($\nu_k > 0$) ties prices to their own past, adding inertia and dampening the pass-through of marginal cost movements. Heterogeneity in (α_k, ν_k) then delivers the observed mix of fast and slow moving sectors.

Inflation. Aggregate inflation equals the expenditure-weighted average of sectoral rates:

$$\pi_t = \sum_{k=1}^{K} n_k \pi_{k,t}. \tag{3-16}$$

Perceived inflation. Agents aggregate with stereotype weights rather than true shares:

$$\tilde{\pi}_t = \sum_{k=1}^{K} \tilde{n}_k \pi_{k,t}. \tag{3-17}$$

Two shortcuts generate $\tilde{n}_k$. First, sampling: households overweight items that change price. Second, representativeness: they amplify sectors whose reset frequency is above the reference rate. Frequent and visible adjustments therefore dominate perceived inflation.

Sectoral demand. Optimal demand for sectoral composites evolves as

$$x_{c_k,t} = x_{c_k,t-1} + \Delta d_{k,t} + \Delta x_{c,t} - \eta(\pi_{k,t} - \tilde{\pi}_t), \tag{3-18}$$

where $\Delta d_{k,t}$ is the change in relative demand and $\Delta x_{c,t}$ is the change in aggregate activity. A larger η makes sectoral gaps more sensitive to perceived relative price wedges.

Natural value-added output. Under flexible prices,

$$c_t^n = \frac{1}{1-\delta}(a_t + \bar{a}_t), \tag{3-19}$$

with a_t aggregate productivity and $a_{k,t}$ sectoral productivity. Greater reliance on intermediates (higher δ) amplifies the response of potential output to productivity shocks.

Natural interest rate. The perceived natural real rate is

$$\tilde{r}_t^n = \mathbb{E}_t[\Delta c_{t+1}^n] + \gamma_t - \mathbb{E}t[\gamma_{t+1}], \tag{3-20}$$

where γ_t is a persistent preference shifter. Faster expected growth in c_{t+1}^n raises $\tilde{r}_t^n$; expected easing of preferences (higher $\mathbb{E}_t[\gamma_{t+1}]$) lowers it.

Taylor rule. Policy follows a standard interest-rate rule:

$$i_t = \rho i_{t-1} + (1-\rho)(\phi_\pi \pi_t + \phi_x x_{c,t}) + \mu_t, \tag{3-21}$$

with μ_t a persistent policy shock.

Equations (3-14)–(3-18), together with the processes for c_t^n and $\tilde{r}_t^n$ in (3-19)–(3-20), form the non policy block of the multisector NK model. The only cognitive element is the use of $(\tilde{\pi}_t, \tilde{n}_k)$ in beliefs and choices. This alone aligns sectoral price dynamics with the observed comovement between experienced price changes and inflation expectations. The next section estimates the model and compares it with a fully rational benchmark and with a data driven $\tilde{n}_k$ specification.

3.3 Inference

We estimate three variants: Rational, Stereotypes, and Arbitrary. Estimation uses full information Bayesian methods. Priors for deep parameters $(\beta, \varphi, \delta, n_k, \alpha_k)$ follow Carvalho, Lee and Park (2021). Remaining parameters have diffuse priors. The posterior combines these priors with the likelihood from the state space form of Eqs. (3-14)–(3-21), evaluated with a Kalman filter and sampled with Metropolis-Hastings.

Adaptive MCMC phases. To explore the high dimensional posterior efficiently, we use an adaptive Metropolis-Hastings schedule with four sub phases of 20k, 60k, 100k, and 400k iterations. After each sub phase we discard the first half of the draws, compute the sample covariance of the retained draws, and rescale it to target an average acceptance rate near 0.23 for the next block. In all runs, the posterior mode was the highest log posterior value visited during adaptation.

Fixed MCMC phase. After adaptation we fix the tuned proposal covariance, re center at the posterior mode, and run a 1000k iteration chain to form the final posterior sample. For the Arbitrary specification, where mixing is slower, we add an extra 400k adaptive iterations before this fixed phase.

Model specifications. In the Rational model, agents aggregate with true shares n_k, so $\pi_t = \sum_k n_k \pi_{k,t}$. In the Stereotypes model, we replace n_k with salience distorted shares $\tilde{n}_k$, estimate the representativeness parameter θ, and define perceived inflation as $\tilde{\pi}_t = \sum_k \tilde{n}_k \pi_{k,t}$.

The Arbitrary model lets the data pick the weights directly. We place a logistic normal prior on $\tilde{n}$.[5] We draw latent utilities $\lambda = (\lambda_1, \ldots, \lambda_K)' \sim \mathcal{N}(0, \sigma^2 I)$ and map them via

$$\tilde{n}_k = \frac{\exp(\lambda_k)}{\sum_{j=1}^{K} \exp(\lambda_j)}, \tag{3-22}$$

which enforces $\tilde{n}_k \geq 0$ and $\sum_k \tilde{n}_k = 1$ while improving mixing by sampling in unconstrained λ space. A symmetric Dirichlet prior is an alternative (see Carvalho, Dam and Lee (2020)), but for simplicity we set $\text{Cov}(\lambda) = \sigma^2 I$ with $\sigma^2 = 2$. A single parameter then governs both dispersion and the induced dependence in $\tilde{n}$.

Convergence diagnostics. We run four independent chains per specification and compute the Gelman Rubin potential scale reduction factor $\hat{R}$ (Gelman; Rubin, 1992). Values near one indicate adequate mixing. In the baseline, most parameters satisfy $\hat{R} < 1.01$ (see Figures B.8 and B.10).

Empirical setups. We estimate on U.S. quarterly data from 1983Q1 to 2019Q4. Sectoral PCE inflation is the percent change in the BEA chain type PCE price indexes. Sectoral consumption growth comes from the corresponding chain type real PCE quantity indexes. In the baseline, the policy rate is the shadow federal funds rate of Wu and Xia (2016), aggregated to quarterly frequency by within quarter averages.

[5] Atchison and Shen (1980) introduce the logistic normal by mapping a multivariate normal through the softmax, yielding a distribution on the positive simplex with flexible covariance.

We augment the baseline with the University of Michigan 1-year median perceived inflation (quarterly, 2016Q1–2019Q4) and the 1-year median expected inflation (monthly, averaged within quarter, 1983Q1–2019Q4).

Model comparison. We compare models using the marginal data density m (reported via $\log m$ and Bayes factors) and a mean absolute error statistic, MAE(ep), that targets the correlation between four quarter accumulated sectoral inflation and 1-year ahead Michigan expectations. This serves as a posterior predictive check rather than the main selection criterion.

Table 3.1: Model fit without survey expectations

	MAE (ep)	$\log m$	BF (vs. Rational)
Rational	0.2052	−12 640.0	–
Stereotypes	0.1912	−12 641.9	−3.7
Arbitrary	0.2135	−12 638.0	+4.1

When we exclude survey expectations (Table 3.1), the Rational benchmark remains competitive. Its $\log m$ trails the Arbitrary model only slightly (BF = +4.1), which is weak evidence by standard cutoffs.[6] On MAE(ep), the Stereotypes model edges out both alternatives, which suggests that salience helps match belief-price comovement even without directly fitting belief data.

Table 3.2: Model fit with survey expectations

	MAE (ep)	$\log m$	BF (vs. Rational)
Rational	0.1331	−12 789.3	–
Stereotypes	0.1036	−12 766.6	+45.5
Arbitrary	0.1461	−12 757.0	+64.7

Including perceived and expected inflation (Table 3.2) changes the picture. The Stereotypes model decisively dominates the Rational benchmark (+45.5 log points). The Arbitrary model attains the highest likelihood but only by adding many free weights (15) and with less stable allocations. As expected, fitting belief moments materially lowers MAE(ep).

[6] Following Kass and Raftery (1995), BF $>$ 10 is very strong evidence, 6–10 strong, and 2–6 positive.

Figure 3.1: Smoothed estimates of the 1-yr expected inflation.

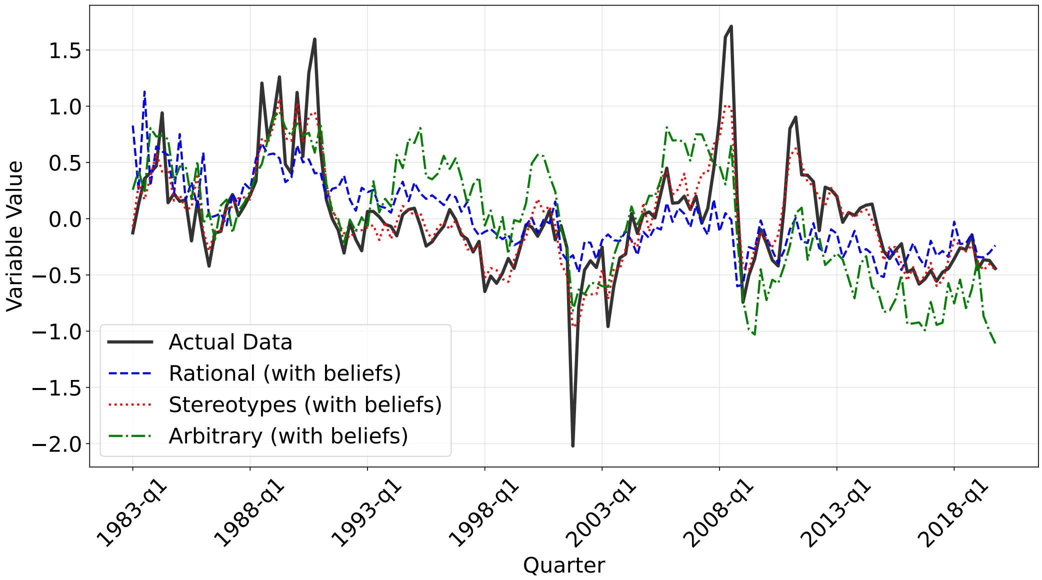


Figure 3.1 shows that, even with data driven weights, the Stereotypes model tracks the level and spikes of one year expected inflation more closely.[7] The Rational and Arbitrary models do worse, even in sample, likely because estimation placed more weight on other moments such as perceived inflation (see Figures B.12–B.13). Out of sample (Figure B.11), all models struggle when belief data are omitted from estimation. This underscores that overweighting flexible price sectors is key for matching expectation dynamics.

When we exclude perceived inflation from the observables, the Arbitrary model matches 1-year expected inflation more closely.[8] This happens because in both Stereotypes and Arbitrary models there is a tradeoff between matching perceived inflation and expected inflation. The Arbitrary model leans toward perceived inflation, while the Stereotypes model gives more weight to expected inflation. This suggests that the conditionally rational on $\tilde{P}_t$ framework is not enough to capture how perceived inflation passes through to expected inflation in the data.

Tables B.3 and B.4 show this inconsistency. When both expected and perceived inflation are included as observables, the Arbitrary model assigns most of the weight to Housing and utilities ($\tilde{n}_9 = 0.4370$) and Food services and accommodations ($\tilde{n}_{13} = 0.3619$). When only expected inflation is included, Food services and accommodations dominates with $\tilde{n}_{13} = 0.9761$. This illustrates the problem of letting the data determine the weights: they are unstable and

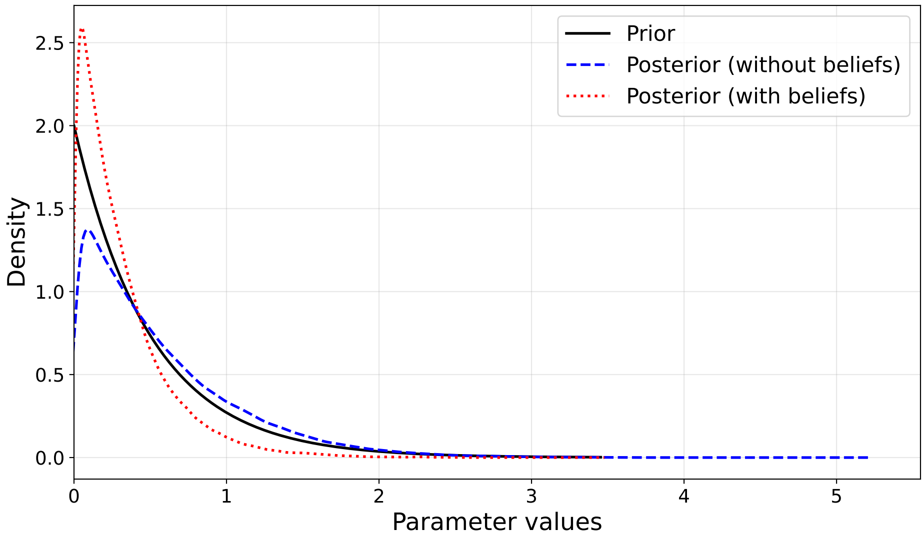
[7] The plotted expected inflation series is demeaned and seasonally adjusted.

[8] See Figure B.14. Compare Figures B.6 and B.7 to see how the Arbitrary model improves its ability to fit the key belief price correlations when perceived inflation is excluded from the data.

difficult to interpret[9]. They look like extra degrees of freedom used to match moments in the data that are unrelated to how sectoral prices affect inflation perceptions.

Empirical evidence on non-rationality. Figure 3.2 shows how the data update the prior $\theta \sim \text{Gamma}(0.5, 0.5)$.[10] Without belief data, the posterior median is 0.42, well within the prior 95 percent credible set but shifted away from zero. With belief data, the posterior tightens and the median falls to 0.22.[11] Neither posterior rejects rationality, but both show that even modest salience ($\theta \approx 0.2$–0.4) improves fit to belief dynamics.

Figure 3.2: Prior and posterior distributions of the salience coefficient θ.



Why does Stereotypes win? It shifts perceived expenditure weight toward categories with frequent and visible price changes (Tables B.2–B.3) and does so consistently across specifications. Estimates of θ are similar with and without belief data, and they match diagnostic expectations magnitudes in Bordalo et al. (2020). By contrast, the Arbitrary model pays for flexibility with unstable weights that understate salient categories such as food and gasoline, which conflicts with micro evidence.

Overall, the Stereotypes model balances parsimony, stability, and fit. It embeds a disciplined behavioral mechanism, salience through reset frequency,

[9]Even though the Food services and accommodations sector contains frequently purchased services and thus has some salience appeal, the empirical model assigns too little weight to highly salient sectors such as gasoline and food. This is at odds with micro evidence.

[10]A uniform prior would be appealing but it slows convergence in this high dimensional setting. The chosen prior puts substantial mass on rationality ($\theta \approx 0$) without ruling out empirically relevant values.

[11]See Tables B.5–B.10.

that both matches belief price comovement and improves empirical performance relative to a rational benchmark.

3.4 Welfare

This section evaluates interest rate rules using a quadratic welfare loss that penalizes two standard New Keynesian inefficiencies: (i) within-sector price dispersion from staggered pricing and (ii) aggregate slack. Two results stand out. First, targeting core inflation minimizes welfare losses. Second, tilting the rule toward non-core prices yields at most small, second order gains and never overturns the case for targeting core.

We solve the model in linear form and measure welfare with the unconditional variances of the target variables[12]. Losses are then attributed to structural shocks using variance decompositions. Structural parameters are fixed at the posterior medians from the Stereotypes estimation with belief data (Section 3.3).

Robustness checks for the baseline model, which features segmented labor markets and roundabout production, appear in Appendix B.1.7. There we derive the additional misallocation terms that disappear in the simplified environment.

Welfare losses are measured as consumption-equivalent deviations from the efficient allocation:

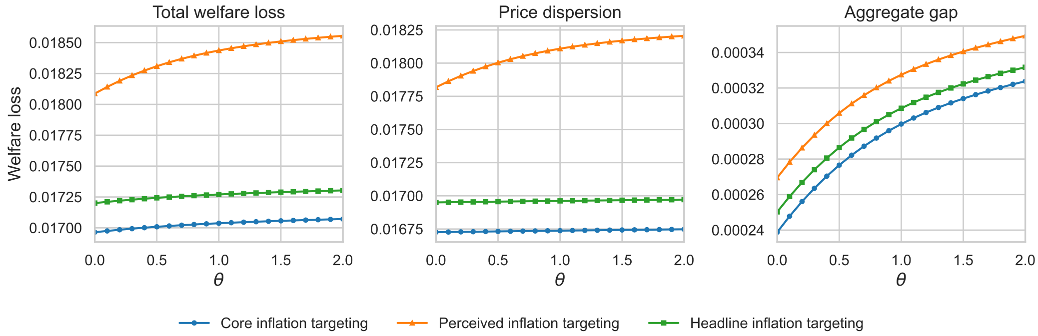
$$\mathcal{L} = \sum_{k=1}^{K} n_k \frac{\lambda_{\pi_k}}{2} \mathrm{Var}[\pi_{k,t}] + \frac{\lambda_c}{2} \mathrm{Var}[x_{c,t}],$$

where $x_{c,t}$ is the aggregate output gap and $\pi_{k,t}$ is sectoral inflation. The weights $(\lambda_c, \lambda_{\pi_k})$ are derived in Proposition B.2.

Following Dietrich (2024) and Rubbo (2023), we compare rules that change the targeted inflation index within the Taylor rule. We contrast three cases. First, headline inflation. Second, perceived inflation $\tilde{\pi}_t$, which is distorted toward flexible price sectors and is the index that households and firms use in decisions. Third, core inflation, defined here as excluding Food (5) and Gasoline (7). Results are robust to excluding other flexible categories. This definition is close to PCE ex food and energy, which is often used in policy practice.

[12] Sectoral parameters used in the welfare analysis are reported in Table B.1.

Figure 3.3: Welfare losses as a function of θ.



Notes: Price-dispersion weights scale with $\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}$, so rigid sectors dominate.

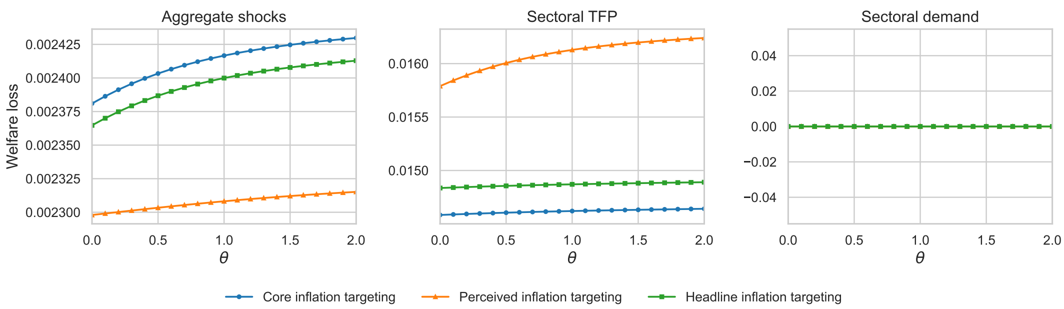
Figure 3.3 shows welfare losses against the salience parameter θ for three inertial Taylor rules:

$$i_t = \rho_i i_{t-1} + (1-\rho_i)(\phi_\pi \pi_t^* + \phi_x x_{c,t}) + \mu_t, \quad \pi_t^* \in \{\pi_t, \tilde{\pi}_t, \pi_{\text{core},t}\} \tag{3-23}$$

All curves slope upward and are concave. Higher θ raises losses but at a diminishing rate. The ranking of rules is stable over $\theta \in [0, 2]$. As θ increases, agents give more weight to flexible price sectors when making intertemporal choices, which shifts aggregate demand. Larger departures from rationality therefore lead to greater welfare losses.

Price dispersion, tied directly to the stickiness principle, dominates. Targeting perceived inflation is more costly than targeting headline or core.

Figure 3.4: Welfare losses shares across shocks: Aggregate shocks, sectoral demand shocks, and sectoral productivity shocks.

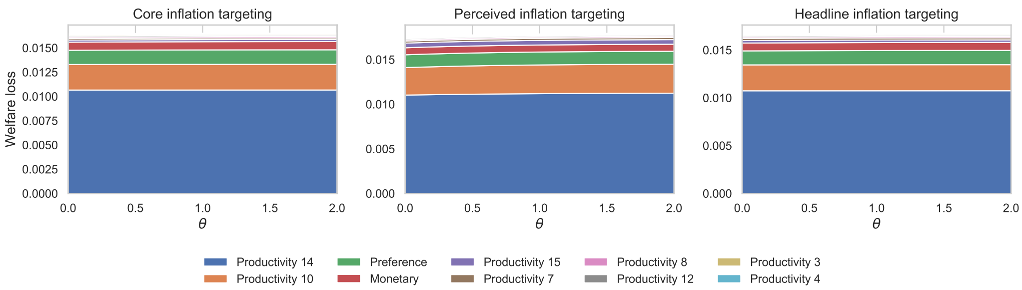


Notes: Productivity shocks dominate because they directly move marginal costs and sectoral inflation, compounding dispersion in sticky sectors. Reacting to $\tilde{\pi}_t$ can stabilize the perceived real rate via expected non-core inflation (expectations channel), but this effect is second-order. Economy-wide labor markets shut down sectoral demand shocks effects on welfare.

Figure 3.4 decomposes welfare losses by shock type. Sectoral productivity shocks are the main source of losses, with dispersion in the most rigid sectors dominating. As in the baseline model, productivity shocks in Financial Services

(14) and Health Care (10) explain more than half of the total. Preference and monetary shocks also contribute in a meaningful way.

Figure 3.5: Welfare losses shares across shocks.

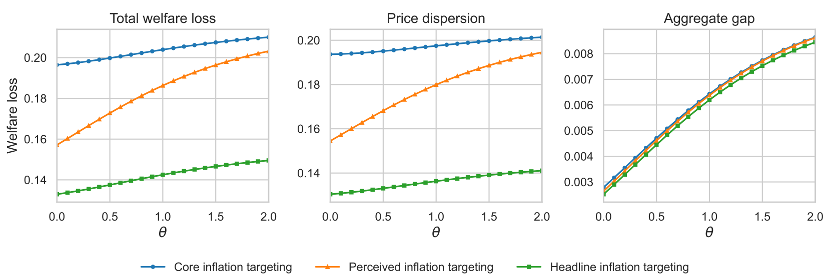


Notes: These figures display the ten shocks that generate the largest welfare losses. Health (sector 10) and Financial Services (sector 14) dominate, reflecting their high nominal rigidity combined with volatile productivity.

Relative to the baseline model with segmented labor markets and input-output linkages, the simplified environment shuts down cross-sector misallocation and the labor-wedge channel. Welfare then depends only on aggregate slack and within-sector dispersion. The ranking of shocks shifts accordingly: productivity disturbances in rigid sectors gain even more weight, while sectoral demand shocks contribute little because they do not move marginal costs or the aggregate gap when labor is pooled and intermediates are absent.

Recovering the headline inflation targeting result. Dietrich (2024) shows that monetary policy may optimally place more weight on noncore inflation, since stabilizing it reduces the volatility of expected noncore inflation and shields the perceived real interest rate from fluctuations in noncore inflation forecasts. We show that in a simplified version of our framework, which closely resembles his setup, targeting headline inflation can indeed be optimal when agents overweight flexible-price sectors in the perceived CPI.

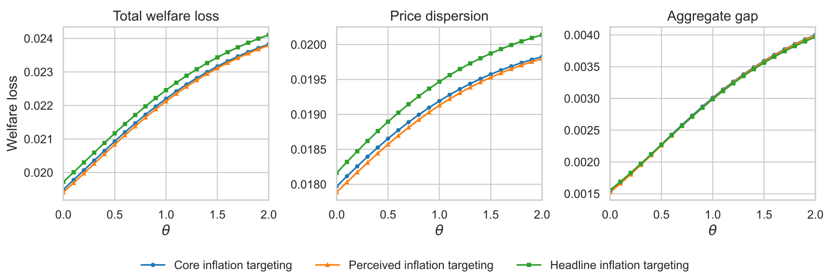
Figure 3.6: Welfare losses as a function of θ.



Notes: This is a simplified two-sector version of the model. It retains segmented labor markets and heterogeneity in price stickiness to remain directly comparable to Dietrich (2024). Other frictions, such as roundabout production and price indexation, are removed.

By reducing the economy to two sectors—a flexible-price and a rigid-price one—and abstracting from roundabout production and price indexation, we recover the optimal headline inflation targeting result[13]. This finding carries an important implication: the result in Dietrich (2024) appears highly sensitive to modeling choices. As he also notes, when the sticky sector is sufficiently rigid, the "stickiness principle" dominates the effect of asymmetric bounded rationality. In a richer and more realistic environment with multiple sectors, additional frictions, and empirically disciplined parameters, our framework instead points to core inflation targeting as the welfare-maximizing policy.

Figure 3.7: Welfare losses as a function of θ.



Notes: This is a simplified two-sector version of the model. It retains segmented labor markets and heterogeneity in price stickiness to remain directly comparable to Dietrich (2024). In this model, we keep roundabout production and price indexation.

In fact, Figure 3.7 shows that simply adding additional frictions, such as roundabout production and price indexation, is enough to partly overturn the headline inflation targeting result. In this richer setting, targeting perceived inflation can be welfare-improving, while targeting core inflation continues to outperform headline inflation targeting.

3.5 Discussion

The estimates show that a parsimonious salience filter, which maps observed reset frequencies into perceived weights with a single parameter θ, captures the belief-price comovement in U.S. data while preserving a standard NK structure. With survey beliefs included, the Stereotypes specification gains about 45 log points over the rational benchmark and reduces MAE(ep) (Tables 3.1–3.2). The posterior for θ remains modest (median around 0.2; Figure 3.2), but even small departures from rational aggregation tilt perceived inflation toward frequent changers and improve the fit.

[13]See Figure 3.6.

Mechanisms. Salience interacts with other frictions and affects welfare through three sufficient statistics: the aggregate output gap, the dispersion of sectoral gaps, and within-sector price dispersion. Perceived indices replace true ones in three places: (i) the Euler equation, where the perceived real rate raises the volatility of the aggregate gap, (ii) sectoral demand, where the wedge between sectoral and perceived inflation reallocates spending with elasticity η, increasing misallocation across sectors, and (iii) price setting, where perceived marginal costs amplify price dispersion, especially in sticky sectors. The intratemporal condition maps these misperceptions into a labor wedge with both aggregate and cross-sector components. Roundabout production ($\delta > 0$) propagates both wedges through costs.

Why core targeting survives salience. Policy experiments confirm the stickiness principle: core targeting minimizes losses across θ and robustness checks. Dispersion dominates the loss function, weighted heavily by nominal rigidity, so stabilizing sticky prices is first order (Aoki-CONDI logic). Responding to perceived inflation can reduce losses by smoothing the perceived real rate, but this gain is small relative to the larger dispersion and misallocation costs it creates.

Who drives the losses. Large, rigid service sectors dominate. Health and Financial Services combine high rigidity, meaningful expenditure shares, and volatile productivity, so their shocks account for a disproportionate share of dispersion losses. Gasoline contributes only indirectly: with $\delta > 0$, its volatile and indexed prices feed into other sectors' costs through intermediates. When $\delta = 0$, this channel disappears. This shows why targeting perceived inflation is particularly costly in economies with strong input-output linkages.

Arbitrary versus disciplined weights. Allowing free weights improves likelihood only by adding degrees of freedom. The resulting weights vary across samples and often underemphasize visibly salient categories. By contrast, the salience mapping disciplines the perceived index with one parameter, aligns with micro evidence on attention, and delivers stable emphasis across specifications.

How much non-rationality? Posterior estimates do not reject rational expectations outright, but they discipline θ to modest values. With belief data, the median diagnosticity coefficient centers near 0.2 and tightens (Figure 3.2). Even small values of θ generate sizable reweighting toward highly flexible sectors when $f_k \gg \bar{f}$, which explains why relatively low levels of representativeness suffice to match the observed comovement of beliefs and prices.

Limitations and extensions. The analysis treats attention as exogenous and uniform across decisions. Endogenizing attention or allowing context-specific distortions could refine the mapping from perceptions to outcomes. A richer input-output structure, with heterogeneous input shares or explicit upstreamness, could also change which sectors matter most. Finally, firm perceptions of input costs differ from household perceptions of consumption prices; micro evidence on producer attention would help separate these channels.

3.6 Conclusion

We develop a fifteen-sector NK model where a single parameter maps reset frequencies into perceived expenditure shares. This disciplined salience mechanism improves the joint fit to prices and beliefs while preserving standard preferences, technology, and policy.

The welfare analysis yields a clear policy conclusion. The stickiness principle survives salience: targeting core inflation consistently minimizes losses across θ and robustness checks. Responding to perceived inflation can modestly reduce aggregate-shock losses by stabilizing the perceived real rate, but this effect is second order relative to the larger dispersion and misallocation costs it amplifies. Size and rigidity place large service sectors, especially Health and Financial Services, at the center of the welfare calculus. Flexible categories like Gasoline matter mainly through propagation, and their role recedes when intermediates are absent.

For policy, the implication is direct: central banks should communicate with awareness of the public's salient price index but set instruments with sticky-price stabilization in mind. For research, natural extensions include endogenizing attention and enriching the input-output structure. Both would sharpen the microfoundations of salience and refine optimal policy design, without overturning the central insight that stabilizing the most rigid prices yields the largest welfare gains.

4
Flexible Prices and the Unanchoring of Inflation Expectations

4.1
Introduction

Sharp movements in a few prices often precede broad shifts in long-run inflation beliefs. Standard New Keynesian (NK) models hold expectations fixed, so they miss this feature of the data. We build a two-sector NK model where sectoral stickiness, segmented labor, and adaptive learning jointly determine whether expectations stay anchored.

Conceptually, the model formalizes a self-referential expectations channel: a distance-based switch between decreasing and constant gains moves the perceived long-run target, which passes through asymmetrically to sectoral inflation and feeds back into forecast errors. Heterogeneous Calvo stickiness and segmented labor make the terms of trade a persistent state that recycles shocks; distorted CPI weights magnify flexible-price surprises and make them more influential in belief formation.

We solve the model using an extended undetermined-coefficients approach that treats the evolving target as a state variable, and we calibrate it to match U.S. data on sectoral inflation, expectations, and the policy rate. Two results stand out. First, flexible prices dominate short-run forecast errors, especially when long-run expectations remain anchored. Second, large and persistent sectoral shocks can accelerate both anchoring and unanchoring by reducing subsequent gain-weighted forecast errors.

The remainder of the paper proceeds as follows. Section 4.2 lays out the model, defines the distorted weights (DW) specification, and describes the learning block and solution method. Section 4.3 discusses calibration and targets. Section 4.3.2 presents model implications, including the decomposition of forecast errors, switching episodes, and policy counterfactual. Section 4.4 concludes.

4.2
A Two-Sector New Keynesian Model with Sector-Specific Price Stickiness and Distorted Beliefs

In this section, we develop a two-sector New Keynesian model with heterogeneous price rigidities, sector-specific labor markets, and endogenous long-run inflation expectations. The framework builds on the multisector structure of Carlstrom et al. (2006) and incorporates a recurrent-learning mechanism in the spirit of Carvalho et al. (2023) (henceforth AIE). The model formalizes how sectoral heterogeneity and adaptive belief formation jointly shape the extent of expectation anchoring. To solve the resulting nonlinear system, we adapt the method of undetermined coefficients in Carlstrom et al. (2006), extending it to account for AIE's self-referential mechanism: shifts in beliefs feed into inflation dynamics, which, in turn, reinforce subsequent beliefs.

Terminology. We denote the distorted-weights specification as DW. In this framework, agents assign excessive weight to the flexible-price sector in perceived CPI, such that $\tilde{n}_1 > n_1$ (and $\tilde{n}_2 = 1 - \tilde{n}_1$).

Model overview. The economy consists of two sectors, each producing a continuum of differentiated goods. Firms set prices subject to sector-specific nominal rigidities, while households supply labor in segmented markets and allocate consumption across sectors. Monetary policy follows a Taylor rule that allows for asymmetric responses to sectoral inflation rates. A central feature of the framework is that agents form inflation expectations through an adaptive learning process, rather than under full-information rational expectations (FIRE).

Sectoral rigidities and labor immobility. Each sector features Calvo-style nominal rigidities: with probability θ_k firms keep prices fixed, while with probability $1 - \theta_k$ they reset optimally. Labor markets are fully segmented, preventing workers from reallocating across sectors. As a result, sectoral marginal costs evolve independently. The joint presence of heterogeneous reset probabilities and immobile labor generates persistent relative-price movements in response to sector-specific shocks or adjustment speeds.

Adaptive long-run beliefs and distorted expenditure shares. Agents form views about the central bank's long-run inflation target, $\bar{\pi}_t$, through a two-gain learning rule. Under normal conditions they update beliefs gradually (decreasing-gain), but when forecast errors accumulate they switch to faster revisions (constant-gain). This mechanism produces alternating periods of anchored and unanchored expectations. At the same time, agents misperceive expenditure weights in the inflation index. Because prices in the flexible sector adjust more visibly,[1] its perceived share $\tilde{n}_k$ exceeds the true share n_k, embedding a salience bias in aggregate inflation measures.

[1]See Chapter 3 for details.

Undetermined-coefficients solution approach. We solve the log-linearized equilibrium by conjecturing linear policy functions for sectoral inflation $\pi_{k,t}$, aggregate consumption c_t, and the terms of trade T_t in terms of the state vector of productivity shocks, monetary policy disturbances, and long-run beliefs $\bar{\pi}_t$. Substituting these conjectures into the Phillips curves and the Euler equation yields nonlinear restrictions on the unknown coefficients. Because adaptive learning and endogenous persistence introduce quadratic and cross-term interactions, the system cannot be solved by direct inversion. We therefore implement an iterative numerical routine to recover the coefficients.

In the next subsection, we detail the full equilibrium conditions and specify the threshold-based rule that governs updates to $\bar{\pi}_t$.

4.2.1 Agents and Learning Mechanisms

Agents depart from FIRE by treating the long-run inflation target as endogenous and subject to learning. Following AIE, they alternate between two updating regimes. When the gap between their subjective forecast and the objective forecast implied by the equilibrium law of motion is small, agents adopt a decreasing-gain rule, treating the target as stationary and gradually downweighting new information as the effective sample grows. When this gap becomes large and persistent, they switch to a constant-gain rule, which keeps responsiveness high and reflects the possibility of a regime shift in inflation. Formally, the perceived target evolves as

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1} f_{t-1}, \tag{4-1}$$

where the one-period-ahead forecast error is $f_{t-1} = \tilde{\pi}_{t-1} - \hat{E}_{t-2}[\tilde{\pi}_{t-1}]$. Under decreasing-gain learning, $k_t = k_{t-1} + 1$, implying declining responsiveness to new information as the sample expands. Under constant-gain learning, $k_t = \bar{g}^{-1}$, which preserves high responsiveness.

The switching criterion is captured by the normalized discrepancy

$$\theta_t = \frac{|\hat{E}_{t-1}[\tilde{\pi}_t] - \mathbb{E}_{t-1}[\tilde{\pi}_t]|}{\sigma_f}, \tag{4-2}$$

where $\hat{E}_{t-1}[\tilde{\pi}_t]$ denotes the agents' subjective forecast and $\mathbb{E}_{t-1}[\tilde{\pi}_t]$ the objective forecast. If $\theta_{t-1} < \bar{\theta}$, agents remain in the decreasing-gain regime, while $\theta_{t-1} > \bar{\theta}$ triggers constant gain. This rule mirrors the distance test in AIE, in which persistent deviations between subjective and objective forecasts determine whether expectations remain anchored.

These evolving, salience-distorted expectations feed back into household consumption and firms' price-setting. Combined with an asymmetric Taylor-rule response to sectoral inflation, they generate a recursive interaction between inflation dynamics and belief formation.

Firms. Each sector contains a continuum of firms producing differentiated goods with a linear technology,

$$Y_{k,t}(i) = A_{k,t}\, H_{k,t}(i),$$

where $A_{k,t}$ follows $a_{k,t} = \ln A_{k,t} = \rho_k a_{k,t-1} + \epsilon_{k,t}$. Labor markets are segmented, so wages and marginal costs evolve independently across sectors. Real marginal cost, defined relative to the salience-weighted aggregate price index $\tilde{P}_t$, is

$$\frac{MC_{k,t}}{\tilde{P}_t} = \frac{W_{k,t}\, H_{k,t}(i)}{\tilde{P}_t\, Y_{k,t}(i)}. \tag{4-3}$$

Log-linearization around the steady state gives

$$\bar{mc}_{k,t} = w_{k,t} - p_{k,t} - a_{k,t}, \tag{4-4}$$

where $w_{k,t}$ and $p_{k,t}$ denote log deviations of the sector-specific wage and price. Sectoral inflation then satisfies a New Keynesian Phillips curve,

$$\pi_{k,t} = \beta \hat{E}_t[\pi_{k,t+1}] + \xi_k \bar{mc}_{k,t}, \tag{4-5}$$

with $\xi_k = (1-\theta_k)(1-\theta_k\beta)/\theta_k$ capturing the degree of Calvo stickiness. Sectors with higher θ_k adjust prices more slowly. Combined with salience-distorted expectations, this inertia amplifies and prolongs relative-price misalignments.

Households. Households choose aggregate consumption C_t and sector-specific labor supplies $H_{1,t}, H_{2,t}$ to maximize

$$U(C_t, H_{1,t}, H_{2,t}) = \ln C_t - \frac{H_{1,t}^{1+\varphi}}{1+\varphi} - \frac{H_{2,t}^{1+\varphi}}{1+\varphi}$$

subject to their budget constraint. Aggregate consumption is a CES composite,

$$C_t = \left(n_1^{\frac{1}{\eta}} C_{1,t}^{\frac{\eta-1}{\eta}} + n_2^{\frac{1}{\eta}} C_{2,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{4-6}$$

with true shares $n_1 + n_2 = 1$. The associated price index is

$$P_t = \left(n_1 P_{1,t}^{1-\eta} + n_2 P_{2,t}^{1-\eta} \right)^{\frac{1}{1-\eta}}. \tag{4-7}$$

In equilibrium, sectoral consumption equals output, $c_{k,t} = a_{k,t} + h_{k,t}$. Optimal labor supply delivers

$$w_{k,t} - \tilde{p}_t = \varphi\,(c_{k,t} - a_{k,t}) + c_t, \tag{4-8}$$

where $\tilde{p}_t$ is the salience-weighted price index and φ governs labor-supply elasticity. Intertemporally, households satisfy the Euler equation,

$$\hat{E}_t[c_{t+1}] - c_t = i_t - \hat{E}_t[\tilde{\pi}_{t+1}], \tag{4-9}$$

and allocate consumption across sectors according to

$$c_{k,t} = c_t - \eta\,(p_{k,t} - \tilde{p}_t). \tag{4-10}$$

Thus, higher relative prices $p_{k,t} - \tilde{p}_t$ depress sectoral consumption by the elasticity η. Because $\tilde{p}_t$ and the long-run target $\bar{\pi}_t$ evolve endogenously under adaptive learning, distorted expectations feed back into both intertemporal choices and cross-sector substitution.

Monetary policy. The central bank follows a sector-aware Taylor rule, allowing for differential responses to price pressures across sectors:

$$i_t = \tau_1\, n_1\, \pi_{1,t} + \tau_2\, n_2\, \pi_{2,t} + \lambda_x\, c_t + \varphi_t, \tag{4-11}$$

where $\tau_k \geq 0$ governs the policy reaction to sector k's inflation, n_k is the sector's true expenditure share, and $\lambda_x \geq 0$ captures responsiveness to aggregate output, which equals consumption in equilibrium. The disturbance term evolves as

$$\varphi_t = \rho\varphi_{t-1} + \epsilon_t, \tag{4-12}$$

with ϵ_t an iid innovation.

4.2.2
Baseline-DW Equilibrium

We define a Baseline-DW as one in which agents, while recognizing that steady-state inflation satisfies $\pi_1 = \pi_2 = \pi = 0$, systematically misperceive the sectoral weights in aggregate inflation. In this equilibrium, the true aggregate price index is

$$p_t = n_1 p_{1,t} + n_2 p_{2,t}, \tag{4-13}$$

while agents track a distorted CPI,

$$\tilde{p}_t = \tilde{n}_1 p_{1,t} + \tilde{n}_2 p_{2,t}, \tag{4-14}$$

where $\tilde{n}_k > n_k$ for sectors with more frequent price adjustments. This distortion reflects the empirical regularity documented in Chapter 2 that high-flexibility sectors receive disproportionate attention in household inflation expectations.

Integrating household labor supply, sectoral demand, and firms' pricing rules yields the log-deviation of marginal cost in sector k:

$$\bar{mc}_{k,t} = (1+\varphi)(c_t - a_{k,t}) - (1+\varphi\eta)\, rp_{k,t}, \tag{4-15}$$

where the relative price $rp_{k,t} \equiv p_{k,t} - \tilde{p}_t$ can be expressed in terms of the terms of trade,

$$T_t = p_{1,t} - p_{2,t}, \tag{4-16}$$

as

$$rp_{1,t} = \tilde{n}_2\, T_t, \tag{4-17}$$

$$rp_{2,t} = -\tilde{n}_1\, T_t. \tag{4-18}$$

Substituting into each sector's New Keynesian Phillips curve gives

$$\pi_{k,t} = \beta\, \hat{E}_t[\pi_{k,t+1}] + \xi_k \Big[(1+\varphi)(c_t - a_{k,t}) - (1+\varphi\eta)\, rp_{k,t}\Big], \tag{4-19}$$

while the Euler equation, combined with the monetary rule, implies

$$\hat{E}_t[c_{t+1}] - c_t = \tau_1\, n_1\, \pi_{1,t} + \tau_2\, n_2\, \pi_{2,t} + \lambda_x\, c_t + \varphi_t - \hat{E}_t[\tilde{\pi}_{t+1}]. \tag{4-20}$$

We conjecture linear policy functions for the endogenous variables,

$$\begin{aligned}
\pi_{1,t} &= \alpha_1^B T_{t-1} + \gamma_1^B a_{1,t} + \gamma_2^B a_{2,t} + \gamma_{i,1}^B \varphi_t,\\
\pi_{2,t} &= \alpha_2^B T_{t-1} + \gamma_3^B a_{1,t} + \gamma_4^B a_{2,t} + \gamma_{i,2}^B \varphi_t,\\
c_t &= \alpha_3^B T_{t-1} + \gamma_5^B a_{1,t} + \gamma_6^B a_{2,t} + \gamma_{i,3}^B \varphi_t,
\end{aligned}$$

so that perceived CPI inflation aggregates as

$$\tilde{\pi}_t = \tilde{\alpha}_4^B T_{t-1} + \tilde{\gamma}_7^B a_{1,t} + \tilde{\gamma}_8^B a_{2,t} + \tilde{\gamma}_{i,4}^B \varphi_t,$$

with each "tilde" coefficient a salience-weighted average of sectoral coefficients:

$$\begin{aligned}
\tilde{\alpha}_4^B &= \tilde{n}_1 \alpha_1^B + \tilde{n}_2 \alpha_2^B,\\
\tilde{\gamma}_7^B &= \tilde{n}_1 \gamma_1^B + \tilde{n}_2 \gamma_3^B,\\
\tilde{\gamma}_8^B &= \tilde{n}_1 \gamma_2^B + \tilde{n}_2 \gamma_4^B,\\
\tilde{\gamma}_{i,4}^B &= \tilde{n}_1 \gamma_{i,1}^B + \tilde{n}_2 \gamma_{i,2}^B.
\end{aligned}$$

Finally, the terms of trade evolve according to

$$T_t = \alpha_5^B T_{t-1} + (\gamma_1^B - \gamma_3^B) a_{1,t} + (\gamma_2^B - \gamma_4^B) a_{2,t} + (\gamma_{i,1}^B - \gamma_{i,2}^B) \varphi_t,$$

where $\alpha_5^B = 1 + \alpha_1^B - \alpha_2^B$ pins down the persistence of relative-price misalignments driven by nominal rigidities and belief distortions.

4.2.3 Anchoring-DW Equilibrium

In the Anchoring-DW equilibrium, agents do not hold static distorted perceptions. Instead, they continuously update their beliefs about the long-run inflation mean. Both households and firms employ a combination of constant- and decreasing-gain learning algorithms to infer whether the inflation target is shifting, updating their estimate $\bar{\pi}_t$ when persistent forecast errors arise.

Households. A log-linear approximation of the boundedly rational household's Euler equation is

$$c_t^i = \hat{E}_t^i[c_{t+1}^i] - \Big(i_t - \hat{E}_t^i[\tilde{\pi}_{t+1}]\Big), \tag{4-21}$$

while the intertemporal budget constraint implies

$$\hat{E}_t^i\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}c_\tau^i\right] = \bar{\omega}_t^i + \hat{E}_t^i\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}y_\tau^i\right], \tag{4-22}$$

where $\bar{\omega}_t^i$ denotes the household's real wealth as a fraction of steady-state income[2]. Backward substitution delivers

$$\hat{E}_t^i[c_\tau^i] = c_t^i + \hat{E}_t^i\left[\sum_{j=t}^{\tau-1}\Big(i_j - \tilde{\pi}_{j+1}\Big)\right],$$

and ultimately

$$c_t^i = (1-\beta)\bar{\omega}_t^i + \hat{E}_t^i\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Big((1-\beta)y_\tau^i - \beta(i_\tau - \tilde{\pi}_{\tau+1})\Big)\right].$$

Aggregating across i and imposing market-clearing ($c_t = y_t$) and zero aggregate real-wealth $\int_0^1 \bar{\omega}_t^i di = 0$ gives

$$c_t = \hat{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Big((1-\beta)c_\tau - \beta(i_\tau - \tilde{\pi}_{\tau+1})\Big)\right].$$

For tractability, we assume that households learn only about the long-run mean of inflation, while their forecasting model for consumption and real interest rates is correct. Substituting the sector-aware Taylor rule and isolating the evolving target $\bar{\pi}_t$ gives

$$\begin{aligned} c_t \;=\; \hat{E}_t\Big[\textstyle\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Big((1-\beta)c_\tau - \beta\Big(\tau_1 n_1\pi_{1,\tau} + \tau_2 n_2\pi_{2,\tau} + \lambda_x c_\tau + \varphi_\tau - \tilde{\pi}_{\tau+1}\Big) \\ - \beta\Big(1 - \tau_1 n_1 - \tau_2 n_2\Big)\bar{\pi}_t\Big)\Big]. \end{aligned} \tag{4-23}$$

[2]See Preston (2003) for details.

As $\bar{\pi}_t$ evolves under persistent forecast errors, long-horizon expectations adjust, feeding back into current demand.

Firms. Firms set prices by projecting future marginal costs and the perceived inflation path:

$$\begin{aligned} \pi_{k,t} \;\; = \;\; & \hat{E}_t \Big[\textstyle\sum_{\tau=t}^{\infty} (\theta_k \beta)^{\tau-t} \Big(\xi_k \Big((1+\varphi)(c_\tau - a_{k,\tau}) - (1+\varphi\eta) rp_{k,\tau} \Big) \\ & \qquad + (1-\theta_k)\beta \Big(\pi_{k,\tau+1} - \bar{\pi}_t \Big) \Big) \Big] . \end{aligned} \tag{4-24}$$

Because $\bar{\pi}_t$ enters firms' perceived steady state, revisions to the learned target amplify sensitivity to recent forecast errors, generating richer sectoral inflation dynamics.

Equilibrium dynamics. We assume both households and firms know the correct law of motion for real variables. Households objectively forecast c_τ, while firms objectively forecast c_τ, $a_{k,\tau}$, and $rp_{k,\tau}$. Inflation is forecast according to:

$$\pi_{1,t} = \bar{\pi}_t + \alpha_1^B T_{t-1} + \gamma_1^B \rho_1 a_{1,t-1} + \gamma_2^B \rho_2 a_{2,t-1} + \gamma_{i,1}^B \rho \varphi_{t-1} + f_{1,t}, \tag{4-25}$$

$$\pi_{2,t} = \bar{\pi}_t + \alpha_2^B T_{t-1} + \gamma_3^B \rho_1 a_{1,t-1} + \gamma_4^B \rho_2 a_{2,t-1} + \gamma_{i,2}^B \rho \varphi_{t-1} + f_{2,t}, \tag{4-26}$$

$$\tilde{\pi}_t = \bar{\pi}_t + \tilde{\alpha}_4^B T_{t-1} + \tilde{\gamma}_7^B \rho_1 a_{1,t-1} + \tilde{\gamma}_8^B \rho_2 a_{2,t-1} + \tilde{\gamma}_{i,4}^B \rho \varphi_{t-1} + \tilde{f}_t, \tag{4-27}$$

where $f_{1,t}$, $f_{2,t}$, and $\tilde{f}_t$ are forecast errors based on the current estimate of $\bar{\pi}_t$.

Apart from possible shifts in the long-run target, agents' forecasts are consistent with the Baseline-DW equilibrium, whose steady state is symmetric zero inflation:

$$\pi = \pi_1 = \pi_2 = 0. \tag{4-28}$$

Beliefs about the inflation target, $\bar{\pi}_t$, therefore enter long-run forecasts, ensuring

$$\lim_{T\to\infty} \hat{E}_t[\pi_T] = \bar{\pi}_t, \tag{4-29}$$

which captures the "shifting endpoint" in agents' models. Anticipated solutions satisfy

$$\hat{E}_{t-1}[\bar{\pi}_T] = \bar{\pi}_t, \quad \text{for all } T \geq t, \tag{4-30}$$

preserving consistency between perceived changes in the target and agents' long-run forecasts.

Thus, belief dynamics nest rational expectations (if no revisions occur, $\bar{\pi}_t = 0$), while allowing for gradual unanchoring when credibility weakens.

We conjecture linear policy functions of the form

$$\pi_{1,t} = \alpha_1 T_{t-1} + \gamma_1 a_{1,t} + \gamma_2 a_{2,t} + \gamma_{i,1}\varphi_t + \gamma_{\pi,1}\bar{\pi}_t,$$
$$\pi_{2,t} = \alpha_2 T_{t-1} + \gamma_3 a_{1,t} + \gamma_4 a_{2,t} + \gamma_{i,2}\varphi_t + \gamma_{\pi,2}\bar{\pi}_t,$$
$$c_t = \alpha_3 T_{t-1} + \gamma_5 a_{1,t} + \gamma_6 a_{2,t} + \gamma_{i,3}\varphi_t + \gamma_{\pi,3}\bar{\pi}_t,$$

so that perceived CPI inflation aggregates as

$$\tilde{\pi}_t = \tilde{\alpha}_4 T_{t-1} + \tilde{\gamma}_7 a_{1,t} + \tilde{\gamma}_8 a_{2,t} + \tilde{\gamma}_{i,4}\varphi_t + \tilde{\gamma}_{\pi,4}\bar{\pi}_t,$$

with "tilde" coefficients denoting salience-weighted averages:

$$\tilde{\alpha}_4 = \tilde{n}_1\alpha_1 + \tilde{n}_2\alpha_2,$$
$$\tilde{\gamma}_7 = \tilde{n}_1\gamma_1 + \tilde{n}_2\gamma_3,$$
$$\tilde{\gamma}_8 = \tilde{n}_1\gamma_2 + \tilde{n}_2\gamma_4,$$
$$\tilde{\gamma}_{i,4} = \tilde{n}_1\gamma_{i,1} + \tilde{n}_2\gamma_{i,2},$$
$$\tilde{\gamma}_{\pi,4} = \tilde{n}_1\gamma_{\pi,1} + \tilde{n}_2\gamma_{\pi,2}.$$

Finally, the terms of trade evolve as

$$T_t = \alpha_5\, T_{t-1} + (\gamma_1 - \gamma_3)a_{1,t} + (\gamma_2 - \gamma_4)a_{2,t} + (\gamma_{i,1} - \gamma_{i,2})\varphi_t + (\gamma_{\pi,1} - \gamma_{\pi,2})\bar{\pi}_t,$$

where $\alpha_5 = 1 + \alpha_1 - \alpha_2$ determines the persistence of relative-price misalignments. The evolving target $\bar{\pi}_t$ closes the feedback loop: forecast errors alter $\bar{\pi}_t$, which in turn reshapes inflation and output dynamics.

4.3 Calibration

Strategy. We follow the multisector New Keynesian tradition and fix preference, aggregation, nominal rigidity, and policy coefficients at rounded values consistent with the literature and our sectoral definitions (see the blocks below). Perceived salience weights are constructed using the stereotypes formula with the representativeness parameter taken from Chapter 3, ensuring that the flexible and rigid distinctions in Table C.1 map into the perceived CPI basket. We then calibrate the remaining parameters, including shock variances and persistences and the learning block $(\bar{\theta}, \bar{g})$, by minimizing the distance between model-simulated and empirical moments in Table 4.1. The target set includes standard deviations, first-order autocorrelations, and selected cross-correlations over 1960Q1 to 2024Q4 (with beliefs available from 1978Q1), with emphasis on the comovement between beliefs and sectoral inflation. Estimating $(\bar{\theta}, \bar{g})$ jointly with the shocks disciplines the persistence and volatility of the perceived long-run target $\bar{\pi}_t$ without relying on ad hoc values.[3]

4.3.1
Blocks and Values

Preferences and aggregation. We set the quarterly discount factor to $\beta = 0.99$. For labor curvature we use a rounded Frisch inverse $\varphi = 2.0$. For across-sector substitution we choose $\eta = 1.0$. These sit inside the multisector NK range (values 1–2 for η are common). We calibrate the mean inflation rate $\pi^* = 3$.

Expenditure weights, nominal rigidities and salience. We fix true CPI expenditure shares at $(n_1, n_2) = (0.38, 0.62)$. For perceived (salience) weights, we set a rounded $\tilde{n}_1 = 0.68$ (and thus $\tilde{n}_2 = 0.32$). The calibration of the perceived share follows the stereotypes formula:

$$\tilde{n}_k = \frac{\frac{f_k\left(\frac{f_k}{\bar{f}}\right)^{\theta}}{\alpha_k\left(\frac{\alpha_k}{\bar{\alpha}}\right)^{\theta} + f_k\left(\frac{f_k}{\bar{f}}\right)^{\theta}}}{\sum_{k'=1}^{K} n_{k'} \frac{f_{k'}\left(\frac{f_{k'}}{\bar{f}}\right)^{\theta}}{\alpha_{k'}\left(\frac{\alpha_{k'}}{\bar{\alpha}}\right)^{\theta} + f_{k'}\left(\frac{f_{k'}}{\bar{f}}\right)^{\theta}}} n_k, \tag{4-31}$$

where $\theta \geq 0$ indexes the strength of representativeness, $\bar{f}$ denotes the average quarterly frequency of price adjustments across sectors, and $\bar{\alpha} = 1 - \bar{f}$. We set $\theta = 0.2$, in line with the estimates reported in Chapter 3. The underlying flexible and rigid price series are listed in Table C.1. Finally, we adopt heterogeneous Calvo stickiness parameters $(\theta_1, \theta_2) = (0.33, 0.74)$, consistent with the sectoral definitions: sector 1 is relatively flexible, while sector 2 is comparatively rigid.[4]

Monetary policy. We implement a sector-aware Taylor rule

$$i_t = \tau_1 n_1 \pi_{1,t} + \tau_2 n_2 \pi_{2,t} + \lambda_x c_t + \varphi_t,$$

[3] Very small switching thresholds can generate excessive regime changes and overly volatile $\bar{\pi}_t$ in tranquil periods; the moment-matching procedure mitigates this by penalizing counterfactual volatility and comovement patterns.

[4] These values are broadly consistent with the evidence reported by Nakamura and Steinsson (2008).

with an asymmetric tilt toward the sticky sector:

$$(\tau_1, \tau_2, \lambda_x) = (1.00, 2.50, 0.20).$$

This specification follows the normative principle in two-sector NK models that policy should target sticky-sector inflation (Aoki, 2001). Our asymmetry ($\tau_2 > \tau_1$) is consistent with sectoral-policy analyses and preserves determinacy for conventional parameter ranges. By contrast, a weaker reaction to the sticky sector would mechanically raise terms of trade persistence (Carlstrom et al., 2006).

Table 4.1: Target Moments: Data vs. Model

Parameter	**Data**	**Model**
		Target Moment
$\sigma_{\text{pce},1}$	0.0112	0.0105
$\sigma_{\text{pce},2}$	0.0055	0.0052
$\sigma_{\bar{\pi}}$	0.0032	0.0028
$\sigma_{\pi^{e,1y}}$	0.0162	0.0181
ρ_{π_1}	0.6032	0.4437
ρ_{π_2}	0.9446	0.8301
$\rho_{\bar{\pi}}$	0.9342	0.8109
$\rho_{\pi^{e,1y}}$	0.9551	0.8947
$\text{corr}(\pi_1, \bar{\pi})$	0.4622	0.3956
$\text{corr}(\pi_2, \bar{\pi})$	0.9009	0.7672
$\text{corr}(\pi_1, \pi^{e,1y})$	0.6240	0.6671
$\text{corr}(\pi_2, \pi^{e,1y})$	0.8204	0.8640
		Non-Target Moment
$\sigma_{\Delta c}$	1.1126	0.9908
$\rho_{\Delta c}$	-0.1168	-0.0393
σ_{ffr}	4.3047	2.4046
ρ_{ffr}	0.9789	0.7890

Note: $\sigma_{\Delta c}$ computed for 100× quarterly consumption growth; σ_{ffr} computed for annualized policy rate $400 \times i_t$. Autocorrelations are first-order.

Shock processes and learning block. The remaining parameters governing the shock processes and learning dynamics are chosen to match the business cycle statistics in Table 4.1, minimizing the relative distance between empirical and model moments. The first column of Table 4.1 lists the calibration targets: U.S. business cycle statistics between 1960Q1 and 2024Q4.

The dataset includes seasonally adjusted, annualized PCE inflation by sector (1960Q1–2024Q4, BEA), median 1-year-ahead inflation expectations ($\pi^{e,1y}$) and five- to ten-year ahead expectations ($\bar{\pi}$) from the Michigan Survey (1978Q1–2024Q4), quarterly PCE quantity growth rates Δc (1960Q1–2024Q4, BEA), and the quarterly shadow federal funds rate (1960Q1–2024Q4, Wu and Xia (2016)). We match standard deviations, autocorrelations, and cross-correlations across variables, with particular emphasis on the comovement between beliefs and sectoral inflation rates.

The calibration matches business cycle dynamics reasonably well. Table C.2 in the Appendix reports the calibrated parameter values. Our estimates for $(\bar{\theta}, \bar{g})$ are close to the median values $(0.02, 0.13)$ in Carvalho et al. (2023). The model implies a higher constant gain, indicating that households are more sensitive to forecast errors when forming views about the long-run inflation target than professional forecasters. The model reproduces standard deviations and key comovements, but it understates first-order autocorrelations and the volatility and persistence of the policy rate out of sample.

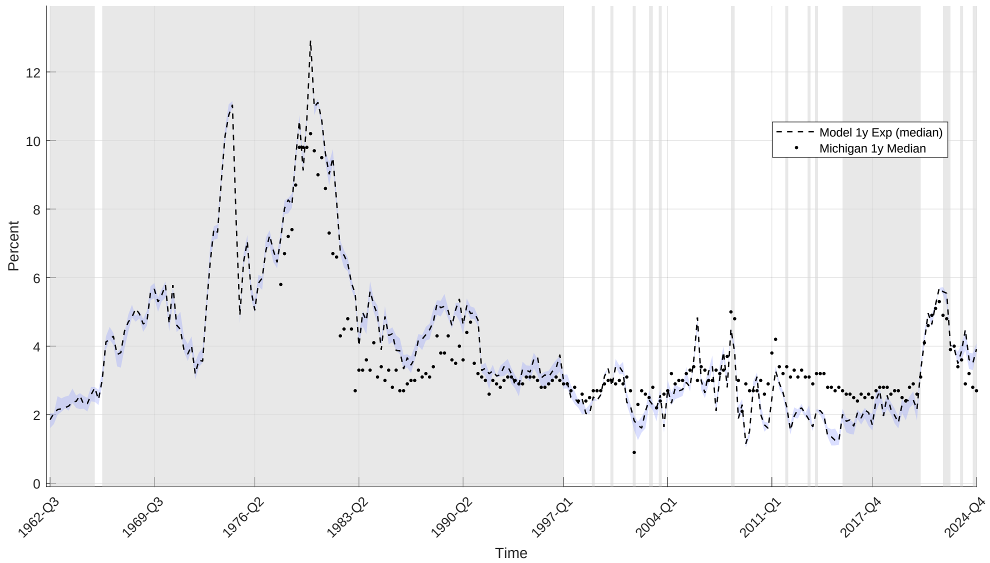
4.3.2 Model Predictions

This section computes smoothed state paths conditional on the calibrated parameters. The algorithms for the joint backward simulation Rao–Blackwellized particle smoother and the marginalized particle filters appear in Sections C.4 and C.5. Section C.3 presents the model's state-space representation.

Figure 4.1 shows the model fit for 1-year inflation forecasts[5]. We calibrate the measurement error to 10% of the data's standard deviation. We use this observable to discipline implied short-term forecasts, although there is no widely used U.S. household survey with a horizon shorter than 12 months (such as 3 or 6 months), which would be ideal since 1-q ahead forecast errors are central to our mechanism. The estimates balance model dynamics and data moments.

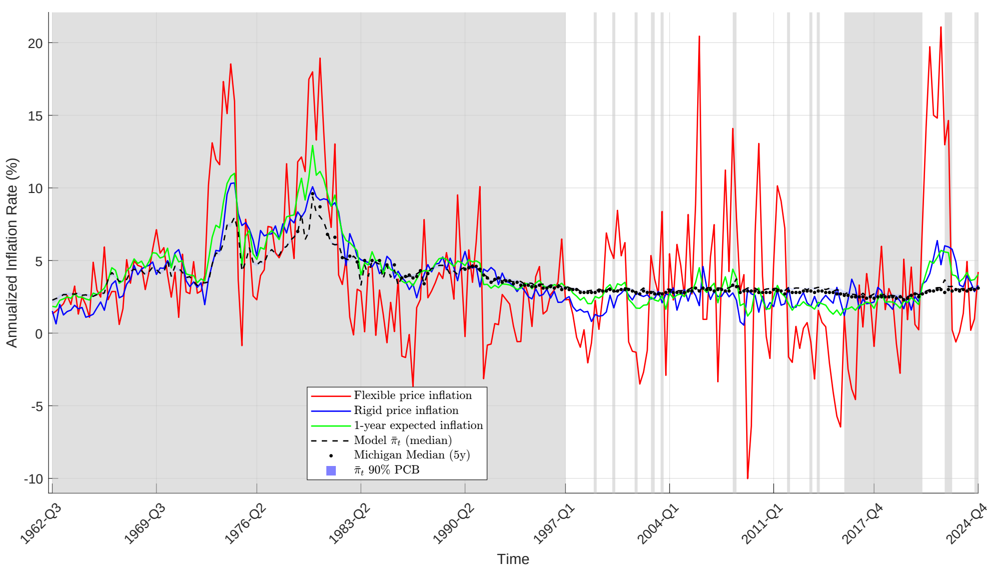
[5]Michigan's short-term inflation forecasts show a sizable upward bias relative to PCE inflation. Carvalho et al. (2023) treat this bias as noise, removing it using SPF forecasts and oil prices. Our framework instead interprets the gap as informative: perceived inflation is intentionally tilted toward flexible prices, so the Michigan bias is part of the propagation mechanism rather than a nuisance. We set the long-run target to $\pi^* = 3$, above the value estimated for professional forecasters in AIE.

Figure 4.1: Short-Term Expectations



Notes: Median 1-year expected inflation (dot) from the University of Michigan Survey of Consumers, together with the smoothed median of $\hat{E}_t[\tilde{\pi}_{t+1,t+4}]$ and its 90% pointwise credible band from the smoothing distribution, conditional on calibrated parameters. Gray shading marks unanchored regimes (constant-gain learning). Units and scaling follow the model's observation equation.

Figure 4.2: Long-Term Expectations

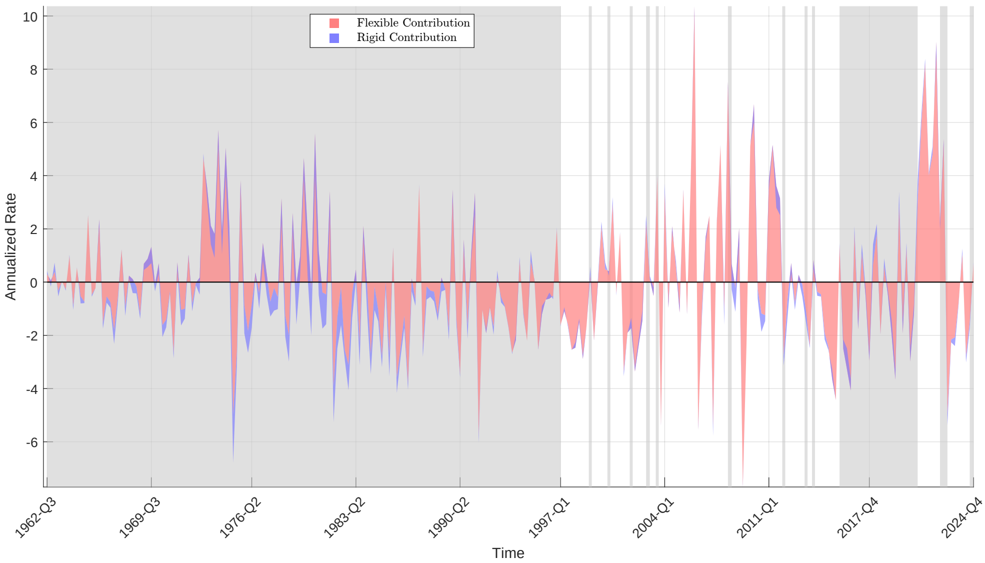


Notes: Flexible-price and rigid-price PCE inflation (annualized), the median 1-year expected inflation and the median long-run expected inflation (dot) from the University of Michigan Survey of Consumers, together with the smoothed median of $\bar{\pi}_t$ and its 90% pointwise credible band from the smoothing distribution, conditional on calibrated parameters. Gray shading marks unanchored regimes (constant-gain learning). Units and scaling follow the model's observation equation.

Figure 4.2 shows predicted long-term inflation expectations with survey data, together with implied inflation for the flexible and rigid price sectors and 1-y ahead expectations. Two points are worth noting. First, the definition of well-anchored inflation expectations is clear: even during large and volatile shocks hitting the flexible price sectors, long-run expectations stayed stable, especially between 2004 and 2012.[6] Second, large shocks sometimes appear to stabilize expectations, potentially triggering anchoring periods. This seems to be the case during the Covid-19 shock: although $\bar{\pi}_t$ was revised up after the shock, expectations remained anchored.

An additional feature of household expectations is that they switch between anchored and unanchored periods more often than professional forecasters. D'Acunto et al. (2024) show that households exhibit weaker anchoring of inflation expectations than professional forecasters, with higher and more right-skewed levels relative to target, greater cross-sectional dispersion, and a larger pass-through of short-run shocks to medium- and long-run beliefs. The latter align with our mechanisms. The model captures the mild increase in expectations up to the early 1980s, the gradual decline through the 1990s, and the stabilization in the 2000s, which persists beyond the Covid-19 shock.

Figure 4.3: Forecast error decomposition: flexible vs. rigid shares.



Notes: Stacked area plot of the smoothed forecast error contributions split into the flexible-price share and the rigid-price share. Gray shading marks unanchored regimes (constant-gain learning). The construction of the contributions and their mapping from policy coefficients are detailed in Appendix C.1.5.

In line with Figure 4.3, the 1-step perceived-CPI forecast error is mainly

[6]This period saw major oil shocks. Retail gasoline prices largely track crude oil, the largest cost component at the pump. The 2004–08 run-up reflected strong world demand, especially from China and other EMs, relative to supply and spare capacity, culminating in the 2008 spike. The late-2008 collapse followed the global financial crisis. Figure C.6 shows the flexible-price inflation decomposition and the large contribution from motor fuel to this volatility.

a flexible-price phenomenon. The flexible block loads more on all drivers, both on the slow nominal drift and on high-frequency shocks, because it is (i) more salient in perceived CPI ($\tilde{n}_1 = 0.68$) and (ii) exhibits stronger anchor pass-through ($\gamma_{\pi,1} > \gamma_{\pi,2}$). Quantitatively, the flexible contribution is

$$\begin{aligned} f_t^F &= \pi_t^F - \hat{E}_{t-1}[\pi_t^F] = \tilde{n}_1[(\gamma_{\pi,1} - 1)\bar{\pi}_t + \gamma_1\epsilon_{1,t} + \gamma_2\epsilon_{2,t} + \gamma_{i,1}\epsilon_t] \\ &= -0.49\bar{\pi}_t - 0.42\epsilon_{1,t} + 0.17\epsilon_{2,t} - 0.61\epsilon_t, \end{aligned}$$

whereas the rigid contribution is

$$\begin{aligned} f_t^R &= \pi_t^R - \hat{E}_{t-1}[\pi_t^R] = \tilde{n}_2[(\gamma_{\pi,2} - 1)\bar{\pi}_t + \gamma_3\epsilon_{1,t} + \gamma_4\epsilon_{2,t} + \gamma_{i,2}\epsilon_t] \\ &= -0.26\bar{\pi}_t + 0.01\epsilon_{1,t} - 0.07\epsilon_{2,t} - 0.18\epsilon_t. \end{aligned}$$

Two implications follow. First, during anchored windows ($\bar{\pi}_t \approx 0$), forecast errors are driven mainly by sector-1 productivity and policy innovations. The flexible share dominates because it loads heavily and negatively on $\epsilon_{1,t}$ and ϵ_t, while the rigid share is smaller and often partially offsets flexible movements through its weak exposures to $\epsilon_{1,t}$ and $\epsilon_{2,t}$. Second, when beliefs drift (unanchored), both shares move with $-(\gamma_{\pi,k} - 1)\bar{\pi}_t$, but the anchor wedge is almost twice as large in the flexible block (-0.49 vs. -0.26). Revisions to $\bar{\pi}_t$ therefore appear mainly in the flexible share and push the distance statistic past the switching threshold. Hence, even though rigid prices become more visible in unanchored episodes, flexible-price surprises remain the primary source of forecast errors that trigger and sustain anchoring dynamics.

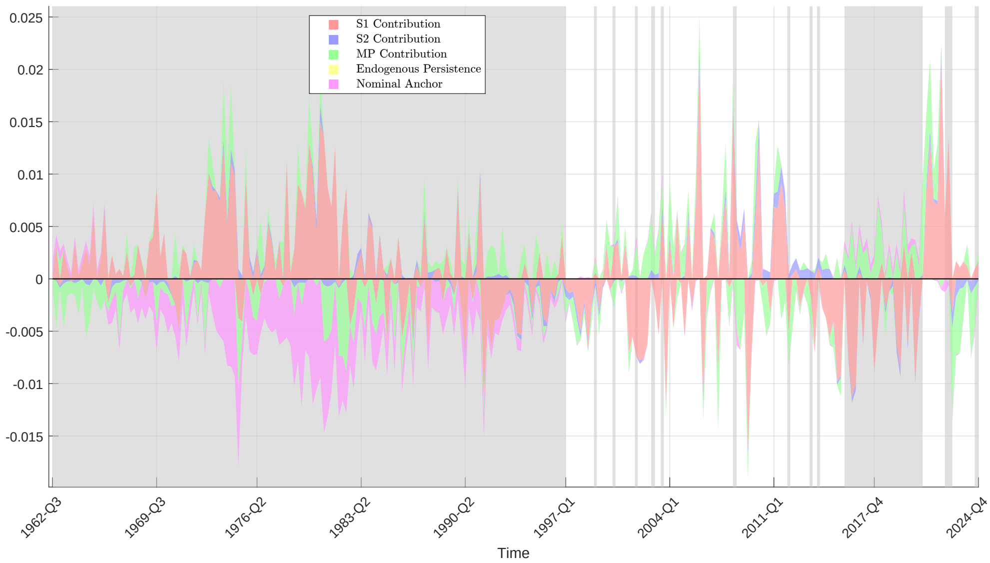
Figure 4.4 further decomposes forecast errors by sources. Interpretation to unanchoring episodes comes readily. Firstly, large productivity shocks[7] in the flexible price sector usually trigger both anchoring and unanchoring episodes, by driving most of forecast errors. Secondly, large unanchoring periods such as the one that starts in the 1960s have some self-stabilizing forecast error dynamics driven by the anchor. A negative $\bar{\pi}_t$ contribution means expectations load more than one-for-one on $\bar{\pi}_t$ relative to realized inflation ($\tilde{\gamma}_{\pi,4} < 1$), so expected inflation exceeds realized inflation.

During Volcker's 1979–83 disinflation, a sequence of large, persistent contractionary policy innovations pushed realized inflation below one-step expectations, appearing as negative monetary contributions to forecast errors. The anchor term worked in the same direction: with high expected inflation, partial contemporaneous pass-through meant expectations rose more than prices, which further lowered forecast errors when other shocks cooperated. At

[7]They potentially come from Motor fuel and Food. See Figure C.6.

the same time, flexible-price shocks often contributed positively to errors, but the Fed's aggressive reaction function overpowered them. This drove inflation from about 9% in August 1979, peaking near 11% in early 1980, to about 4% by the end of 1983. After the burst of tight policy that contributed to the deep 1981–82 recession, forecast errors became less volatile as inflation stabilized.

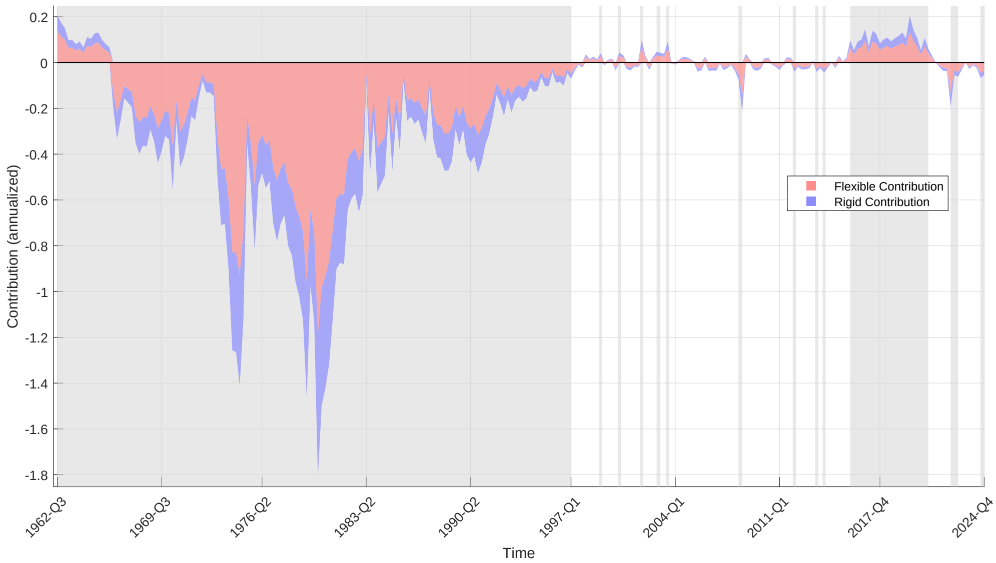
Figure 4.4: Forecast error decomposition by state: shocks, terms of trade, and anchor.



Notes: Stacked area plot of smoothed forecast error contributions by state: sectoral productivity shocks, monetary-policy shock, terms-of-trade component, and the long-run inflation target. Gray shading marks unanchored regimes (constant-gain learning). See Appendix C.1.5 for the algebra and loadings.

Overall, the results are consistent with U.S. monetary history. The constant-gain regime lasts until the late 1990s, driven by persistent negative surprises, first during the Volcker disinflation and later during the early 1990s disinflation under Greenspan after favorable shocks. Figure 4.5 shows the evolution of the switching statistic component $(\tilde{\gamma}_{\pi,4} - 1)\bar{\pi}_t$ decomposed into flexible and rigid price contributions. The flexible component is the main driver of its dynamics. After 2016, the realization of shocks revised the anchor downward persistently, similar to the experience under Greenspan in the 1990s.

Figure 4.5: Evolution of the Switching Statistic



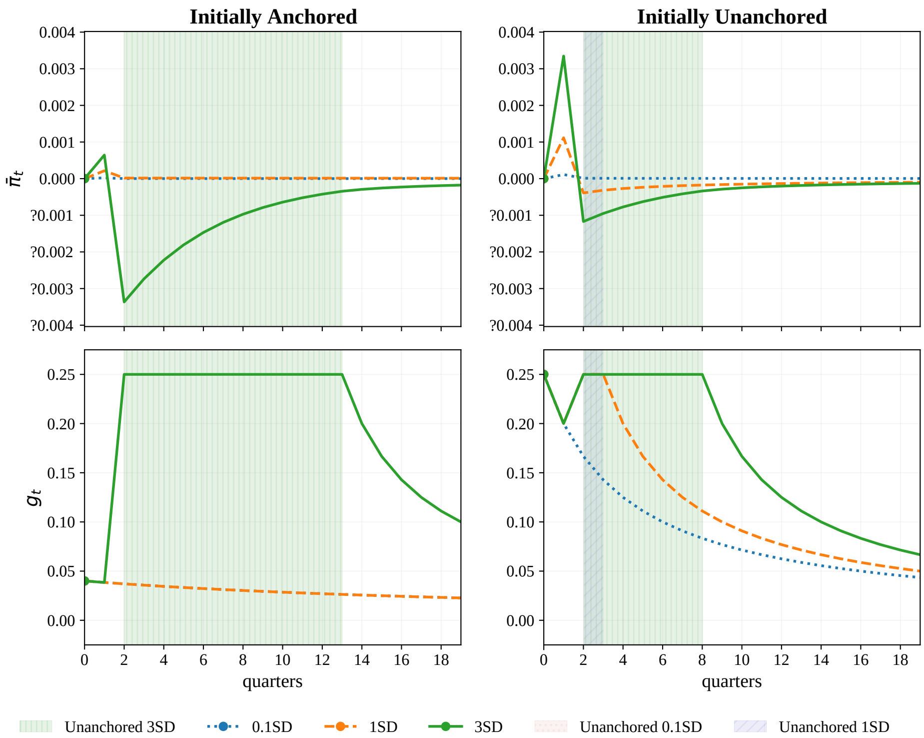
Notes: The figure shows a stacked area plot decomposing the switching statistic component $(\tilde{\gamma}_{\pi,4} - 1)\bar{\pi}_t$ into flexible $\tilde{n}_1(\gamma_{\pi,1} - 1)$ and rigid $\tilde{n}_2(\gamma_{\pi,2} - 1)$ shares. This term enters the switching statistic θ_t, which, after scaling by σ_f, triggers unanchoring when it exceeds the threshold $\bar{\theta}$. Gray shading marks unanchored regimes under constant-gain learning. All observables enter with measurement-error standard deviations equal to 10% of each series' sample standard deviation.

Learning and salience under sector-1 productivity shocks. Beliefs evolve as $\bar{\pi}_t = \bar{\pi}_{t-1} + g_t f_{t-1}$ with $g_t = 1/k_t$, switching when the distance statistic exceeds its threshold. The perceived endpoint $\bar{\pi}_t$ feeds into sectoral inflation rates with loadings $\gamma_{\pi,1} > \gamma_{\pi,2}$ and thus back into $\tilde{\pi}_t$ and f_t. This creates a loop: forecast errors move the anchor, the anchor moves inflation, and inflation shapes the next forecast error. Appendix C.1.5 shows that bounded feedback keeps $\bar{\pi}_t$ stationary under decreasing gain and AR(1)-stationary under constant gain, so beliefs gradually re-anchor after the switch provided that $\tilde{\gamma}_{\pi,4} < 1$.

Figure 4.6 shows that the duration of unanchoring episodes depends on the shock type, the shock size, and the initial gain g_t.[8] Large shocks can, counterintuitively, trigger less persistent unanchoring regimes. Forecast errors are initially larger, but because $\bar{\pi}_t$ jumps up, the next gain-weighted forecast error can be smaller, allowing θ_t to converge back to zero faster. Thus, the anchored or unanchored regimes identified by the model reflect both the shock realizations and the interaction between shock type, shock size, and the prevailing gain g_t. These factors shape forecast errors in subsequent periods and determine the path of $\bar{\pi}_t$ conditional on $\{\epsilon_{1,t}, \epsilon_{2,t}, \epsilon_t\}$.

[8]Appendix C.8.2 reports additional impulse responses.

Figure 4.6: Long-run anchor $\bar{\pi}_t$ and gain g_t after sector-1 shocks (a_1).



Notes: Columns: Initially Anchored ($k_0 = 25 \Rightarrow g_0 = 0.04$) and Initially Unanchored ($k_0 = 1/\bar{g}$). Rows: $\bar{\pi}_t$ (top) and g_t (bottom). Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

Self-referentiality and the role of salience. Self-referentiality means that the perceived long-run mean $\bar{\pi}_t$ feeds into short-run inflation with coefficients different from one, creating a wedge between subjective and objective forecasts. In our setting, the wedges are sectoral and salience-weighted: $\tilde{n}_1(\gamma_{\pi,1} - 1)\bar{\pi}_t$ in the flexible block, $\tilde{n}_2(\gamma_{\pi,2} - 1)\bar{\pi}_t$ in the rigid block, and $(\tilde{\gamma}_{\pi,4} - 1)\bar{\pi}_t$ in perceived CPI. If $\gamma_{\pi,k} = 1$, sector k generates no self-reference; if $\gamma_{\pi,k} \neq 1$, any drift in $\bar{\pi}_t$ creates a systematic forecast wedge. Because agents overweight flexible prices ($\tilde{n}_1 > n_1$), the flexible-price component dominates the contribution to perceived CPI and drives most of the forecast wedge.

Endogenous persistence via T_{t-1}, salience, and asymmetric anchor pass-through. Segmented labor markets make the terms of trade T_t an endogenous state that recycles shocks even after their primitives fade. When labor is mobile, this channel shuts down and dynamics reduce to a purely forward-looking system, so immobility is necessary for endogenous persistence in the two-sector NK benchmark.[9] Because the flexible sector is both more

[9]See Carlstrom et al. (2006).

responsive ($\gamma_{\pi,1} > \gamma_{\pi,2}$) and more salient ($\tilde{n}_1 > \tilde{n}_2$), small shocks tilt inflation toward sector 1, raise T_t, and feed back into sectoral marginal costs. This loop prolongs the effects of even transitory disturbances.

The salience wedge further amplifies persistence by overweighting the flexible sector in perceived CPI, so a given relative-price movement generates larger perceived inflation and forecast errors. At the same time, policy reacts to true CPI weights n_k, while expectations are shaped by perceived weights $\tilde{n}_k$. This misalignment allows T_{t-1} to transmit persistence into aggregates unless policy responds strongly enough at the salient margin. Finally, the anchor $\bar{\pi}_t$ adjusts gradually, so partial pass-through extends the horizon over which shocks matter.

Policy tilt, decomposition, and anchoring. Switching the Taylor rule weights from emphasizing sticky prices (Fig. 4.4) to emphasizing flexible prices (Fig. C.3) shifts the one-step forecast error decomposition toward monetary policy shocks. Because flexible price inflation is more volatile and more salient in perceived CPI, leaning on it makes the interest rate path comove more with sector 1 disturbances, so a larger share of the inflation surprise is attributed to the policy innovation component while the rigid sector share shrinks[10]. This is primarily an accounting reallocation (routing more of the same underlying surprises through the policy channel) rather than "policy creating the errors". In policy terms, the swap changes the composition and volatility of short-run dynamics but, in our calibration, leaves anchoring essentially unchanged: the switching statistic and the duration of unanchored episodes show no substantial shifts, as the gain process and the self-referential wedge $(\tilde{\gamma}_{\pi,4} - 1)\bar{\pi}_t$ are only weakly affected.

4.4 Conclusion

We extend AIE to a two-sector New Keynesian framework with sector-specific stickiness, segmented labor, a sector-aware Taylor rule, and salience-distorted perceived inflation. This structure allows belief drift in the long-run target ($\bar{\pi}_t$) to pass through asymmetrically to sectoral prices and interact with an endogenous terms of trade state. All results are conditional on our calibration of the perceived weight $\tilde{n}_1$, disciplined by the theory in Chapter 3. The smoothed estimates show that perceived CPI forecast errors are dominated by the flexible block (owing to salience, stronger anchor pass-through ($\gamma_{\pi,1} >$

[10]Under rational expectations, as in (Carlstrom et al., 2006), assigning greater weight to the sticky sector dampens endogenous persistence via T_{t-1}, suggesting a similar mechanism here.

$\gamma_{\pi,2}$), and volatile productivity shocks), while large shocks can trigger but need not prolong unanchoring under the estimated gains. The model organizes U.S. monetary history in a familiar way. A policy counterfactual that tilts the Taylor rule toward flexible price inflation reallocates the one-step forecast error decomposition toward the policy innovation channel and compresses the rigid sector share (an accounting effect) while leaving our anchoring metric and the duration of unanchored episodes essentially unchanged. Consistent with AIE, long-run expectations are endogenous, switch between decreasing and constant gain regimes, and become self-referential when credibility weakens. Our contribution is to show, in a multisector, salience-weighted, policy-aware environment, where these forces matter most.

5
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A
Appendix of Sectoral Comovement with Inflation Beliefs

A.1
Data and Measurement

A.1.1
NY Fed Survey of Consumer Expectations

Survey design. The New York Fed's *Survey of Consumer Expectations* (SCE) is a monthly internet-based rotating panel of about 1,300 U.S. household heads. Each respondent remains in the sample for up to twelve consecutive months, ensuring both fresh cross-sectional coverage and short panels for individual dynamics. The sample is quota-balanced to match the national distribution of age, gender, education, income, and region.

Inflation modules. Since its launch in June 2013 the SCE has elicited point and probabilistic forecasts for 1-year and medium-term (3-year) inflation. A long-term (5-year ahead) module was added in January 2023. The survey uses ten predefined inflation bins (from $< -10\%$ to $\geq 14\%$) and asks respondents to allocate probabilities across them. This bin-probability format reduces extreme outliers and makes respondents' uncertainty explicit.

Point forecasts. For each respondent we convert the probability mass function into a point forecast

$$\hat{\pi} = \sum_{b=1}^{10} p_b m_b,$$

where p_b is the reported probability for bin b and m_b is that bin's midpoint. Median point forecasts, computed with the survey weights supplied by the NY Fed, form our benchmark measure of inflation expectations.

Demographic splits. The rich background questionnaire allows us to stratify expectations by (i) income: <\$50k, \$50–100k, >\$100k; (ii) age: <\$40, 40–60, >\$60; (iii) education: high school or less, some college, college degree; and (iv) region: Northeast, Midwest, South, West. These cells, identical to those used for the CPI correlations in the regression analysis, contain sufficient observations in every month of 2013-2024, yielding a balanced panel for our empirical work.

A.1.2 Survey of Consumers: University of Michigan

Survey design. The *University of Michigan Survey of Consumers* has tracked U.S. household sentiment every month since 1946. Each wave interviews about 500 nationally representative households. In January 2024 the survey moved from a phone and mixed-mode design to a fully web-based questionnaire, improving response rates and reducing interviewer effects.

Inflation modules. The survey elicits two horizons of expected inflation: (i) short-term, defined as the next twelve months; (ii) long-term, defined as five to ten years ahead. Respondents first state whether they expect prices to rise, fall, or remain flat, then report a numeric percentage. Long-horizon answers are coded to the midpoint of the stated range (for example, "about 3 percent per year"). Extreme values are top- and bottom-coded at the 99.5th and 0.5th percentiles to maintain comparability over time.

Data cleaning. Missing or "don't know" answers are imputed using hot-deck draws from respondents with identical demographics and survey month. Since the early 1980s the questionnaire has also recorded expected price declines. Negative replies are retained but capped at -5 percent to limit leverage.

Demographic splits. Weighting variables supplied by Michigan make the estimates nationally representative. For subgroup analysis we follow the survey's standard partitions: (i) age: 18–34, 35–54, 55+; (ii) region: Northeast, Midwest, South, West; (iii) gender: male, female; (iv) income: bottom, middle, and top terciles; (v) education: high school or less, some college, college degree. These strata align with our CPI groupings, allowing direct comparison between sectoral price movements and belief dynamics across population segments.

A.1.3 Consumer Expenditure Surveys

Survey design. The Bureau of Labor Statistics runs two complementary instruments: the *Interview Survey* (large, infrequent purchases) and the *Diary*

Survey (small, high-frequency purchases). Public-use microdata report every transaction together with household demographics and survey weights.

Variable construction. We rely on the Diary files (2015–2024) because they record daily outlays over a two-week window, allowing precise purchase-frequency metrics. Universal Classification Codes (UCC) are mapped to CPI Entry-Level Items (ELI) using the BLS CE-CPI concordance. For each household we compute expenditure shares and purchase frequencies across categories. We then aggregate n_{ik} and f_{ik} to match the cells used in the Michigan and NY Fed surveys. Survey weights ensure that each CE cell represents its population share before we merge the CE metrics into the inflation-belief panel.

A.1.4 Consumer Price Index

Index description. The CPI measures the monthly price of a fixed Laspeyres urban consumption basket. Although the Federal Reserve targets PCE inflation, the CPI remains the public's reference point and the basis for cost-of-living adjustments.

Regional dimension. The BLS publishes CPI series for the four Census regions (Northeast, Midwest, South, West). We exploit this granularity to align sectoral price indices with respondents' geography in the Michigan and NY Fed surveys.

Extending sector coverage. Some regional CPI components are missing. Following BLS methodology, we impute four additional regional series by reweighting related published indices: (i) *Fuel oil and other fuels* from aggregate CPI codes AH21 and EHF; (ii) *Water, sewer, trash collection* from aggregate AH2 and AH21; (iii) *Household operations* from aggregate AH3 and AH31; and (iv) *Public transportation* from aggregate AT and AT1. Details and weight formulas appear in Appendix Table A.21. The final dataset covers 72 CPI sectors across four regions for 2000M1–2024M12, providing the price side of our sector-belief correlation analysis.

A.1.5 Data Limitations

Survey evidence is indispensable for gauging inflation expectations, but several frictions qualify our inferences:

(i) *Question wording.* Respondents do not always equate inflation with price changes. Heterogeneous financial literacy can add noise to answers that economists would regard as interchangeable.

(ii) *Priming.* Mentioning the latest CPI figure, or offering narrow answer ranges, anchors replies toward reasonable values, biasing both means and dispersions.

(iii) *Sampling and non-response.* Falling response rates and the shift to web surveys tilt samples toward younger, more tech-savvy households. Some older or less-connected groups are underrepresented.

(iv) *Panel conditioning.* In rotating panels such as the NY Fed's SCE, repeat respondents learn the questionnaire and gradually adjust their reporting style, potentially damping measured volatility.

(v) *Cognitive load of probability bins.* Bin-probability formats reveal subjective uncertainty but are numerically demanding. Less-numerate respondents may drop out or allocate probabilities inconsistently.

(vi) *CE microdata.* The Diary files underreport irregular or low-salience purchases, while the Interview files miss high-frequency spending. These imperfections can blur our purchase-frequency metric.[1]

We rely exclusively on the CE Diary Survey to maintain a consistent definition of purchase frequency across sectors, but the above limitations caution against overstatement. Throughout the empirical sections we interpret results with these frictions in mind and treat them as avenues for future survey improvement.

A.2
Interpreting the Negative Coefficient on Volatility

This appendix develops a simple signal-noise framework to explain why the coefficient on regional CPI volatility is negative in our panel regressions after controlling for salience margins-purchase frequency f_{ik} (exposure) and price-change frequency α_k (news arrival). The key idea is that, conditional on these salience channels, residual volatility behaves like transitory, sector-specific noise that inflates the denominator of the correlation without increasing the informative covariance with expectations.

[1] Bee, Meyer and Sullivan (2012) reviews under-reporting, zero expenditures, and other Diary Survey issues. In our context the reported transactions still proxy the frequency of recalled purchases within a sector.

Signal-noise decomposition. Let sector k's 12-month inflation in region i be

$$\pi_{ik,t} = s_k S_t + u_{ik,t}, \qquad \pi^e_{i,t} = b_i S_t + v_{i,t}, \tag{A-1}$$

where S_t is a common news component that households attend to, s_k loads the sector on that news, and $u_{ik,t}$ captures idiosyncratic sector-region fluctuations (sales cycles, weather, taxes, measurement error). Expectations load on the same S_t with slope b_i and are perturbed by $v_{i,t}$. Assume $\{S_t, u_{ik,t}, v_{i,t}\}$ are mutually uncorrelated with finite second moments.

The population correlation that underlies our Fisher-z outcome is

$$\rho_{ik} = \frac{\mathrm{Cov}(\pi_{ik,t}, \pi^e_{i,t})}{\sqrt{V(\pi_{ik,t})V(\pi^e_{i,t})}} = \frac{s_k b_i\, V(S_t)}{\sqrt{\Big(s_k^2 V(S_t) + V(u_{ik})\Big)\Big(b_i^2 V(S_t) + V(v_i)\Big)}}. \tag{A-2}$$

Holding s_k and b_i fixed (i.e., conditioning on α_k and f_{ik}), the numerator $s_k b_i V(S_t)$ is constant, while the denominator rises with $V(u_{ik})$. Hence, more idiosyncratic volatility reduces ρ_{ik}, generating a negative partial slope on volatility once salience margins are accounted for.

A.3
Additional Data on Consumer and Firm Expectations

To test whether the U.S. patterns generalize, we add central-bank surveys from Japan, Canada, and the United Kingdom. Each country provides a household and a firm survey that focus on expected inflation but differ in sampling frame and horizon.

Japan. (i) Opinion Survey on the General Public's Views and Behavior — Bank of Japan, quarterly since 1993; adults aged 20+ report perceived price changes over the past year and expected changes over short- and long-run horizons. (ii) Tankan — Bank of Japan, quarterly since 1957; roughly 10,000 enterprises describe sales, investment, profits, and (since 2014) 1-year-ahead inflation expectations.

Canada. (i) Canadian Survey of Consumer Expectations (CSCE) — Bank of Canada, quarterly since 2014; households report perceived inflation, one- and longer-horizon expectations, and views on labour markets and finance. (ii) Business Outlook Survey (BOS) — Bank of Canada, quarterly since 1999; about 100 firms report future sales, investment, input costs, output prices, and inflation expectations.

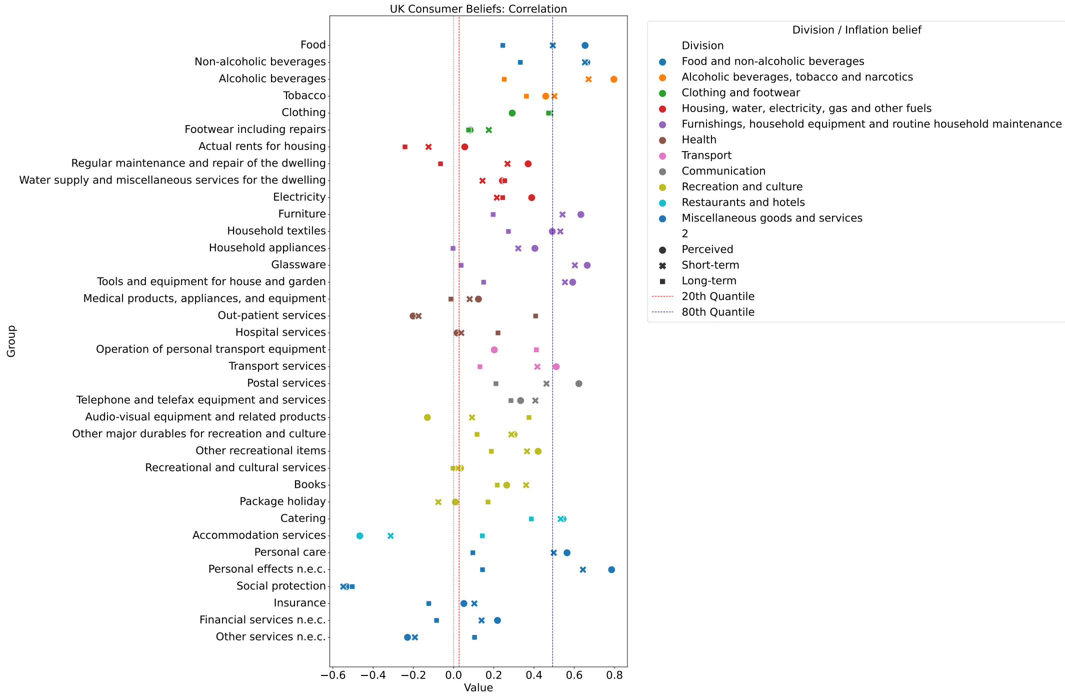
United Kingdom. (i) Inflation Attitudes Survey — Bank of England, quarterly since 2001; roughly 2,000 respondents report perceived, 1-year, and 5-year inflation expectations and views on Bank Rate decisions. (ii) Decision Maker Panel (DMP) — Bank of England, monthly since 2016; CFOs of roughly 3,000 firms report current and expected costs, prices, and inflation at 1- and 3-year horizons. We drop observations from March 2020 to June 2021 to avoid pandemic distortions.

Cross-country sectoral comovement. Appendix A.4 plots sector-belief correlations for every survey. Four categories—Food, Food Away from Home, Domestic services, and Energy goods—consistently rank in the top quintile for both consumers and firms across all three countries. This recurrence strengthens our main result: flexible, shock-sensitive prices dominate short-run inflation expectations, while stickier sectors shape longer-run beliefs.

A.4
Sectoral Comovement across Countries

Figure A.1: This figure shows sectoral covariances with perceived inflation (2016Q1–2019Q4), and 1-year and 5-year ahead inflation expectations (2000M1–2019M12) from the University of Michigan Survey of Consumers.

Figure A.2: This figure shows sectoral comovement with perceived inflation, 1-year and 5-year ahead inflation expectations (2000Q1–2019Q4) from the Bank of England Inflation Attitudes Survey.



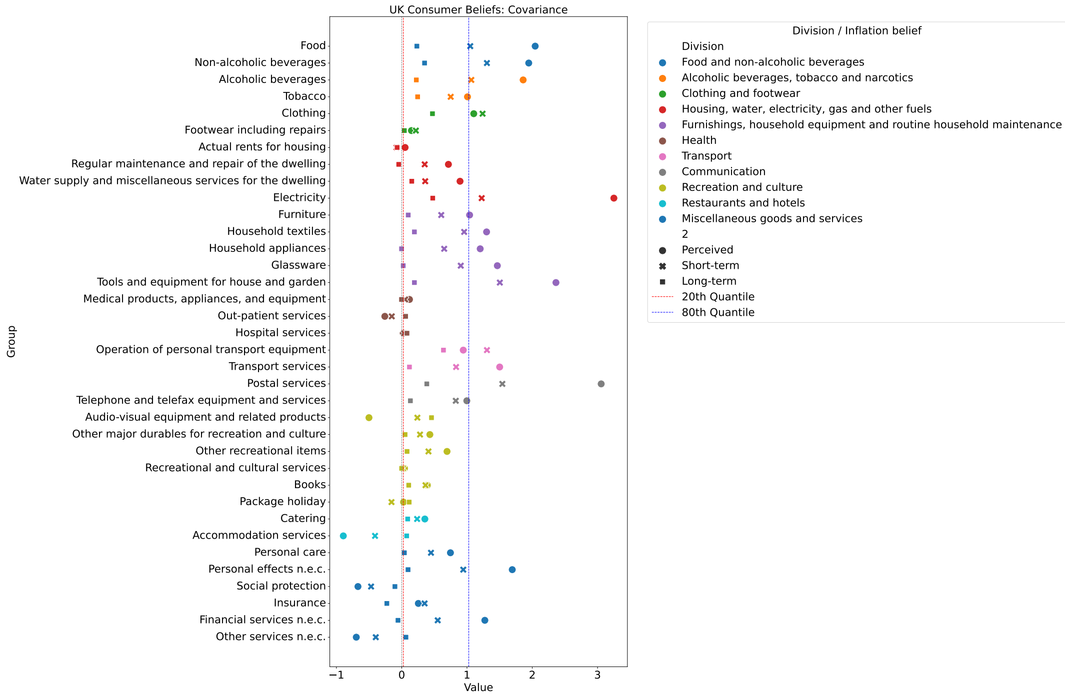


Figure A.3: This figure shows sectoral comovement with perceived inflation, 1-year, and 3-year ahead inflation expectations (2022M5–2024M7) from the Bank of England Decision Maker Panel (DMP) survey.

Figure A.4: This figure shows sectoral comovement with perceived inflation, 1-year and 5-year ahead inflation expectations (2014Q4–2019Q4) from the Bank of Canada Survey of Consumer Expectations.

Figure A.5: This figure shows sectoral comovement with 1-year and 5-year ahead inflation expectations (2022M4–2024M9) from the Bank of Canada Business Outlook Survey.

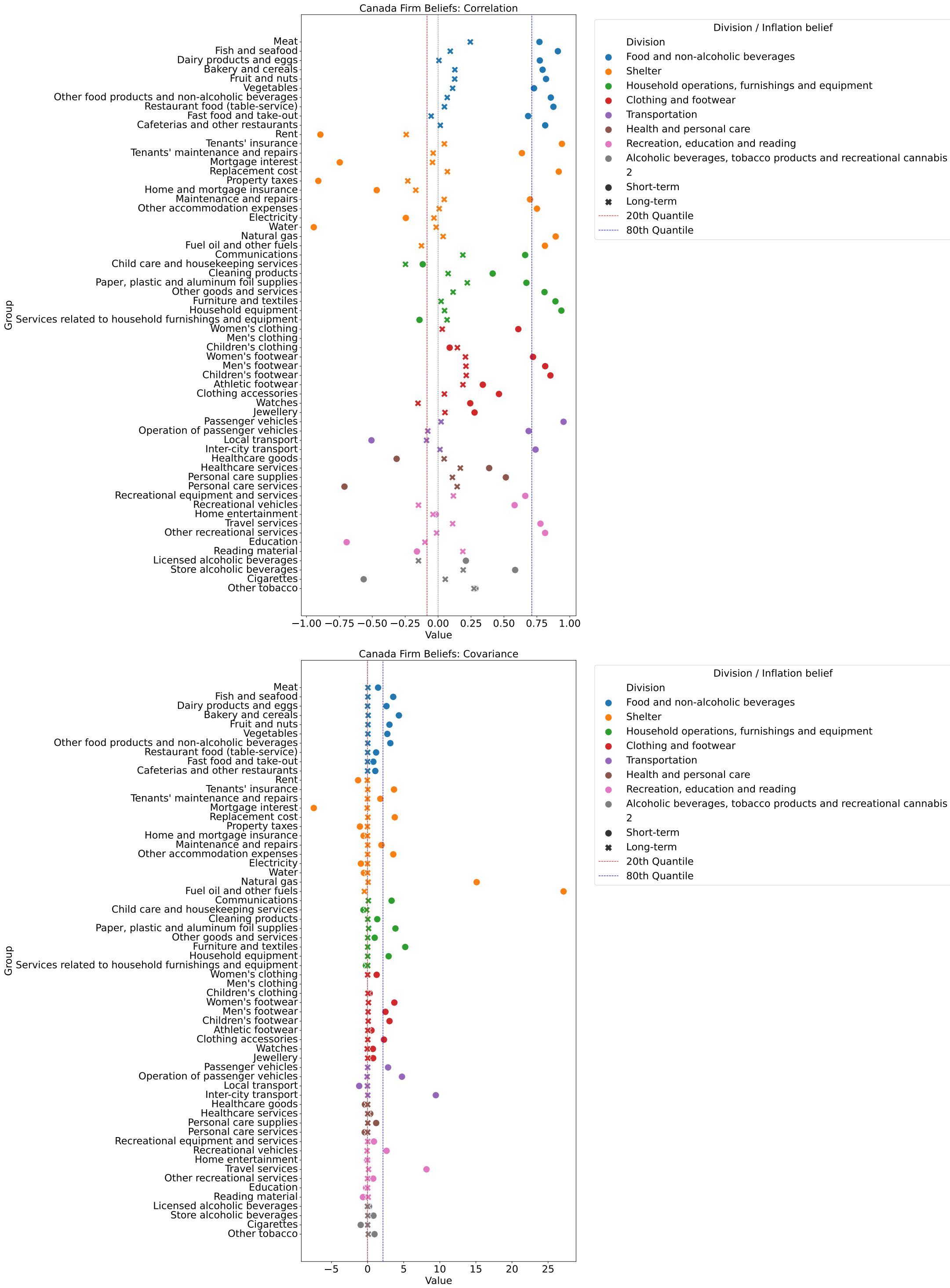
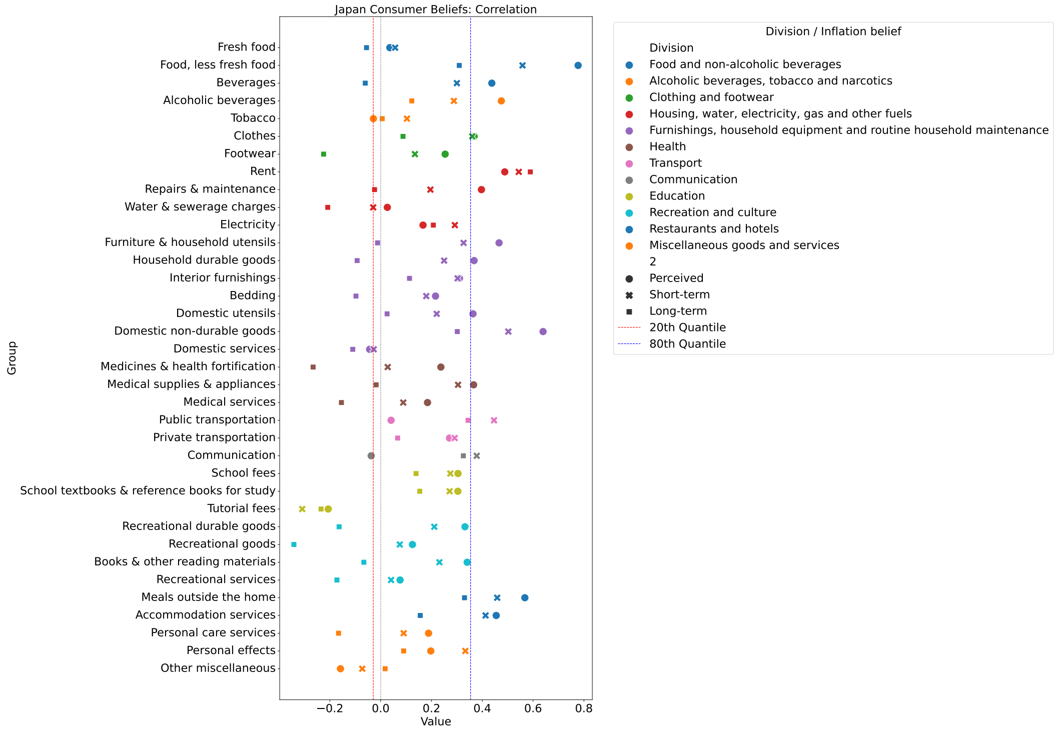


Figure A.6: This figure shows sectoral comovement with perceived inflation, 1-year and 5-year ahead inflation expectations (2006Q2–2019Q4) from the Bank of Japan Opinion Survey on the General Public's Views and Behavior.



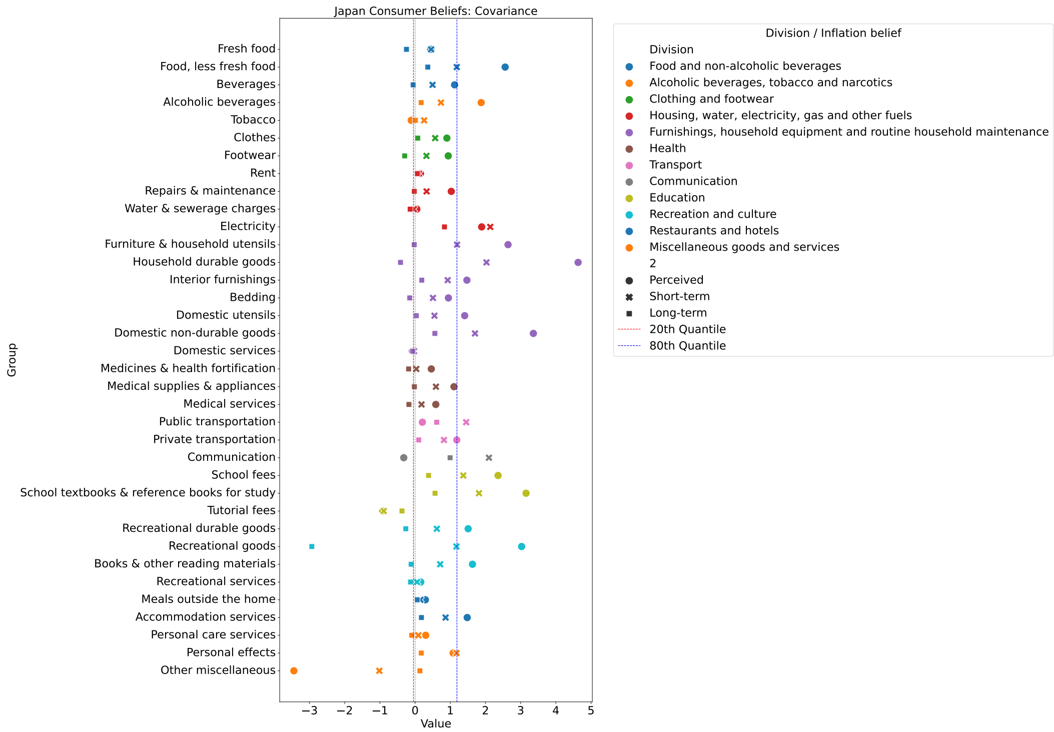
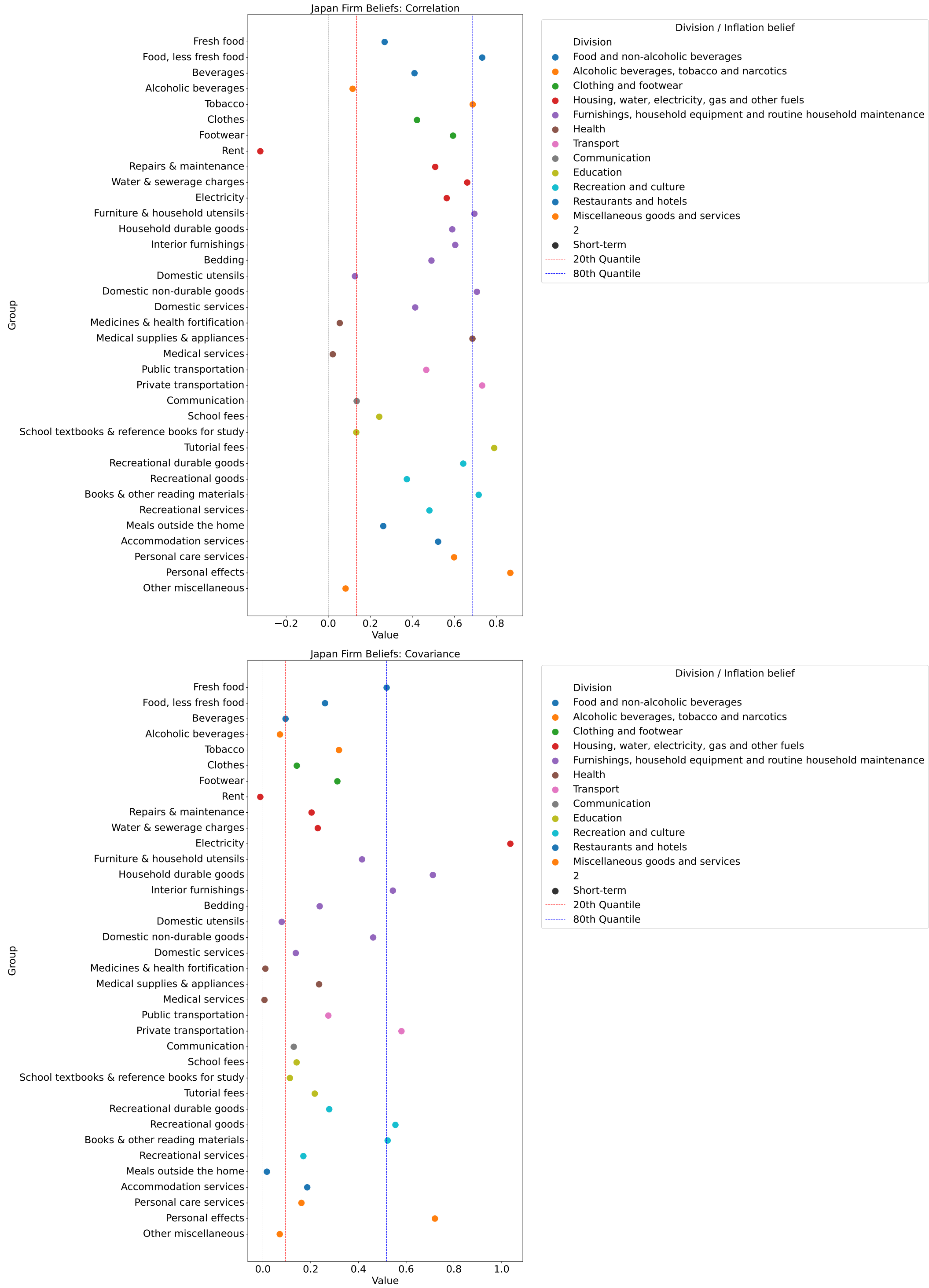


Figure A.7: This figure shows sectoral comovement with 1-year ahead inflation expectations (2014Q1–2019Q4) from the Bank of Japan Tankan survey, which collects data from enterprises, including their inflation expectations.



A.5
Additional Regressions

Table A.1: This table shows panel regressions where the dependent variable is the correlation between median 1-Yr ahead inflation expectations across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (1-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.27	-1.84**	-1.79**	-0.27	-1.85**	-1.81**
	(0.36)	(0.72)	(0.75)	(0.37)	(0.74)	(0.77)
Freq. of Price Changes	0.45***	0.48***	0.44**	0.45***	0.48***	0.44**
	(0.13)	(0.12)	(0.19)	(0.13)	(0.13)	(0.19)
Regional Volatility	-0.19**	-0.16**	-0.15	-0.19**	-0.16**	-0.15
	(0.07)	(0.06)	(0.09)	(0.08)	(0.07)	(0.09)
Purchase Frequency		0.42**	0.41**		0.43**	0.41*
		(0.18)	(0.19)		(0.19)	(0.20)
Freq. of Price Increases			-0.04			-0.04
			(0.15)			(0.15)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.07	0.09	0.09	0.13	0.15	0.15
Within R^2	0.06	0.08	0.08	0.06	0.08	0.09

Notes: Standard errors are clustered by sector.

Table A.2: This table shows panel regressions where the dependent variable is the correlation between median 3-Yr ahead inflation expectations across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (3-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.16	-1.58**	-1.57*	-0.16	-1.60**	-1.58*
	(0.35)	(0.71)	(0.74)	(0.35)	(0.71)	(0.75)
Freq. of Price Changes	0.43***	0.45***	0.44*	0.43***	0.45***	0.44*
	(0.15)	(0.14)	(0.21)	(0.15)	(0.14)	(0.21)
Regional Volatility	-0.19**	-0.17**	-0.17*	-0.19**	-0.17**	-0.17*
	(0.08)	(0.07)	(0.09)	(0.08)	(0.07)	(0.09)
Purchase Frequency		0.38*	0.38*		0.39*	0.38*
		(0.18)	(0.19)		(0.18)	(0.19)
Freq. of Price Increases			-0.02			-0.01
			(0.17)			(0.17)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.06	0.08	0.08	0.12	0.14	0.14
Within R^2	0.05	0.07	0.07	0.05	0.07	0.07

Notes: Standard errors are clustered by sector and consumer group.

Table A.3: This table shows panel regressions where the dependent variable is the correlation between median 3-Yr ahead inflation expectations across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (3-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.16	-1.58**	-1.57*	-0.16	-1.60**	-1.58*
	(0.35)	(0.73)	(0.77)	(0.36)	(0.75)	(0.79)
Freq. of Price Changes	0.43***	0.45***	0.44*	0.43***	0.45***	0.44*
	(0.14)	(0.14)	(0.21)	(0.14)	(0.14)	(0.22)
Regional Volatility	-0.19**	-0.17**	-0.17*	-0.19**	-0.17**	-0.17
	(0.07)	(0.07)	(0.09)	(0.08)	(0.07)	(0.10)
Purchase Frequency		0.38*	0.38*		0.39*	0.38*
		(0.19)	(0.19)		(0.19)	(0.20)
Freq. of Price Increases			-0.02			-0.01
			(0.17)			(0.18)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.06	0.08	0.08	0.12	0.14	0.14
Within R^2	0.05	0.07	0.07	0.05	0.07	0.07

Notes: Standard errors are clustered by sector.

Table A.4: This table shows panel regressions where the dependent variable is the correlation between median 1-Yr ahead inflation expectations across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors. CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (1-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	0.40	-1.47	-0.32	0.40	-1.47	-0.32
	(0.86)	(1.20)	(1.13)	(0.85)	(1.19)	(1.13)
Freq. of Price Changes	0.78***	0.79***	0.45*	0.78***	0.79***	0.45*
	(0.26)	(0.24)	(0.23)	(0.26)	(0.24)	(0.23)
Volatility	-0.67***	-0.69***	-0.63***	-0.67***	-0.69***	-0.63***
	(0.23)	(0.24)	(0.20)	(0.23)	(0.24)	(0.20)
Purchase Frequency		0.91***	0.70**		0.91**	0.70**
		(0.34)	(0.34)		(0.34)	(0.35)
Freq. of Price Increases			-0.63***			-0.63***
			(0.18)			(0.18)
Fixed Effects						
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Standard-Errors		Sector		Sector & Consumer Group		
Observations	5,076	5,076	5,076	5,076	5,076	5,076
R^2	0.29	0.31	0.36	0.29	0.31	0.36
Within R^2	0.09	0.12	0.18	0.09	0.12	0.18

Notes: Standard errors are clustered by sector and consumer group.

Table A.5: This table shows panel regressions where the dependent variable is the correlation between median 3-Yr ahead inflation expectations across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors. CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (3-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.34	0.22	0.68	-0.34	0.22	0.68
	(0.28)	(0.51)	(0.48)	(0.27)	(0.52)	(0.49)
Freq. of Price Changes	0.45***	0.44***	0.30***	0.45***	0.44***	0.30***
	(0.09)	(0.09)	(0.08)	(0.10)	(0.10)	(0.08)
Volatility	-0.19	-0.18	-0.16	-0.19	-0.18	-0.16
	(0.14)	(0.12)	(0.11)	(0.14)	(0.13)	(0.11)
Purchase Frequency		-0.27*	-0.36**		-0.27*	-0.36**
		(0.14)	(0.14)		(0.16)	(0.16)
Freq. of Price Increases			-0.25***			-0.25***
			(0.07)			(0.06)
Fixed Effects						
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Standard-Errors	Sector			Sector & Consumer Group		
Observations	5,076	5,076	5,076	5,076	5,076	5,076
R^2	0.17	0.17	0.19	0.17	0.17	0.19
Within R^2	0.07	0.07	0.09	0.07	0.07	0.09

Notes: Standard errors are clustered by sector and consumer group.

A.6
Robustness and Additional Specifications

Table A.6: This table shows panel regressions where the dependent variable is the correlation between median 1-Year (or 5-Year) ahead inflation expectations across income groups, sourced from the Survey of Consumers of the University of Michigan, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors. CPI data and expenditure shares are obtained from the U.S. Bureau of Labor Statistics (BLS), covering the period from January 2000 to December 2019 for CPI and reflecting average values for the years 2000 to 2019 for expenditure shares. Frequency of purchases are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Corr (1-Yr Ahead)			Corr (5-Yr Ahead)		
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.14	-0.55	-0.56	-1.56***	-1.78***	-1.84***
	(0.42)	(0.45)	(0.45)	(0.46)	(0.49)	(0.55)
Purchase Frequency	0.45	0.34	0.33	0.62*	0.56*	0.48*
	(0.30)	(0.23)	(0.23)	(0.34)	(0.30)	(0.26)
Freq. of Price Increases	-0.36*	0.07	0.07	0.28	0.52***	0.54***
	(0.18)	(0.20)	(0.20)	(0.17)	(0.18)	(0.20)
Freq. of Price Changes		0.55***	0.58***		0.31**	0.58**
		(0.14)	(0.21)		(0.15)	(0.22)
Volatility			-0.03			-0.29*
			(0.12)			(0.15)
Fixed Effects						
INCOME FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Observations	141	141	141	141	141	141
R^2	0.11	0.28	0.28	0.18	0.23	0.27
Within R^2	0.09	0.26	0.26	0.14	0.20	0.24

Notes: Standard errors are clustered by sector.

Table A.7: This table shows panel regressions where the dependent variable is the correlation between median 1-Year (or 5-Year) ahead inflation expectations across age groups, sourced from the Survey of Consumers of the University of Michigan, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors. CPI data and expenditure shares are obtained from the U.S. Bureau of Labor Statistics (BLS), covering the period from January 2000 to December 2019 for CPI and reflecting average values for the years 2000 to 2019 for expenditure shares. Frequency of purchases are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Corr (1-Yr Ahead)			Corr (5-Yr Ahead)		
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.34	-0.67	-0.68	-1.65***	-1.85***	-1.91***
	(0.42)	(0.44)	(0.45)	(0.46)	(0.48)	(0.54)
Purchase Frequency	0.61**	0.52**	0.50**	0.59*	0.53*	0.45*
	(0.29)	(0.24)	(0.23)	(0.33)	(0.29)	(0.25)
Freq. of Price Increases	-0.38**	-0.02	-0.02	0.24	0.46**	0.48**
	(0.19)	(0.21)	(0.21)	(0.17)	(0.18)	(0.21)
Freq. of Price Changes		0.46***	0.50**		0.28*	0.56**
		(0.15)	(0.22)		(0.15)	(0.22)
Volatility			-0.05			-0.29*
			(0.13)			(0.15)
Fixed Effects						
AGE FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Observations	141	141	141	141	141	141
R^2	0.14	0.25	0.25	0.15	0.20	0.24
Within R^2	0.13	0.24	0.24	0.14	0.19	0.22

Notes: Standard errors are clustered by sector.

Table A.8: This table shows panel regressions where the dependent variable is the correlation between median 1-Year (or 5-Year) ahead inflation expectations across education groups, sourced from the Survey of Consumers of the University of Michigan, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors. CPI data and expenditure shares are obtained from the U.S. Bureau of Labor Statistics (BLS), covering the period from January 2000 to December 2019 for CPI and reflecting average values for the years 2000 to 2019 for expenditure shares. Frequency of purchases are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Corr (1-Yr Ahead)			Corr (5-Yr Ahead)		
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.20	-0.60	-0.60	-1.45***	-1.70***	-1.77***
	(0.43)	(0.46)	(0.47)	(0.45)	(0.47)	(0.54)
Purchase Frequency	0.42	0.32	0.31	0.53*	0.47*	0.39*
	(0.28)	(0.24)	(0.24)	(0.31)	(0.26)	(0.23)
Freq. of Price Increases	-0.43**	-0.04	-0.04	0.22	0.46**	0.49**
	(0.19)	(0.21)	(0.21)	(0.16)	(0.17)	(0.19)
Freq. of Price Changes		0.49***	0.51**		0.31**	0.58***
		(0.14)	(0.21)		(0.15)	(0.21)
Volatility			-0.02			-0.28*
			(0.12)			(0.14)
Fixed Effects						
EDUC FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Observations	141	141	141	141	141	141
R^2	0.12	0.25	0.25	0.17	0.24	0.27
Within R^2	0.12	0.25	0.25	0.12	0.19	0.23

Notes: Standard errors are clustered by sector.

Table A.9: This table shows panel regressions where the dependent variable is the correlation between median 1-Year (or 5-Year) ahead inflation expectations across regions, sourced from the Survey of Consumers of the University of Michigan, and sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data and expenditure shares are obtained from the U.S. Bureau of Labor Statistics (BLS), covering the period from January 2000 to December 2019 for CPI and reflecting average values for the years 2000 to 2019 for expenditure shares. Frequency of purchases are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Corr (1-Yr Ahead)			Corr (5-Yr Ahead)		
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-1.30*	-1.39**	-1.34*	-1.31**	-1.33***	-1.56***
	(0.71)	(0.57)	(0.67)	(0.46)	(0.45)	(0.46)
Purchase Frequency	0.18*	0.26***	0.26***	0.30***	0.32***	0.31***
	(0.08)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)
Freq. of Price Increases	-0.58**	0.03	0.01	0.16	0.31	0.38**
	(0.26)	(0.22)	(0.24)	(0.24)	(0.18)	(0.16)
Freq. of Price Changes		0.59***	0.54*		0.14	0.37*
		(0.16)	(0.28)		(0.15)	(0.17)
Volatility			0.05			-0.21**
			(0.16)			(0.08)
Fixed Effects						
region FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Observations	68	68	68	68	68	68
R^2	0.25	0.43	0.43	0.19	0.21	0.23
Within R^2	0.23	0.42	0.42	0.17	0.18	0.21

Notes: Standard errors are clustered by sector.

Table A.10: This table shows panel regressions where the dependent variable is the Fisher-z transformed correlation between the monthly revision in the 1-Yr ahead expected inflation across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and current monthly sectoral inflation varying by region. Regressors include the frequency of price changes, median size of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (1-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	0.04	-0.24**	-0.30**	0.04	-0.24**	-0.30**
	(0.06)	(0.10)	(0.12)	(0.06)	(0.11)	(0.13)
Freq. of Price Changes	0.07**	0.07**	0.10**	0.07**	0.07**	0.10**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Regional Volatility	0.01	0.02	0.01	0.01	0.02	0.01
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Purchase Frequency		0.07***	0.09***		0.07***	0.09***
		(0.02)	(0.03)		(0.02)	(0.03)
Freq. of Price Increases			0.05			0.05
			(0.03)			(0.03)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.05	0.05	0.05	0.17	0.18	0.18
Within R^2	0.03	0.04	0.04	0.04	0.04	0.04

Notes: Standard errors are clustered by sector and consumer group.

Table A.11: This table shows panel regressions where the dependent variable is the Fisher-z transformed correlation between the monthly revision in the 1-Yr ahead expected inflation across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and current monthly sectoral inflation varying by region. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (1-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	0.04	-0.24*	-0.30**	0.04	-0.24*	-0.30**
	(0.06)	(0.12)	(0.14)	(0.06)	(0.12)	(0.14)
Freq. of Price Changes	0.07**	0.07**	0.10***	0.07**	0.07**	0.10**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Regional Volatility	0.01	0.02	0.01	0.01	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Purchase Frequency		0.07***	0.09***		0.07***	0.09***
		(0.03)	(0.03)		(0.02)	(0.03)
Freq. of Price Increases			0.05			0.05
			(0.04)			(0.04)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.05	0.05	0.05	0.17	0.18	0.18
Within R^2	0.03	0.04	0.04	0.04	0.04	0.04

Notes: Standard errors are clustered by sector.

Table A.12: This table shows panel regressions where the dependent variable is the Fisher-z transformed correlation between the monthly revision in the 3-Yr ahead expected inflation across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and current monthly sectoral inflation varying by region. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (3-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	0.01	0.02	0.03	0.01	0.03	0.03
	(0.02)	(0.05)	(0.06)	(0.03)	(0.07)	(0.07)
Freq. of Price Changes	0.02	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Regional Volatility	0.02	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Purchase Frequency		0.00	0.00		0.00	-0.01
		(0.01)	(0.02)		(0.02)	(0.02)
Freq. of Price Increases			0.00			0.00
			(0.01)			(0.01)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.02	0.02	0.02	0.14	0.14	0.14
Within R^2	0.01	0.01	0.01	0.01	0.01	0.01

Notes: Standard errors are clustered by sector and consumer group.

Table A.13: This table shows panel regressions where the dependent variable is the Fisher-z transformed correlation between the monthly revision in the 3-Yr ahead expected inflation across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and current monthly sectoral inflation varying by region. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (3-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	0.01	0.02	0.03	0.01	0.03	0.03
	(0.02)	(0.08)	(0.08)	(0.02)	(0.08)	(0.09)
Freq. of Price Changes	0.02	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Regional Volatility	0.02	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Purchase Frequency		0.00	0.00		0.00	-0.01
		(0.02)	(0.02)		(0.02)	(0.02)
Freq. of Price Increases			0.00			0.00
			(0.01)			(0.01)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.02	0.02	0.02	0.14	0.14	0.14
Within R^2	0.01	0.01	0.01	0.01	0.01	0.01

Notes: Standard errors are clustered by sector.

Table A.14: This table shows panel regressions where the dependent variable is the Fisher-z transformed correlation between the monthly revision in the 3-Yr ahead expected inflation across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and current monthly sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors. CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (1-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.02	-0.01	-0.07	-0.02	-0.01	-0.07
	(0.07)	(0.13)	(0.14)	(0.06)	(0.15)	(0.16)
Freq. of Price Changes	0.13***	0.13***	0.15***	0.13***	0.13***	0.15***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Volatility	-0.07***	-0.07***	-0.08***	-0.07***	-0.07***	-0.08***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Purchase Frequency		0.00	0.01		0.00	0.01
		(0.05)	(0.05)		(0.06)	(0.06)
Freq. of Price Increases			0.03			0.03
			(0.02)			(0.02)
Fixed Effects						
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Standard-Errors		Sector		Sector & Consumer Group		
Observations	5,076	5,076	5,076	5,076	5,076	5,076
R^2	0.03	0.03	0.03	0.03	0.03	0.03
Within R^2	0.02	0.02	0.02	0.02	0.02	0.02

Notes: Standard errors are clustered by sector and consumer group.

Table A.15: This table shows panel regressions where the dependent variable is the Fisher-z transformed correlation between the monthly revision in the 3-Yr ahead expected inflation across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and current monthly sectoral inflation. Regressors include the frequency of price changes, frequency of price increases, expenditure shares, frequency of purchases, and sectoral inflation volatility across sectors. CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (3-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.04	0.07	0.06	-0.04	0.07	0.06
	(0.04)	(0.07)	(0.07)	(0.04)	(0.11)	(0.12)
Freq. of Price Changes	0.05***	0.04***	0.05***	0.05***	0.04***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Volatility	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Purchase Frequency		-0.05**	-0.05*		-0.05	-0.05
		(0.02)	(0.02)		(0.05)	(0.05)
Freq. of Price Increases			0.01			0.01
			(0.01)			(0.01)
Fixed Effects						
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Income FE	Yes	Yes	Yes	Yes	Yes	Yes
Education FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Statistics						
Standard-Errors		Sector		Sector & Consumer Group		
Observations	5,076	5,076	5,076	5,076	5,076	5,076
R^2	0.01	0.01	0.01	0.01	0.01	0.01
Within R^2	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors are clustered by sector and consumer group.

Table A.16: This table shows panel regressions where the dependent variable is the correlation between median 1-Yr ahead inflation expectations across consumer groups, sourced from the NYFED Survey of Consumer Expectations, and sectoral inflation. Regressors include the frequency of price changes, expenditure shares, frequency of purchases, and sectoral inflation volatility and persistence across sectors and regions. Regional CPI data is sourced from the BLS (2013-06 to 2019-12), frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Dependent Variable:	Sectoral Comovement (1-Year Ahead)					
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Expenditure Share	-0.27	-1.84**	-1.83**	-0.27	-1.85**	-1.84**
	(0.36)	(0.71)	(0.67)	(0.36)	(0.71)	(0.67)
Freq. of Price Changes	0.45***	0.48***	0.47***	0.45***	0.48***	0.47***
	(0.13)	(0.13)	(0.11)	(0.14)	(0.13)	(0.11)
Regional Volatility	-0.19**	-0.16**	-0.16**	-0.19**	-0.16**	-0.16**
	(0.08)	(0.07)	(0.06)	(0.08)	(0.07)	(0.06)
Purchase Frequency		0.42**	0.42**		0.43**	0.43**
		(0.18)	(0.18)		(0.18)	(0.18)
Regional Persistence (Abs)			-0.02			-0.02
			(0.15)			(0.15)
Fixed Effects						
Age FE	Yes	Yes	Yes			
Income FE	Yes	Yes	Yes			
Education FE	Yes	Yes	Yes			
Region FE	Yes	Yes	Yes			
Consumer Group FE				Yes	Yes	Yes
Statistics						
Observations	1,836	1,836	1,836	1,836	1,836	1,836
R^2	0.07	0.09	0.09	0.13	0.15	0.15
Within R^2	0.06	0.08	0.08	0.06	0.08	0.08

Notes: Standard errors are clustered by sector and consumer group.

A.7 Professional Forecasters

Table A.17: Sectoral Correlation Regressions: 1-Y Ahead Inflation Expectations

Dependent Variable:	Correlation with 1-Year Ahead Inflation Expectations					
Survey	Michigan			SPF		
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Constant	0.37***	0.37***	0.37***	0.25***	0.25***	0.25***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
CPI Weight	0.04	0.04	0.05	0.07**	0.07**	0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
Freq. of Price Changes	0.09**	0.09*	0.04	-0.07	-0.07	-0.08
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)
Inflation Volatility	-0.07	-0.07	-0.06	0.02	0.02	0.02
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
Purchase Frequency (sq.)		0.02	0.02		-0.01	-0.01
		(0.03)	(0.03)		(0.03)	(0.03)
Freq. of Price Increases			-0.06			-0.01
			(0.04)			(0.05)
Statistics						
Observations	47	47	47	47	47	47
R^2	0.12	0.13	0.17	0.18	0.18	0.18
Adj. R^2	0.06	0.04	0.06	0.12	0.10	0.08

Notes: Standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. All regressors are standardized (demeaned and scaled to unit variance).

Table A.18: Sectoral Correlation Regressions: 5-Year Ahead Inflation Expectations

Dependent Variable:	Correlation with 5-Y Ahead Inflation Expectations					
Survey		Michigan			SPF	
Model	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variables						
Constant	0.29***	0.29***	0.29***	0.19***	0.19***	0.19***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
CPI Weight	0.05	0.05	0.06	0.06*	0.07*	0.07*
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Freq. of Price Changes	-0.05	-0.05	-0.07	-0.12**	-0.12**	-0.11*
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)
Inflation Volatility	-0.02	-0.02	-0.02	0.05	0.05	0.05
	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Purchase Frequency (sq.)		-0.02	-0.02		-0.02	-0.02
		(0.03)	(0.03)		(0.04)	(0.04)
Freq. of Price Increases			-0.02			0.01
			(0.05)			(0.05)
Statistics						
Observations	47	47	47	47	47	47
R^2	0.16	0.17	0.18	0.22	0.23	0.23
Adj. R^2	0.10	0.09	0.08	0.16	0.15	0.13

Notes: Standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. All regressors are standardized (demeaned and scaled to unit variance).

A.8 Sector Aggregation

Table A.19: First entry level item (ELI) aggregation

Code	Sector name	Subcategories
AA	Men's apparel	AA01, AA02, AA03, AA04, AA09
AB	Boys' apparel	AB

Continued on next page

Code	Sector name	Subcategories
AC	Women's apparel	AC01, AC02, AC03, AC04, AC09
AD	Girls' apparel	AD
AE	Footwear	AE01, AE02, AE03
AF	Infants' and toddlers' apparel	AF
AG	Jewelry and watches	AG01, AG02
EA	Educational books and supplies	EA
EB	Tuition, other school fees, and childcare	EB01, EB02, EB03, EB04, EB09
EC	Postage and delivery services	EC01, EC02
ED	Telephone services	ED03, ED04
EE	Information technology, hardware and services	EE01, EE02, EE03, EE04, EE09
FA	Cereals and cereal products	FA01, FA02, FA03
FB	Bakery products	FB01, FB02, FB03, FB04
FC	Beef and veal	FC01, FC02, FC03, FC04
FD	Pork	FD01, FD02, FD03, FD04
FE	Other meats	FE
FF	Poultry	FF01, FF02
FG	Fish and seafood	FG01, FG02
FH	Eggs	FH
FJ	Dairy and related products	FJ01, FJ02, FJ03, FJ04
FK	Fresh fruits	FK01, FK02, FK03, FK04
FL	Fresh vegetables	FL01, FL02, FL03, FL04
FM	Processed fruits and vegetables	FM01, FM02, FM03

Continued on next page

Code	Sector name	Subcategories
FN	Juices and nonalcoholic drinks	FN01, FN02, FN03
FP	Beverage materials including coffee and tea	FP01, FP02
FR	Sugar and sweets	FR01, FR02, FR03
FS	Fats and oils	FS01, FS02, FS03
FT	Other foods	FT01, FT02, FT03, FT04, FT05, FT06
FV	Food away from home	FV01, FV02, FV03, FV04, FV05
FW	Alcoholic beverages at home	FW01, FW02, FW03
FX	Alcoholic beverages away from home	FX
HA	Rent of primary residence	HA
HB	Lodging away from home	HB01, HB02
HC	Owners' equivalent rent of residences	HC01, HC09
HD	Tenants' and household insurance	HD
HE	Fuel oil and other fuels	HE01, HE02
HF	Energy services	HF01, HF02
HG	Water and sewer and trash collection services	HG01, HG02
HH	Window and floor coverings and other linens	HH01, HH02, HH03
HJ	Furniture and bedding	HJ01, HJ02, HJ03, HJ09
HK	Appliances	HK01, HK02, HK09
HL	Other household equipment and furnishings	HL01, HL02, HL03, HL04

Continued on next page

Code	Sector name	Subcategories
HM	Tools, hardware, outdoor equipment and supplies	HM01, HM02, HM09
HN	Housekeeping supplies	HN01, HN02, HN03
HP	Household operations	HP01, HP02, HP03, HP04, HP09
MC	Professional services	MC01, MC02, MC03, MC04
MD	Hospital and related services	MD01, MD02, MD03
ME	Health insurance	ME
MF	Medicinal drugs	MF01, MF02
MG	Medical equipment and supplies	MG
GA	Tobacco and smoking products	GA01, GA02, GA09
GB	Personal care products	GB01, GB02, GB09
GC	Personal care services	GC
GD	Miscellaneous personal services	GD01, GD02, GD03, GD04, GD05, GD09
GE	Miscellaneous personal goods	GE
RA	Video and audio	RA01, RA02, RA03, RA04, RA05, RA06, RA09
RB	Pets, pet products and services	RB01, RB02
RC	Sporting goods	RC01, RC02, RC09
RD	Photography	RD01, RD02, RD09
RE	Other recreational goods	RE01, RE02, RE03, RE09
RF	Other recreation services	RF01, RF02, RF03, RF09
RG	Recreational reading materials	RG01, RG02, RG09
TA	New and used motor vehicles	TA01, TA02, TA03, TA04, TA09
TB	Motor fuel	TB01, TB02

Continued on next page

Code	Sector name	Subcategories
TC	Motor vehicle parts and equipment	TC01, TC02
TD	Motor vehicle maintenance and repair	TD01, TD02, TD03, TD09
TE	Motor vehicle insurance	TE
TF	Motor vehicle fees	TF01, TF03, TF09
TG	Public transportation	TG01, TG02, TG03, TG09

Table A.20: Second sector aggregation

Sector name	Subcategories
1 - Men's and Boy's apparel	AA, AB
2 - Women's and girls' apparel	AC, AD
3 - Children's and infants' apparel	AF
4 - Other clothing materials and footwear	AE
5 - Jewelry and watches	AG
6 - Education	EA, EB, EC, EE
7 - Telephone services	ED
8 - Cereals and cereal products	FA
9 - Bakery products	FB
10 - Beef	FC
11 - Pork	FD
12 - Other meats	FE
13 - Poultry	FF

Continued on next page

Sector name	Subcategories
14 - Fish and seafood	FG
15 - Eggs	FH
16 - Dairy products	FJ
17 - Fresh fruits	FK
18 - Fresh vegetables	FL
19 - Processed fruits and vegetables	FM
20 - Nonalcoholic beverages	FN, FP
21 - Sugar and sweets	FR
22 - Fats and oils	FS
23 - Other foods	FT
24 - Food away from home	FV
25 - Alcoholic beverages	FW, FX
26 - Shelter	HA, HB, HD
27 - Fuel oil and other fuels	HE
28 - Energy services	HF
29 - Water and other public services	HG
30 - Household operations	HP
31 - Housekeeping supplies	HN
32 - Furnishings and durable household equipment	HH, HJ, HK, HL, HM
33 - Medical services	MD
34 - Medical care commodities	MF, MG
35 - Tobacco and smoking products	GA
36 - Personal care products and services	GB, GC

Continued on next page

Sector name	Subcategories
37 - Miscellaneous	GD, GE
38 - Video and audio	RA
39 - Pets, toys, hobbies, and playground equipment	RB, RC, RD, RE
40 - Fees and admissions	RF
41 - Reading	RG
42 - New and used motor vehicles	TA
43 - Motor fuel	TB
44 - Motor vehicle maintenance and repair	TD
45 - Motor vehicle fees	TF
46 - Vehicle insurance	TE
47 - Public transportation	TG

Table A.21: Third sector aggregation

Sector name	CPI Code	Subcategory
Apparel	AA	1 - Men's and Boy's apparel
		2 - Women's and girls' apparel
		4 - Other clothing materials and footwear
		3 - Children's and infants' apparel
		5 - Jewelry and watches
Education and communication	AE	6 - Education
		7 - Telephone services
Food at home	AF11	8 - Cereals and cereal products
		9 - Bakery products
		10 - Beef

Continued on the next page...

Sector name	CPI Code	Subcategory
		11 - Pork
		12 - Other meats
		13 - Poultry
		14 - Fish and seafood
		15 - Eggs
		16 - Dairy products
		17 - Fresh fruits
		18 - Fresh vegetables
		19 - Processed fruits and vegetables
		20 - Nonalcoholic beverages
		21 - Sugar and sweets
		22 - Fats and oils
		23 - Other foods
		25 - Alcoholic beverages
Other goods and services	AG	37 - Miscellaneous
		35 - Tobacco and smoking products
		36 - Personal care products and services
Shelter	AH1	26 - Shelter
Fuel oil and other fuels	AH21,EHF	27 - Fuel oil and other fuels
Energy services	EHF	28 - Energy services
Water and sewer and trash collection services	AH2,AH21	29 - Water and other public services
Household furnishings and supplies	AH31	31 - Housekeeping supplies
		32 - Furnishings and durable household equipment
Household operations	AH3, AH31	30 - Household operations
Medical care commodities	AM1	34 - Medical care commodities
Medical care services	AM2	33 - Medical services

Continued on the next page...

Sector name	CPI Code	Subcategory
Recreation	AR	38 - Video and audio
		39 - Pets, toys, hobbies, and playground equipment
		40 - Fees and admissions
		41 - Reading
Public transportation	AT,AT1	47 - Public transportation
Food away from home	EFV	24 - Food away from home
New and used motor vehicles	ETA	42 - New and used motor vehicles
Motor fuel	ETB	43 - Motor fuel

A.9
Additional Sectoral Statistics

Figure A.8: This figure shows the sectoral comparison of normalized statistics across U.S. consumption categories. The statistics were first normalized within each statistic by dividing each sector's value by the maximum value of that statistic across sectors. The resulting normalized values were then scaled such that the sum of all normalized statistics for each sector is divided by the maximum sector total, ensuring comparability across sectors. The frequency of purchase is calculated as the average number of expenditures on goods or services within each sector over the reference period.

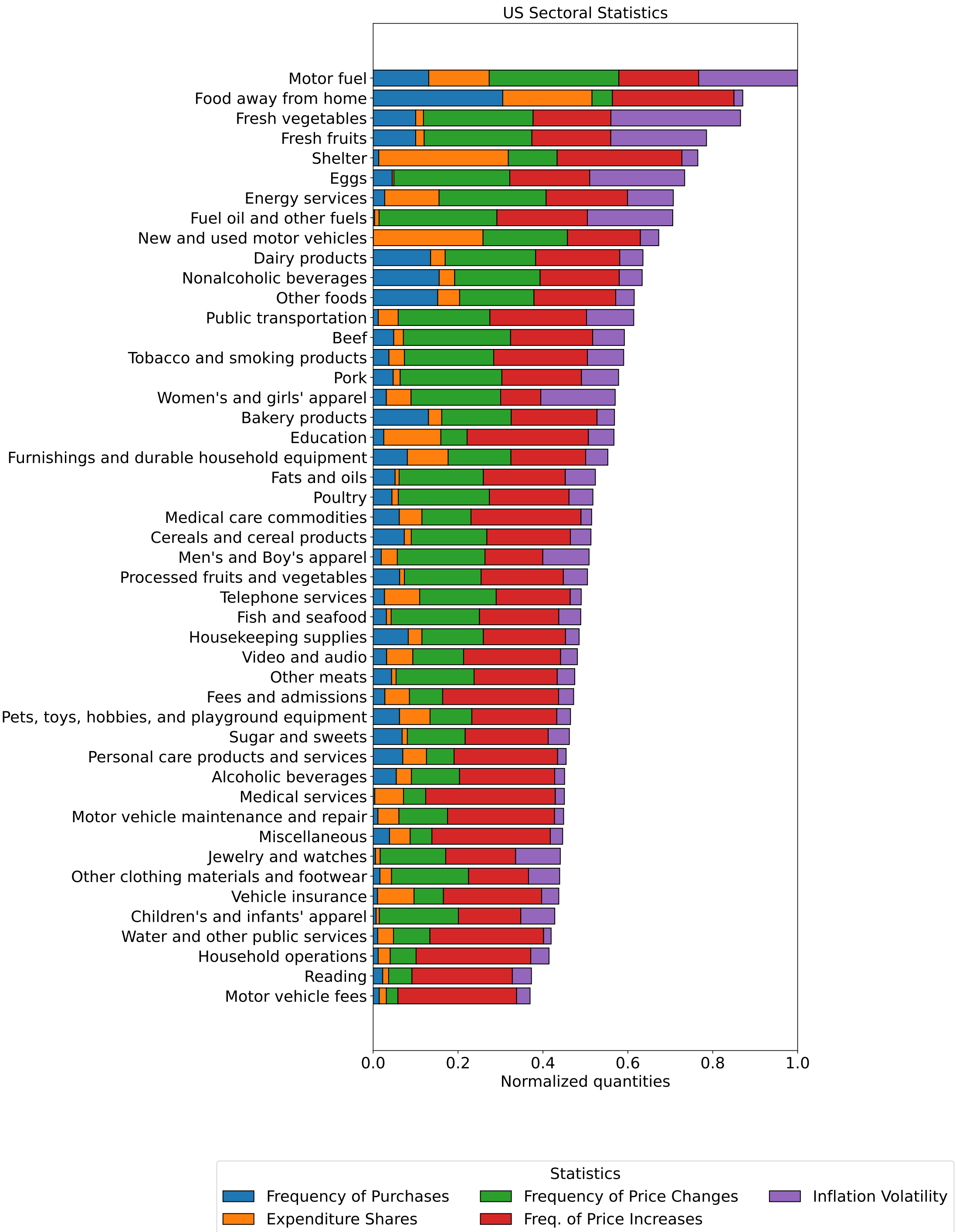


Figure A.9: This figure presents the correlogram of sectoral annual CPI inflation rates from 2000-M1 to 2019-M12 for the United States.

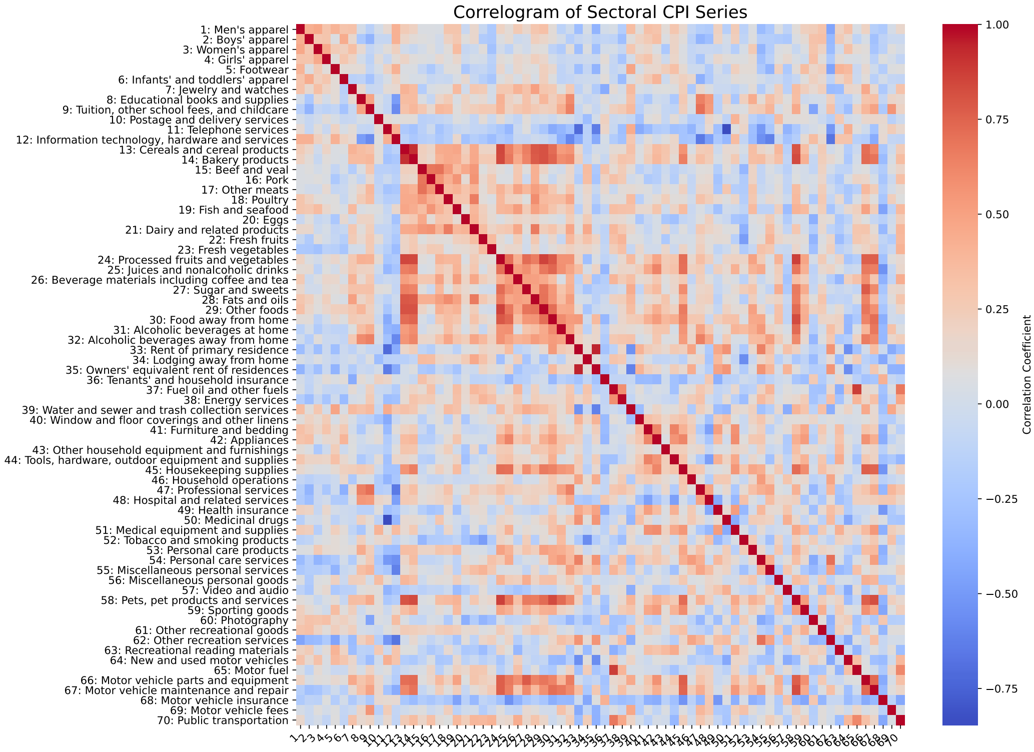


Figure A.10: This figure presents the correlogram of sectoral annual CPI inflation rates from 2000-M1 to 2019-M12 for the United Kingdom.

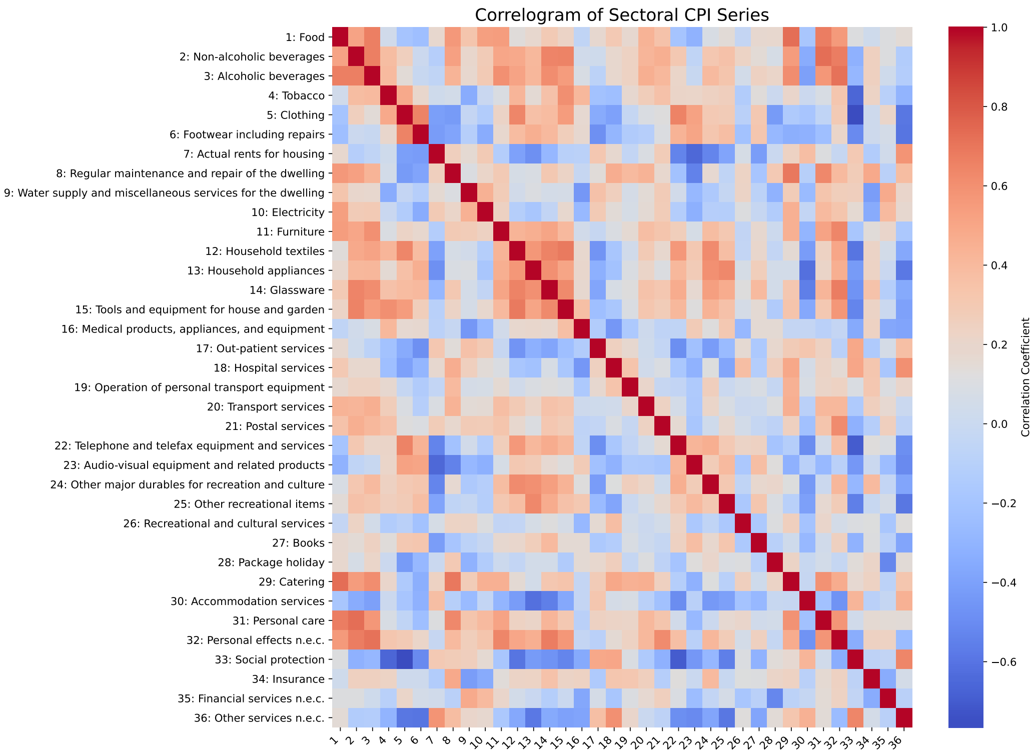


Figure A.11: This figure presents the correlogram of sectoral annual CPI inflation rates from 2000-M1 to 2019-M12 for Canada.

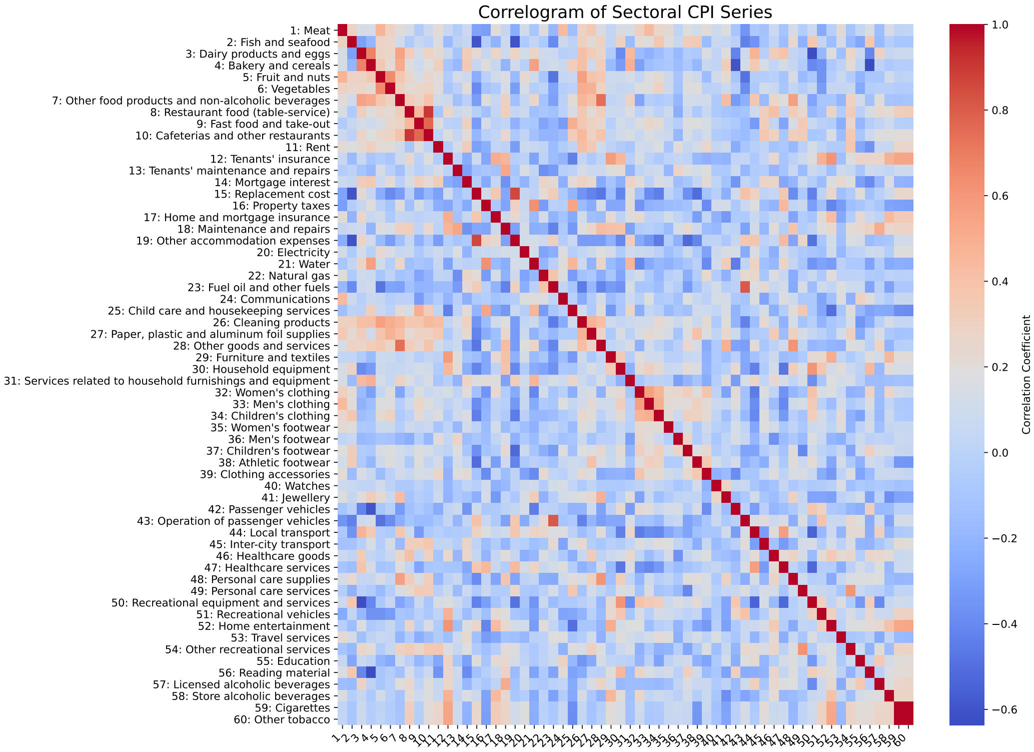


Figure A.12: This figure presents the correlogram of sectoral annual CPI inflation rates from 2000-M1 to 2019-M12 for Japan.

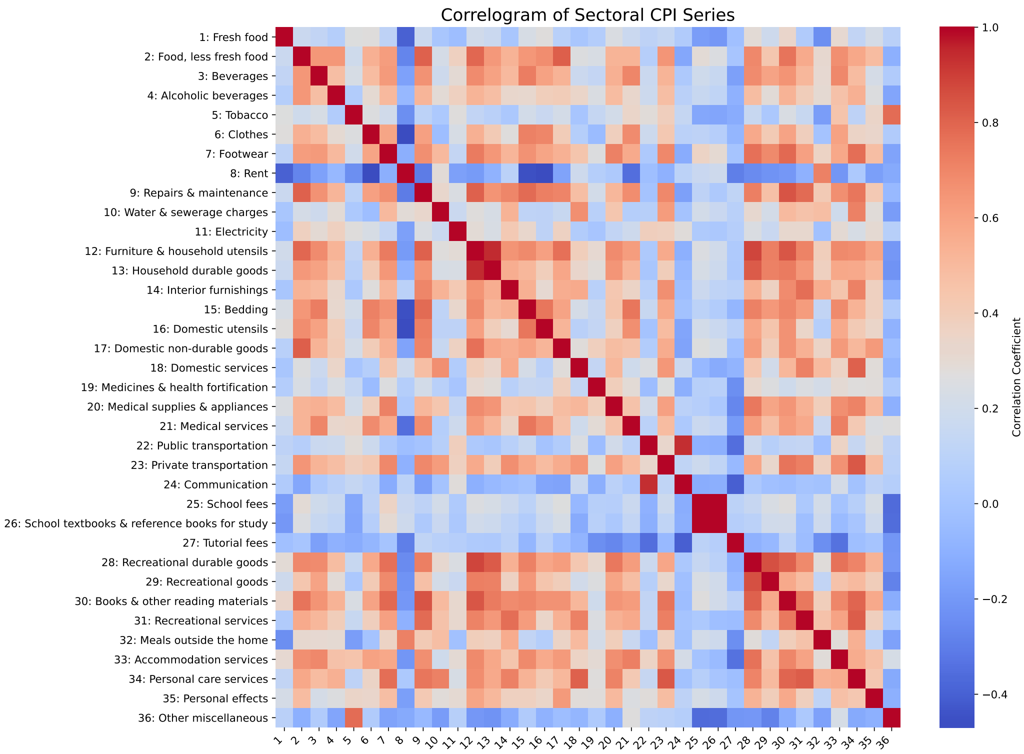


Figure A.13: This figure illustrates the correlations between the current and lagged in CPI monthly inflation rates from 2000-M1 to 2019-M12 for the Food away from home and Food sectors, respectively.

A.10
Results from Poisson Regressions

We estimate Poisson regressions to examine determinants of household purchase frequency across product sectors. Table A.22 presents three specifications, each incorporating fixed effects to account for unobserved heterogeneity and reporting robust standard errors clustered by sector and household. Specification (i) includes only sector fixed effects; specification (ii) adds fixed effects for region, survey wave, and education; specification (iii) replaces those with household fixed effects to absorb all time-invariant individual characteristics.

Table A.22: This table shows Poisson regressions where the dependent variable is the individuals' purchase frequency across sectors. Regressors individuals' expenditure shares across sectors and sectoral statistics. Frequency of purchases and expenditure shares are derived from the Diary Survey (CE PUMD) using microdata spanning 2000 to 2023, and additional sectoral statistics are taken from Nakamura and Steinsson (2008).

Model	(i)	(ii)	(iii)
Expenditure Share	3.274***	4.476***	6.275***
	(0.651)	(0.244)	(0.230)
Male	-0.034**	-0.023	
	(0.015)	(0.016)	
Married	0.238***	0.249***	
	(0.017)	(0.013)	
Household Size	0.088***	0.087***	
	(0.007)	(0.007)	
Age	0.003***	0.003***	
	(0.001)	(0.001)	
Log Income	0.017***	0.016***	
	(0.002)	(0.002)	
Freq. of Price Increases		3.936***	3.862***
		(1.036)	(1.045)
Freq. of Price Changes		1.887**	1.863**
		(0.841)	(0.857)
Size of Price Increases		3.397**	3.978**
		(1.665)	(1.616)
Sector FE	Yes		
Region, Survey, Educ FE	Yes	Yes	
Individual FE			Yes
Number of observations: 18,132,268.			
Pseudo R^2	0.260	0.178	0.235

Notes: Standard errors are clustered by sector and individual.

Specification (i): Sector Fixed Effects

Specification (i) controls for unobserved, time-invariant factors at the sector level. Expenditure share emerges as a highly significant predictor of purchase frequency (coefficient 3.274, $p < 0.01$), indicating that households allocate more shopping occasions to sectors commanding larger budget shares. Among demographic controls, marital status, household size, age, and log(income) all exhibit positive, statistically significant effects. The male indicator is negative and significant (coefficient –0.034, $p < 0.05$), suggesting that, conditional on budget share and other covariates, male respondents make marginally fewer shopping trips than female respondents.

Specification (ii): Region, Survey Wave, and Education Fixed Effects

In specification (ii), we introduce fixed effects for region, survey wave, and educational attainment. The coefficient on expenditure share strengthens to 4.476 ($p < 0.01$), reaffirming its central role. Demographic coefficients remain similar in sign and significance to those in specification (i). Crucially, sectoral pricing variables now enter the model:

- Frequency of price increases (coefficient 3.936, $p < 0.05$),
- Frequency of any price change (coefficient 1.887, $p < 0.05$), and
- Median size of price increases (coefficient 3.397, $p < 0.05$)

all exhibit positive, statistically significant effects. These results indicate that sectors with more frequent or larger price adjustments tend to elicit higher purchase frequency, consistent with a salience mechanism in consumer purchasing behavior.

Specification (iii): Household Fixed Effects

Specification (iii) replaces region, wave, and education fixed effects with household fixed effects to absorb all time-invariant individual traits. Even after accounting for unobserved heterogeneity at the household level, expenditure share remains highly significant (coefficient 6.275, $p < 0.01$). Sectoral pricing variables continue to be statistically significant: frequency of price increases (coefficient 3.862, $p < 0.01$), frequency of price changes (coefficient 1.863, $p < 0.05$), and median size of price increases (coefficient 3.978, $p < 0.05$). Thus, the association between greater price flexibility and higher purchase frequency persists once any constant household characteristics are absorbed.

Interpretation of Findings

Across all three specifications, expenditure share consistently predicts higher purchase frequency, implying that households devote more shopping occasions to sectors where they allocate larger budget shares. Demographic factors—household size, age, and marital status—also exert positive effects, while the negative coefficient on the male indicator suggests modest gender differences in shopping behavior. Importantly, sectoral pricing variables retain statistical significance in specifications (ii) and (iii), demonstrating that sectors characterized by more frequent or sizable price adjustments tend to generate higher consumer engagement. In combination, these results highlight that purchase frequency is jointly determined by (i) budget importance (expenditure share), (ii) respondent characteristics (demographics), and (iii) sectoral pricing dynamics.

B
Appendix of Sector-Biased Perceived Inflation

B.1
Baseline model

This appendix contains the detailed derivations for the equations presented in the Model section.

B.1.1
Households

The household problem. A continuum of households $j \in [0,1]$ enjoys consumption, supplies different types of labor to firms in different sectors, and has access to a complete set of state-contingent claims. The problem of the household is given by

$$\max_{\{C_\tau, B_\tau, \text{‘}H_{1,\tau}, \ldots, H_{K,\tau}\}_{\tau=t}^{\infty}} \tilde{E}_t \left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \Gamma_\tau \left(\ln C_\tau - \sum_{k=1}^{K} \omega_k \frac{H_{k,\tau}^{1+\varphi}}{1+\varphi} \right) \right]$$

s.t.

$$\sum_{k=1}^{K} \int_{\mathcal{I}_k} P_{k,t}(i) C_{k,t}(i) di + B_t = R_{t-1} B_{t-1} + \sum_{k=1}^{K} W_{k,t} H_{k,t} + \sum_{k=1}^{K} \int_{\mathcal{I}_k} \Pi_{k,t}(i) di + T_t$$

and the no-Ponzi condition

$$\lim_{\tau \to \infty} \mathbb{E}_t \left(\prod_{s=0}^{\tau-t} R_{t+s} \right)^{-1} B_{\tau+1} \geq 0,$$

where $\tilde{E}_t[\cdot]$ denotes non-rational expectations, $P_{k,t}(i)$ denotes variety ik's price, C_t denotes the households' consumption of the composite good, $H_{k,t}$ denotes the hours of labor supplied to sector k, B_t denotes bond holdings (which in equilibrium are in zero net supply), $W_{k,t}$ is the wage rate in sector k, T_t denotes lump sum taxes and transfers, and $\Pi_{k,t}(i)$ denotes profits of firm ik. The parameters $\omega_1, \ldots, \omega_K$ are the relative disutilities of supplying hours to sector k, and labor is fully mobile within each sector, but immobile across sectors.

Sectoral allocation of resources. Households also must decide how to allocate its consumption expenditures among varieties from different sectors. Given aggregate consumption C_t and the price levels $P_{k,t}$ and P_t, the optimal demand for type-i good in sector k is given by:

$$C_{k,t}(i) = D_{k,t} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(\frac{P_{k,t}}{P_t} \right)^{-\eta} C_t,$$

where $D_{k,t}$ is a relative demand shock satisfying $\sum_{k=1}^{K} n_k D_{k,t} = 1$, η denotes the elasticity of substitution between the sectoral consumption composites, θ is within-sector elasticity of substitution between consumption varieties, and P_t is given by

$$P_t = \left(\sum_{k=1}^{K} (n_k D_{k,t}) P_{k,t}^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

The aggregate consumption composite is:

$$C_t = \left(\sum_{k=1}^{K} (n_k D_{k,t})^{\frac{1}{\eta}} C_{k,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}},$$

Sectoral consumption composites are given by

$$C_{k,t} = \left(\left(\frac{1}{n_k} \right)^{\frac{1}{\theta}} \int_{\mathcal{I}_k} C_{k,t}(i)^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}},$$

with corresponding sectoral price indices

$$P_{k,t} = \left(\frac{1}{n_k} \int_{\mathcal{I}_k} P_{k,t}(i)^{1-\theta} di \right)^{\frac{1}{1-\theta}}.$$

Agents' expectation formation. We assume that agents perfectly observe all objective payoff-relevant details of the economic environment, but they might diverge from the policy function that delineates rational behavior given the observed state. Particularly, when deliberating about the best course of action given current circumstances, agents fail to aggregate P_t with the correct weights. Agents perceive a distorted price index:

$$\tilde{P}_t = \left(\sum_{k=1}^{K} (\tilde{n}_k D_{k,t}) P_{k,t}^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

Boundedly rational allocation. Agents' demand for type-i good in sector k becomes

$$C_{k,t}(i) = D_{k,t} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(\frac{P_{k,t}}{\tilde{P}_t} \right)^{-\eta} C_t, \tag{B-1}$$

implying that sectoral consumption is now defined by the relative the price of the sectoral composite concerning the distorted price index. The adjusted policy function has implications for the expenditure function:

$$\begin{aligned}\sum_{k=1}^{K}\int_{\mathcal{I}_k} P_{k,t}(i)C_{k,t}(i)di &= \sum_{k=1}^{K}\int_{\mathcal{I}_k} P_{k,t}(i)D_{k,t}\left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta}\left(\frac{P_{k,t}}{\tilde{P}_t}\right)^{-\eta} C_t di \\ &= \left(\frac{P_t}{\tilde{P}_t}\right)^{-\eta} P_t C_t,\end{aligned}$$

which now differs from P_tC_t. After defining the boundedly rational allocation between varieties, the rational household's problem can be formulated as:

$$\max_{\{C_\tau,B_\tau,`H_{1,\tau},\dots,H_{K,\tau}\}_{\tau=t}^{\infty}} \mathbb{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\left(\ln C_\tau - \sum_{k=1}^{K}\omega_k\frac{H_{k,\tau}^{1+\varphi}}{1+\varphi}\right)\right]$$

s.t.

$$\left(\frac{P_t}{\tilde{P}_t}\right)^{-\eta} P_tC_t + B_t = R_{t-1}B_{t-1} + \sum_{k=1}^{K} W_{k,t}H_{k,t} + \sum_{k=1}^{K}\int_{\mathcal{I}_k}\Pi_{k,t}(i)di + T_t$$

and the no-Ponzi condition

$$\lim_{\tau\to\infty}\mathbb{E}_t\left(\prod_{s=0}^{\tau-t}R_{t+s}\right)^{-1}B_{\tau+1}\geq 0,$$

A rational course of action requires:

$$\beta\mathbb{E}_t\left[\frac{\Gamma_{t+1}}{\Gamma_t}\frac{C_t}{C_{t+1}}\frac{R_t}{\pi_{t+1}}\left(\frac{\pi_{t+1}}{\tilde{\pi}_{t+1}}\right)^{\eta}\right]=1$$

$$\frac{W_{k,t}}{P_t}=\omega_k H_{k,t}^{\varphi}C_t\left(\frac{P_t}{\tilde{P}_t}\right)^{-\eta}$$

where $Q_{t,t+1}\equiv\beta\frac{\Gamma_{t+1}P_tC_t}{\Gamma_tP_{t+1}C_{t+1}}\left(\frac{\pi_{t+1}}{\tilde{\pi}_{t+1}}\right)^{\eta}$ is the stochastic discount factor. Therefore, the boundedly rational agent optimality conditions are given by

$$\beta\hat{E}_t\left[\frac{\Gamma_{t+1}}{\Gamma_t}\frac{C_t}{C_{t+1}}\frac{R_t}{\pi_{t+1}}\left(\frac{\pi_{t+1}}{\tilde{\pi}_{t+1}}\right)^{\eta}\right]=\beta\mathbb{E}_t\left[\frac{\Gamma_{t+1}}{\Gamma_t}\frac{C_t}{C_{t+1}}\frac{R_t}{\tilde{\pi}_{t+1}}\right]=1$$

$$\frac{W_{k,t}}{\tilde{P}_t}=\omega_k H_{k,t}^{\varphi}C_t$$

Log-linearized equations. Euler equation

$$c_t=\mathbb{E}_t[c_{t+1}]-(i_t-\mathbb{E}_t[\tilde{\pi}_{t+1}])+\mathbb{E}_t\gamma_{t+1}-\gamma_t$$

Optimal labor supply condition

$$w_{k,t} - \tilde{p}_t = \varphi h_{k,t} + c_t$$

Aggregating over sectors, we get the following aggregate labor supply condition

$$w_t - \tilde{p}_t = \varphi h_t + c_t$$

B.1.2
Firms

B.1.2.1
Production

Technology. Firms use sector-specific labor and other (intermediate) goods to produce according to

$$Y_{k,t}(i) = A_t A_{k,t} H_{k,t}(i)^{1-\delta} Z_{k,t}(i)^{\delta},$$

where $Y_{k,t}(i)$ is the production of firm ik, A_t is economy-wide productivity, $A_{k,t}$ is sector-specific productivity, $H_{k,t}(i)$ denotes hours of labor that firm ik employs, $Z_{k,t}(i)$ is firm ik's usage of other goods as intermediate inputs, and δ is the elasticity of output with respect to intermediate inputs.

Firms combine varieties of goods in each sector to form sectoral composites of intermediate inputs. These sectoral inputs are further assembled into the composite intermediate input that is used for production. The total quantity of intermediate inputs employed by firm ik is a Dixit-Stiglitz aggregator of sectoral composites with the same across-sector elasticity of substitution as the aggregate consumption composite:

$$Z_{k,t}(i) = \left(\sum_{k'=1}^{K} (n_{k'} D_{k',t})^{\frac{1}{\eta}} Z_{k,k',t}(i)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}$$

where the sectoral intermediate input $Z_{k,k',t}(i)$ denotes the amount of sector k' output that firm ik uses as intermediate inputs, and is given by

$$Z_{k,k',t}(i) = \left(\left(\frac{1}{n_{k'}} \right)^{\frac{1}{\theta}} \int_{\mathcal{I}_{k'}} Z_{k,k',t}(i,i')^{\frac{\theta-1}{\theta}} di' \right)^{\frac{\theta}{\theta-1}},$$

where $Z_{k,k',t}(i,i')$ denotes the quantity of goods that firm ik purchases from firm $i'k'$. Given the composite $Z_{k,t}(i)$ and the price levels $P_{k',t}(i')$, $P_{k',t}$ and P_t, the firm ik's rational demand for type-i' good in sector k' is given by:

$$Z_{k,k',t}(i,i') = D_{k',t} \left(\frac{P_{k',t}(i')}{P_{k',t}} \right)^{-\theta} \left(\frac{P_{k',t}}{P_t} \right)^{-\eta} Z_{k,t}(i)$$

Boundedly rational allocation. Because firm managers aggregate prices with distorted weights, we have:

$$Z_{k,k',t}(i,i') = D_{k',t} \left(\frac{P_{k',t}(i')}{P_{k',t}} \right)^{-\theta} \left(\frac{P_{k',t}}{\tilde{P}_t} \right)^{-\eta} Z_{k,t}(i). \tag{B-2}$$

The adjusted policy function has implications for the expenditure function:

$$\begin{aligned}
&\sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} P_{k',t}(i') Z_{k,k',t}(i,i') di' \\
&= \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} P_{k',t}(i') D_{k',t} \left(\frac{P_{k',t}(i')}{P_{k',t}} \right)^{-\theta} \left(\frac{P_{k',t}}{\tilde{P}_t} \right)^{-\eta} Z_{k,t}(i) di' \\
&= \left(\frac{P_t}{\tilde{P}_t} \right)^{-\eta} P_t Z_{k,t}(i).
\end{aligned}$$

Firm ik's profit maximization. Taking prices $\tilde{P}_t$, P_t, $P_{k',t}$, $P_{k',t}(i')$ and wages $W_{k,t}$ as given, firm ik decides how much of each input to employ in production. Specifically, the firm chooses $H_{k,t}(i)$ and $Z_{k,t}(i)$ to maximize the following profit function:[1]

$$(1-\tau_{k,t}) P_{k,t}(i) A_t A_{k,t} H_{k,t}(i)^{1-\delta} Z_{k,t}(i)^{\delta} - \left(\frac{P_t}{\tilde{P}_t} \right)^{-\eta} P_t Z_{k,t}(i) - W_{k,t} H_{k,t}(i)$$

FOC w.r.t $H_{k,t}(i)$:

$$(1-\delta)(1-\tau_{k,t}) \frac{Y_{k,t}(i)}{H_{k,t}(i)} = W_{k,t}.$$

FOC w.r.t $Z_{k,t}(i)$:

$$\delta(1-\tau_{k,t}) \frac{Y_{k,t}(i)}{Z_{k,t}(i)} = \left(\frac{P_t}{\tilde{P}_t} \right)^{-\eta} P_t.$$

This implies the following rational allocation:

$$Z_{k,t}(i) = \frac{\delta}{1-\delta} \left(\frac{P_t}{\tilde{P}_t} \right)^{\eta} \frac{W_{k,t}}{P_t} H_{k,t}(i).$$

[1] Note that every firm, identified as ik, incurs the identical price, $P_{k',t}(i')$, for accessing the differentiated good offered by any other firm $i'k'$. This uniform pricing is applicable whether the goods are employed as inputs for production or for consumption.

Boundedly rational allocation. Therefore, the boundedly rational allocation is given by:

$$Z_{k,t}(i) = \frac{\delta}{1-\delta}\frac{W_{k,t}}{\tilde{P}_t}H_{k,t}(i). \tag{B-3}$$

Firm ik's total output has to satisfy the sum of household consumption and demand by all other firms:

$$\begin{aligned}
Y_{k,t}(i) &= C_{k,t}(i) + \sum_{k'=1}^{K}\int_{\mathcal{I}_{k'}} Z_{k',k,t}(i',i)di' \\
&= \frac{1}{n_k}\left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta}\left(C_{k,t} + \sum_{k'=1}^{K}\int_{\mathcal{I}_{k'}} Z_{k',k,t}(i')di'\right) \\
&= Y_t D_{k,t}\left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta}\left(\frac{P_{k,t}}{\tilde{P}_t}\right)^{-\eta},
\end{aligned}$$

where $Y_t = C_t + Z_t = C_t + \sum_{k'=1}^{K}\int_{\mathcal{I}_{k'}} Z_{k',t}(i')di'$. Solving for firm ik's nominal profit:

$$\begin{aligned}
\Pi_{k,t}(i) &= (1-\tau_{k,t})P_{k,t}(i)Y_{k,t}(i) - W_{k,t}H_{k,t}(i) - \left(\frac{P_t}{\tilde{P}_t}\right)^{-\eta} P_t Z_{k,t}(i) \\
&= (1-\tau_{k,t})P_{k,t}(i)Y_{k,t}(i) - \left(1 + \left(\frac{P_t}{\tilde{P}_t}\right)^{1-\eta}\frac{\delta}{1-\delta}\right) W_{k,t}H_{k,t}(i) \\
&= (1-\tau_{k,t})P_{k,t}(i)Y_{k,t}(i) \\
&\quad - \left(1 + \left(\frac{P_t}{\tilde{P}_t}\right)^{1-\eta}\frac{\delta}{1-\delta}\right) W_{k,t}\frac{Y_{k,t}(i)}{A_t A_{k,t}}\left(\frac{\delta}{1-\delta}\frac{W_{k,t}}{\tilde{P}_t}\right)^{-\delta}.
\end{aligned}$$

Therefore,

$$\Pi_{k,t}(i) =$$

$$\left((1-\tau_{k,t})P_{k,t}(i) - \left(\left(\frac{\tilde{P}_t}{P_t}\right) + \frac{\delta}{1-\delta}\left(\frac{\tilde{P}_t}{P_t}\right)^{\eta}\right)\left(\frac{\delta}{1-\delta}\right)^{-\delta}\left(\frac{W_{k,t}}{\tilde{P}_t}\right)^{1-\delta}\frac{P_t}{A_t A_{k,t}}\right) Y_{k,t}(i),$$

where $MC_{k,t} = \left(\left(\frac{\tilde{P}_t}{P_t}\right) + \frac{\delta}{1-\delta}\left(\frac{\tilde{P}_t}{P_t}\right)^{\eta}\right)\left(\frac{\delta}{1-\delta}\right)^{-\delta}\left(\frac{W_{k,t}}{\tilde{P}_t}\right)^{1-\delta}\frac{P_t}{A_t A_{k,t}}$ is the nominal marginal cost.

Log-linearized equations. Profit maximization:

$$w_{k,t} - \tilde{p}_t = z_{k,t}(i) - h_{k,t}(i).$$

Firm ik's total output:

$$y_{k,t}(i) = (1-\delta)c_{k,t}(i) + \delta \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} z_{k',k,t}(i',i)di'.$$

Nominal marginal cost:

$$mc_{k,t} = (1-\delta)(w_{k,t} - \tilde{p}_t) - a_{k,t} - a_t + p_t - (1+(\eta-1)\delta)(p_t - \tilde{p}_t).$$

Perceived marginal cost:

$$\tilde{mc}_{k,t} = (1-\delta)(w_{k,t} - \tilde{p}_t) - a_{k,t} - a_t + \tilde{p}_t.$$

B.1.2.2 Price setting

Flexible price equilibrium. Firm ik's profit maximization problem when prices are fully flexible:

$$\max_{P_{k,t}(i)} \left((1-\tau_{k,t})P_{k,t}(i) - MC_{k,t}\right) D_{k,t} \left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta} \left(\frac{P_{k,t}}{\tilde{P}_t}\right)^{-\eta} Y_t.$$

It follows that, when prices are flexible, the equilibrium price is the same for all firms in a given sector and is given by:

$$P_{k,t}^{**} = \frac{\theta}{\theta-1}(1-\tau_{k,t})^{-1} MC_{k,t},$$

where $(1-\tau_{k,t})^{-1}\theta/(\theta-1)$ is the mark-up. The boundedly rational optimal price is given by:

$$P_{k,t}^{**} = \frac{\theta}{\theta-1}(1-\tau_{k,t})^{-1} \tilde{MC}_{k,t},$$

where $\tilde{MC}_{k,\tau} \equiv \frac{1}{1-\delta}\left(\frac{\delta}{1-\delta}\right)^{-\delta}\left(\frac{W_{k,t}}{\tilde{P}_t}\right)^{1-\delta}\frac{\tilde{P}_t}{A_t A_{k,t}}$ is the perceived nominal marginal cost.

Sticky price equilibrium. Under the assumed price-setting environment, the dynamics of the sectoral price must be computed. Let $\mathcal{I}_{k,t} \setminus \mathcal{I}_{k,t}^*$ be the set of firms not reoptimizing their posted price at t and $\mathcal{I}_{k,t}^*$, whose measure is $n_k(1-\alpha_k)$, be the set of firms that fully optimized their prices, i.e., they all choose an identical price $P_{k,t}^*$. Until a firm reoptimizes prices again, it adjusts its price with partial indexation to past inflation, with a degree denoted by ν_k.

In this scenario, the sectoral price level is determined as follows:

$$\begin{aligned} P_{k,t} &= \left(\frac{1}{n_k} \int_{\mathcal{I}^*_{k,t}} {P^*_{k,t}}^{1-\theta} di + \frac{1}{n_k} \int_{\mathcal{I}_{k,t} \setminus \mathcal{I}^*_{k,t}} (P_{k,t-1}(i) \Pi^{\nu_k}_{k,t-1})^{1-\theta} di \right)^{\frac{1}{1-\theta}} \\ &= \left((1-\alpha_k) {P^*_{k,t}}^{1-\theta} + \alpha_k (P_{k,t-1} \Pi^{\nu_k}_{k,t-1})^{1-\theta} \right)^{\frac{1}{1-\theta}} . \end{aligned}$$

When dividing both sides of the previous equation by $P_{k,t-1}$, we obtain:

$$\Pi^{1-\theta}_{k,t} = (1-\alpha_k) \left(\frac{P^*_{k,t}}{P_{k,t-1}} \right)^{1-\theta} + \alpha_k \Pi^{\nu_k(1-\theta)}_{k,t-1}.$$

Rational managers that adjust at time t set their prices to maximize the present discounted value of profits net of sales taxes, conditional on the price chosen at time t still being charged:

$$\max_{P_{k,t}(i)} \mathbb{E}_t \left[\sum_{\tau=t}^{\infty} \alpha_k^{\tau-t} Q_{t,\tau} \Pi_{k,\tau}(i) \right],$$

where $Q_{t,\tau} = \prod_{s=t}^{\tau-1} Q_{s,s+1}$ is the nominal stochastic discount factor between t and τ, and

$$\begin{aligned} \Pi_{k,\tau}(i) = &\left((1-\tau_{k,\tau}) P_{k,t}(i) \prod_{s=1}^{\tau-t} \Pi^{\nu_k}_{k,t+s-1} - P_\tau RMC_{k,\tau} \right) \\ &\times D_{k,\tau} \left(\frac{P_{k,t}(i)}{P_{k,\tau}} \prod_{s=1}^{\tau-t} \Pi^{\nu_k}_{k,t+s-1} \right)^{-\theta} \left(\frac{P_{k,\tau}}{\tilde{P}_\tau} \right)^{-\eta} C_\tau \end{aligned}$$

is the nominal profit at τ. Note that we are accommodating a stationary process for sales taxes $\tau_{k,\tau}$, which leads to exogenous fluctuations in desired markups. The first-order condition associated with the optimization problem above takes the form:

$$\begin{aligned} \mathbb{E}_t \Bigg[&\sum_{\tau=t}^{\infty} \alpha_k^{\tau-t} Q_{t,\tau} D_{k,\tau} \left(\frac{P^*_{k,t}}{P_{k,\tau}} \prod_{s=1}^{\tau-t} \Pi^{\nu_k}_{k,t+s-1} \right)^{-\theta} \left(\frac{P_{k,\tau}}{\tilde{P}_\tau} \right)^{-\eta} Y_\tau \\ &\times \left((1-\tau_{k,\tau}) P^*_{k,t} \prod_{s=1}^{\tau-t} \Pi^{\nu_k}_{k,t+s-1} - \frac{\theta}{\theta-1} MC_{k,\tau} \right) \Bigg] = 0, \end{aligned}$$

where $MC_{k,\tau} = P_\tau RMC_{k,\tau}$ is the nominal marginal cost.

Boundedly rational allocation. The boundedly rational allocation is given by:

$$\begin{aligned} \mathbb{E}_t \Bigg[&\sum_{\tau=t}^{\infty} \alpha_k^{\tau-t} Q_{t,\tau} D_{k,\tau} \left(\frac{P^*_{k,t}}{P_{k,\tau}} \prod_{s=1}^{\tau-t} \Pi^{\nu_k}_{k,t+s-1} \right)^{-\theta} \left(\frac{P_{k,\tau}}{\tilde{P}_\tau} \right)^{-\eta} Y_\tau \\ &\times \left((1-\tau_{k,\tau}) P^*_{k,t} \prod_{s=1}^{\tau-t} \Pi^{\nu_k}_{k,t+s-1} - \frac{\theta}{\theta-1} \tilde{MC}_{k,\tau} \right) \Bigg] = 0, \end{aligned}$$

where $\tilde{MC}_{k,\tau} = \frac{1}{1-\delta}\left(\frac{\delta}{1-\delta}\right)^{-\delta}\left(\frac{W_{k,t}}{\tilde{P}_t}\right)^{1-\delta}\frac{\tilde{P}_t}{A_t A_{k,t}}$ is the perceived nominal marginal cost. We define new variables $\overline{P}^*_{k,t} \equiv P^*_{k,t}/P_{k,t}$ and $\overline{MC}_{k,t} \equiv \tilde{MC}_{k,t}/P_{k,t}$. This implies:

$$\mathbb{E}_t\left[\sum_{\tau=t}^{\infty}\alpha_k^{\tau-t}Q_{t,\tau}D_{k,\tau}\left(\overline{P}^*_{k,t}\prod_{s=1}^{\tau-t}\Pi^{\nu_k}_{k,t+s-1}\right)^{-\theta}\left(\frac{P_{k,\tau}}{\tilde{P}_\tau}\right)^{-\eta}Y_\tau\right.$$
$$\left.\times\left((1-\tau_{k,\tau})\overline{P}^*_{k,t}\prod_{s=1}^{\tau-t}\frac{\Pi^{\nu_k}_{k,t+s-1}}{\Pi_{k,t+s}}-\frac{\theta}{\theta-1}\overline{MC}_{k,\tau}\right)\right]=0.$$

Log-linearized equations. Price setting:

$$\overline{p}^*_{k,t} = (1-\alpha_k\beta)\mathbb{E}_t\left[\sum_{\tau=t}^{\infty}(\alpha_k\beta)^{\tau-t}\left(\overline{mc}_{k,\tau}-\sum_{s=1}^{\tau-t}(\nu_k\pi_{k,t+s-1}-\pi_{k,t+s})\right)\right],$$

Solving for $\overline{p}^*_{k,t}$:

$$\begin{aligned}\frac{\overline{p}^*_{k,t}}{1-\alpha_k\beta} &= \overline{mc}_{k,t} + \mathbb{E}_t\left[\sum_{\tau=t+1}^{\infty}(\alpha_k\beta)^{\tau-t}\left(\overline{mc}_{k,\tau}-\sum_{s=1}^{\tau-t}(\nu_k\pi_{k,t+s-1}-\pi_{k,t+s})\right)\right]\\ &= \overline{mc}_{k,t} + \alpha_k\beta\mathbb{E}_t\left[-\frac{(\nu_k\pi_{k,t}-\pi_{k,t+1})}{1-\alpha_k\beta}\right.\\ &\left.+\mathbb{E}_{t+1}\left[\sum_{\tau=t+1}^{\infty}(\alpha_k\beta)^{\tau-t-1}(\overline{mc}_{k,\tau}-\sum_{s=1}^{\tau-t-1}(\nu_k\pi_{k,t+s-1}-\pi_{k,t+s}))\right]\right]\\ &= \overline{mc}_{k,t} + \frac{\alpha_k\beta}{1-\alpha_k\beta}\mathbb{E}_t\left[\overline{p}^*_{k,t+1}-(\nu_k\pi_{k,t}-\pi_{k,t+1})\right].\end{aligned}$$

We can utilize the relationship $p^*_{k,t}-p_{k,t}=\overline{p}^*_{k,t}=\alpha_k(1-\alpha_k)^{-1}(\pi_{k,t}-\nu_k\pi_{k,t-1})$ to derive the following sectoral Phillips curve:

$$\pi_{k,t}-\nu_k\pi_{k,t-1}=\beta\mathbb{E}_t[\pi_{k,t+1}-\nu_k\pi_{k,t}]+\frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k}\overline{mc}_{k,t}.$$

It can be rewritten as:

$$\pi_{k,t}=\frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1}+\frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}]+\frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k(1+\beta\nu_k)}(\tilde{mc}_{k,t}-p_{k,t})$$

B.1.3
Stationary equilibrium

We solve the model by log-linearizing equilibrium conditions around a symmetric non-stochastic zero-inflation steady state. We make two assumptions that deliver a symmetric steady state: i) the steady-state levels of productivities are the same across sectors: $A_k = 1$ for all k; ii) $\omega_k = n_k^{-\varphi}$ for all k. The latter assumption equalizes steady-state sectoral wages. We also assume that the sector-specific subsidy τ_k offsets the markup charged by firms in steady state[2], implying that we have an efficient stationary equilibrium.

After we solve for $\{Y, C, Z, H, W/P, \Pi/P\}$, sectoral and micro variables can be characterized using the symmetric nature of the steady-state:

$$Y_k = n_k Y_k(i) = n_k Y$$

$$C_k = n_k C_k(i) = n_k C$$

$$Z_{k,k'}(i) = n_{k'} Z_{k,k'}(i,i') = n_{k'} Z$$

$$H_k = n_k H_k(i) = n_k H$$

$$\Pi_k(i)/P = \Pi/P$$

$$\frac{W_k}{P} = \frac{W}{P}$$

$$\frac{P(i)}{P} = \frac{P_k}{P} = 1$$

$$\frac{\tilde{P}}{P} = 1$$

Equilibrium conditions can be reduced to the following equations:

$$R = \beta^{-1} \tag{B-4}$$

$$T = \tau Y \tag{B-5}$$

$$C = \frac{W}{P} H + \frac{\Pi}{P} + T \tag{B-6}$$

$$\frac{W}{P} = H^{\varphi} C \tag{B-7}$$

$$Y = H^{1-\delta} Z^{\delta} \tag{B-8}$$

$$Y = C + Z \tag{B-9}$$

[2]It must be the case that $1 - \tau_k = \frac{\theta}{\theta - 1}$ for all $k = 1, \ldots, K$.

$$\frac{\Pi}{P} = (1-\tau)Y - \frac{W}{P}H - Z \tag{B-10}$$

$$Z = \frac{\delta}{1-\delta}\frac{W}{P}H \tag{B-11}$$

$$\frac{MC}{P} = \frac{1}{1-\delta}\left(\frac{\delta}{1-\delta}\right)^{-\delta}\left(\frac{W}{P}\right)^{1-\delta} \tag{B-12}$$

where $MC/P = 1$ and $\tau_k = \tau$ for all $k = 1, \dots, K$. We can use these equations to solve for the steady state values of aggregate gross output:

$$Y = \left[\left(\frac{1}{\chi}\right)^{\frac{1}{1-\delta}} \delta^{\frac{\delta\varphi}{1-\delta}} (1-\delta)^{-1}\right]^{\frac{1}{1+\varphi}}.$$

Real profits:

$$\frac{\Pi}{P} = -\tau Y = \frac{1}{\theta - 1}Y.$$

Aggregate value added-output (GDP):

$$C = (1-\delta)Y.$$

Aggregate intermediate input usage:

$$Z = \delta Y.$$

Aggregate hours:

$$H = \delta^{-\frac{\delta}{1-\delta}}Y.$$

Real wage:

$$\frac{W}{P} = \left(\frac{1}{\chi}\right)^{\frac{1}{1-\delta}},$$

where $\chi \equiv \frac{1}{1-\delta}\left(\frac{\delta}{1-\delta}\right)^{-\delta}$.

B.1.4
Log-linearized equilibrium

Aggregate intermediate input:

$$z_t = \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} z_{k',t}(i')di'.$$

Sectoral output:

$$\begin{aligned} y_{k,t} &= \frac{1}{n_k} \int_{\mathcal{I}_k} y_{k,t}(i) di \\ &= (1-\delta) c_{k,t} + \delta \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} z_{k',k,t}(i') di'. \end{aligned}$$

Aggregate gross output:

$$\begin{aligned} y_t &= (1-\delta) c_t + \delta z_t \\ &= \sum_{k=1}^{K} n_k y_{k,t}. \end{aligned}$$

Aggregate wage:

$$w_t = \sum_{k=1}^{K} n_k w_{k,t}.$$

Sectoral labor input:

$$h_{k,t} = \frac{1}{n_k} \int_{\mathcal{I}_k} h_{k,t}(i) di.$$

Aggregate hours:

$$h_t = \sum_{k=1}^{K} n_k h_{k,t}.$$

We can solve for firm ik's total output as:

$$y_{k,t}(i) - y_{k,t} = -\theta (p_{k,t}(i) - p_{k,t}).$$

Using the definition of sectoral output and sectoral labor input, one can show that:

$$y_{k,t} = a_t + a_{k,t} + (1-\delta) h_{k,t} + \frac{\delta}{n_k} \int_{\mathcal{I}_k} z_{k,t}(i) di.$$

It follows that:

$$y_t = a_t + \sum_{k=1}^{K} n_k a_{k,t} + (1-\delta) h_t + \delta z_t.$$

Integrating both sides of profit maximization equation over $\mathcal{I}_k$ and aggregating over sectors leads to:

$$w_t - \tilde{p}_t = z_t - h_t.$$

Using the demand for sectoral consumption and the demand for sector k good by firm $i'k'$:

$$\begin{aligned} y_{k,t} &= (1-\delta)c_{k,t} + \delta \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} z_{k',k,t}(i')di' \\ &= y_t - \eta(p_{k,t} - \tilde{p}_t) + d_{k,t}. \end{aligned}$$

Therefore, relative consumption for sector k good is equal to relative output of sector k:

$$y_{k,t} - y_t = c_{k,t} - c_t.$$

It follows that:

$$y_{k,t} = \delta z_t + c_{k,t} - \delta c_t.$$

Through some tedious algebraic manipulation, we can express the sectoral real marginal cost as:

$$\begin{aligned} \tilde{mc}_{k,t} - \tilde{p}_t &= \frac{(1-\delta)\varphi}{1+\delta\varphi} y_{k,t} - \frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t} + \frac{1-\delta}{1+\delta\varphi} c_t \\ &= \frac{(1-\delta)\varphi}{1+\delta\varphi} c_{k,t} + \frac{(1-\delta)(1-\delta\varphi)}{1+\delta\varphi} c_t + \frac{(1-\delta)\delta\varphi}{1+\delta\varphi} z_t - \frac{1+\varphi}{1+\delta\varphi} a_t - \frac{1+\varphi}{1+\delta\varphi} a_{k,t}. \end{aligned}$$

The sectoral Phillips curve can be rewritten as:

$$\begin{aligned} \pi_{k,t} &= \frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1} + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}] \\ &+ \frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k(1+\beta\nu_k)}(\tilde{mc}_{k,t} - \tilde{p}_t + \tilde{p}_t - p_{k,t}) \\ &= \frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1} + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}] \\ &+ \frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k(1+\beta\nu_k)}\left(\tilde{mc}_{k,t} - \tilde{p}_t + \frac{1}{\eta}(c_{k,t} - c_t - d_{k,t})\right) \\ &= \frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1} + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}] + \frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k(1+\beta\nu_k)}\left(\left(\frac{(1-\delta)\varphi}{1+\delta\varphi} + \frac{1}{\eta}\right)c_{k,t}\right. \\ &+ \left.\left(\frac{(1-\delta)(1-\delta\varphi)}{1+\delta\varphi} - \frac{1}{\eta}\right)c_t + \frac{(1-\delta)\delta\varphi}{1+\delta\varphi}z_t - \frac{1+\varphi}{1+\delta\varphi}a_t - \frac{1+\varphi}{1+\delta\varphi}a_{k,t} - \frac{1}{\eta}d_{k,t}\right). \end{aligned}$$

Aggregate inflation is given by:

$$\pi_t = \sum_{k=1}^{K} n_k \pi_{k,t}.$$

Perceived inflation is given by:

$$\tilde{\pi}_t = \sum_{k=1}^{K} \tilde{n}_k \pi_{k,t}.$$

B.1.4.1
Flexible price equilibrium

In the flexible price equilibrium, we have $\tilde{mc}_{k,t} - p_{k,t} = 0$ for all $k = 1, \ldots, K$. This implies[3]:

$$c_t^n = \mathbb{E}_t[c_{t+1}^n] - r_t^n + \mathbb{E}_t[\tilde{\pi}_{t+1}^n - \pi_{t+1}^n] + \mathbb{E}_t \gamma_{t+1} - \gamma_t \tag{B-13}$$

$$\left[\frac{(1-\delta)\varphi}{1+\delta\varphi} + \frac{1}{\eta}\right] c_{k,t}^n + \left[\frac{1-\delta}{1+\delta\varphi}(1+\delta\varphi(1+\varphi)) - \frac{1}{\eta}\right] c_t^n - (1+\varphi)a_t \\ -\frac{(1+\varphi)\delta\varphi}{1+\delta\varphi}\bar{a}_t - \frac{1+\varphi}{1+\delta\varphi}a_{k,t} - \frac{1}{\eta}d_{k,t} = 0 \tag{B-14}$$

$$\pi_{k,t}^n = \frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1}^n + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}^n] \tag{B-15}$$

where $\{c_t^n, c_{k,t}^n, x_t^n, r_t^n\}$ represents the counterparts in a flexible prices equilibrium for consumption, sectoral consumption, price bias and the real interest rate, respectively. Aggregating (B-14) over k and solving for c_t^n

$$c_t^n = \frac{1}{(1-\delta)}(a_t + \bar{a}_t), \tag{B-16}$$

where $\bar{a}_t \equiv \sum_{k=1}^{K} n_k a_{k,t}$, and $\bar{d}_t \equiv \sum_{k=1}^{K} n_k d_{k,t} = 0$.

We denote the gap of variable c_t from the flexible price equilibrium by $x_{c,t} \equiv c_t - c_t^n$. We assume that monetary policy is given by the following generalized Taylor rule

$$i_t = \rho i_{t-1} + r_t^n + \phi_\pi \pi_t + \phi_x x_{c,t} + \mu_t,$$

which perform relatively well across a range of models in terms of welfare.

[3]Note that we can use (B-18), (B-19), and (B-20) to solve for z_t

$$z_t = (2+\varphi)c_t - \frac{1+\varphi}{1-\delta}(a_t + \bar{a}_t)$$

B.1.4.2
Equilibrium dynamics

The equilibrium dynamics of $\{c_t, c_t^n, r_t^n, \pi_t, \tilde{\pi}_t, z_t, i_t, h_t, w_t - \tilde{p}_t, \{c_{k,t}, \pi_{k,t}, \pi_{k,t}^n\}_{k=1}^K\}$ is given by the following equations:

$$c_t = \mathbb{E}_t[c_{t+1}] - (i_t - \mathbb{E}_t[\tilde{\pi}_{t+1}]) + \mathbb{E}_t\gamma_{t+1} - \gamma_t \tag{B-17}$$

$$w_t - \tilde{p}_t = \varphi h_t + c_t \tag{B-18}$$

$$(1-\delta)c_t = a_t + \bar{a}_t + (1-\delta)h_t \tag{B-19}$$

$$w_t - \tilde{p}_t = z_t - h_t \tag{B-20}$$

$$\begin{aligned}\pi_{k,t} &= \frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1} + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}] \\ &+\frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k(1+\beta\nu_k)}\left\{\left[\frac{(1-\delta)\varphi}{1+\delta\varphi}+\frac{1}{\eta}\right]c_{k,t}+\left[\frac{(1-\delta)(1-\delta\varphi)}{1+\delta\varphi}-\frac{1}{\eta}\right]c_t\right. \\ &\left.+\frac{(1-\delta)\delta\varphi}{1+\delta\varphi}z_t - \frac{1+\varphi}{1+\delta\varphi}a_t - \frac{1+\varphi}{1+\delta\varphi}a_{k,t} - \frac{1}{\eta}d_{k,t}\right\}\end{aligned} \tag{B-21}$$

$$\pi_t = \sum_{k=1}^K n_k \pi_{k,t} \tag{B-22}$$

$$\tilde{\pi}_t = \sum_{k=1}^K \tilde{n}_k \pi_{k,t} \tag{B-23}$$

$$c_{k,t} = c_{k,t-1} + \Delta c_t - \eta(\pi_{k,t} - \tilde{\pi}_t) + \Delta d_{k,t} \tag{B-24}$$

$$i_t = \rho i_{t-1} + (1-\rho)(r_t^n + \phi_\pi \pi_t + \phi_x(c_t - c_t^n)) + \mu_t \tag{B-25}$$

$$c_t^n = \frac{1}{1-\delta}(a_t + \bar{a}_t) \tag{B-26}$$

$$r_t^n = \mathbb{E}_t[\Delta c_{t+1}^n] + \mathbb{E}_t[\tilde{\pi}_{t+1}^n - \pi_{t+1}^n] \tag{B-27}$$

$$\pi_t^n = \sum_{k=1}^K n_k \pi_{k,t}^n \tag{B-28}$$

$$\tilde{\pi}_t^n = \sum_{k=1}^K \tilde{n}_k \pi_{k,t}^n \tag{B-29}$$

$$\pi_{k,t}^n = \frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1}^n + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}^n] \tag{B-30}$$

B.1.5
Dixit-Stiglitz model

Demand for sector k's composite. In the standard model, the aggregate consumption composite is:

$$C_t = \left(\sum_{k=1}^{K} (n_k D_{k,t})^{\frac{1}{\eta}} C_{k,t}^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}},$$

where η is the elasticity of substitution between the sectoral consumption composites, and $D_{k,t}$ is a relative demand shock satisfying $\sum_{k=1}^{K} n_k D_{k,t} = 1$. Given aggregate consumption C_t and the price levels $P_{k,t}$ and P_t, the expenditure minimization problem is given by :

$$\min_{\{C_{k,t}\}_{k=1}^{K}} \sum_{k=1}^{K} P_{k,t} C_{k,t}$$
$$s.t. \quad C_t^{\frac{\eta-1}{\eta}} - \sum_{k=1}^{K} (n_k D_{k,t})^{\frac{1}{\eta}} C_{k,t}^{\frac{\eta-1}{\eta}} = 0.$$

This implies that the aggregate price level and the sectoral demands are given by

$$P_t = \left(\sum_{k=1}^{K} (n_k D_{k,t}) P_{k,t}^{1-\eta} \right)^{\frac{1}{1-\eta}},$$
$$C_{k,t} = n_k D_{k,t} \left(\frac{P_{k,t}}{P_t} \right)^{-\eta} C_t,$$

where $P_{k,t}$ is the sectoral price index associated with sectoral consumption composite $C_{k,t}$. In the symmetric steady state we have $P_k = P$ and $C_k = n_k C$.

We define an index of all varieties' prices as P_t because it represents the true cost of living index, making the expenditure function $P_t C_t$. In the standard Dixit-Stiglitz model, this price index is consistent with the first-order condition for the consumption index, dictating how households allocate between sectoral consumption composites. However, this feature is not realistic, as households tend to aggregate prices with distorted weights.

Log-linearized equations. The log-linearized counterparts are as follows:

$$c_t = \sum_{k=1}^{K} n_k c_{k,t} \tag{B-31}$$

$$p_t = \sum_{k=1}^{K} n_k p_{k,t} \tag{B-32}$$

$$c_{k,t} - c_t = -\eta(p_{k,t} - p_t) + d_{k,t} \tag{B-33}$$

Demand for firm ik's good. Sectoral consumption composites are given by:

$$C_{k,t} = \left(\left(\frac{1}{n_k} \right)^{\frac{1}{\theta}} \int_{\mathcal{I}_k} C_{k,t}(i)^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}},$$

where θ denotes the within-sector elasticity of substitution between consumption varieties.

Given sectoral consumption $C_{k,t}$ and the price levels $P_{k,t}(i)$ and $P_{k,t}$, the (standard) expenditure minimization problem is given by:

$$\min_{\{C_{k,t}(i)\}_{i \in \mathcal{I}_k}} \int_{\mathcal{I}_k} P_{k,t}(i) C_{k,t}(i) di \quad s.t. \quad C_{k,t}^{\frac{\theta-1}{\theta}} - \left(\frac{1}{n_k} \right)^{\frac{1}{\theta}} \int_{\mathcal{I}_k} C_{k,t}(i)^{\frac{\theta-1}{\theta}} di = 0.$$

This implies that the sectoral price level and the optimal demand for type-i good in sector k are given by:

$$P_{k,t} = \left(\frac{1}{n_k} \int_{\mathcal{I}_k} P_{k,t}(i)^{1-\theta} di \right)^{\frac{1}{1-\theta}},$$
$$C_{k,t}(i) = \frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} C_{k,t}.$$

Log-linearized equations. Sectoral price level:

$$p_{k,t} = \frac{1}{n_k} \int_{\mathcal{I}_k} p_{k,t}(i) di.$$

Sectoral consumption:

$$c_{k,t} = \frac{1}{n_k} \int_{\mathcal{I}_k} c_{k,t}(i) di.$$

Consumption of an ik good:

$$c_{k,t}(i) - c_{k,t} = -\theta (p_{k,t}(i) - p_{k,t}).$$

Firm ik's demand for sector k's composite. Cost minimization problem with respect composites of all sectors is given by:

$$\min_{\{Z_{k,k',t}(i)\}_{k'=1}^{K}} \sum_{k'=1}^{K} P_{k',t} Z_{k,k',t}(i) \quad s.t. \quad \left(\sum_{k'=1}^{K} (n_{k'} D_{k',t})^{\frac{1}{\eta}} Z_{k,k',t}(i)^{\frac{\eta-1}{\eta}} \right) - Z_{k,t}(i)^{\frac{\eta-1}{\eta}} = 0.$$

FOC w.r.t. $Z_{k,k',t}(i)$:

$$Z_{k,k',t}(i) = n_{k'} D_{k',t} \left(\frac{(\eta - 1)\lambda_{ik}}{\eta P_{k',t}} \right)^{\eta},$$

where λ_{ik} is the Lagrange multiplier. Substituting into the cost function:

$$\sum_{k'=1}^{K} P_{k',t} Z_{k,k',t}(i) = \left(\frac{(\eta - 1)\lambda_{ik}}{\eta} \right)^{\eta} P_t^{1-\eta}.$$

Hence:

$$Z_{k,k',t}(i) = n_{k'} D_{k',t} \left(\frac{P_t}{P_{k',t}} \right)^{\eta} \frac{1}{P_t}.$$

Recall that the sectoral composite is given by:

$$\begin{aligned} Z_{k,t}(i) &= \left(\sum_{k'=1}^{K} (n_{k'} D_{k',t})^{\frac{1}{\eta}} Z_{k,k',t}(i)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \\ &= \left(\sum_{k'=1}^{K} n_{k'} D_{k',t} \left(\frac{(\eta - 1)\lambda_{ik}}{\eta P_{k',t}} \right)^{\eta-1} \right)^{\frac{\eta}{\eta-1}} \\ &= \left(\frac{(\eta - 1)\lambda_{ik}}{\eta} \right)^{\eta} P_t^{-\eta}. \end{aligned}$$

This implies:

$$\begin{aligned} P_t Z_{k,t}(i) &= \sum_{k'=1}^{K} P_{k',t} Z_{k,k',t}(i), \\ Z_{k,k',t}(i) &= n_{k'} D_{k',t} \left(\frac{P_{k',t}}{P_t} \right)^{-\eta} Z_{k,t}(i), \end{aligned}$$

where P_t is the ideal price index.

Log-linearized equations. Production function:

$$y_{k,t}(i) = a_t + a_{k,t} + (1 - \delta) h_{k,t}(i) + \delta z_{k,t}(i).$$

Intermediate input used by firm ik:

$$z_{k,t}(i) = \sum_{k'=1}^{K} n_{k'} z_{k,k',t}(i).$$

Intermediate input produced by sector k' used by firm ik:

$$z_{k,k',t}(i) = \frac{1}{n_{k'}} \int_{\mathcal{I}_{k'}} z_{k,k',t}(i,i')di'.$$

Firm ik's demand for sector k' good:

$$z_{k,k',t}(i) - z_{k,t}(i) = -\eta(p_{k',t} - \tilde{p}_t) + d_{k',t}.$$

Firm ik's demand for sector k''s intermediate input. Cost minimization problem with respect sector k' intermediate inputs by firm ik is given by:

$$\min_{\{Z_{k,k',t}(i,i')\}_{i' \in \mathcal{I}_{k'}}} \int_{\mathcal{I}_{k'}} P_{k',t}(i') Z_{k,k',t}(i,i')di'$$
$$s.t. \quad \left(\frac{1}{n_{k'}}\right)^{\frac{1}{\theta}} \int_{\mathcal{I}_{k'}} Z_{k,k',t}(i,i')^{\frac{\theta-1}{\theta}} di' - Z_{k,k',t}(i)^{\frac{\theta-1}{\theta}} = 0.$$

FOC w.r.t $Z_{k,k',t}(i,i')$:

$$Z_{k,k',t}(i,i') = \frac{1}{n_{k'}} \left(\frac{\theta-1}{\theta} \frac{\lambda_{ik}}{P_{k',t}(i')}\right)^{\theta},$$

where λ_{ik} is the Lagrange multiplier. Substituting into the cost function:

$$\int_{\mathcal{I}_{k'}} P_{k',t}(i') Z_{k,k',t}(i,i')di' = \left(\frac{(\theta-1)\lambda_{ik}}{\theta}\right)^{\theta} P_{k,t}^{1-\theta}.$$

Recall that the sectoral intermediate input $Z_{k,k',t}(i)$ is given by:

$$\begin{aligned} Z_{k,k',t}(i) &= \left(\left(\frac{1}{n_{k'}}\right)^{\frac{1}{\theta}} \int_{\mathcal{I}_{k'}} Z_{k,k',t}(i,i')^{\frac{\theta-1}{\theta}} di'\right)^{\frac{\theta}{\theta-1}} \\ &= \left(\frac{(\theta-1)\lambda_{ik}}{\theta}\right)^{\theta} P_{k',t}^{-\theta}. \end{aligned}$$

This implies:

$$\begin{aligned} P_{k',t} Z_{k,k',t}(i) &= \int_{\mathcal{I}_{k'}} P_{k',t}(i') Z_{k,k',t}(i,i')di' \\ Z_{k,k',t}(i,i') &= \frac{1}{n_{k'}} \left(\frac{P_{k',t}(i')}{P_{k',t}}\right)^{-\theta} Z_{k,k',t}(i). \end{aligned}$$

Log-linearized equations. Firm ik's demand for firm $i'k'$ good:

$$z_{k,k',t}(i,i') - z_{k,k',t}(i) = -\theta(p_{k',t}(i') - p_{k',t}).$$

B.1.6 BCGS Stereotypes Formula

In this appendix, we present a step-by-step derivation showing how the representativeness formula of Bordalo et al. (2016) maps directly onto our Calvo-pricing, multisector framework. Throughout, let n_k denote the true expenditure share of sector k, and let

$$f_k \;=\; 1 - \alpha_k \tag{B-34}$$

be the true probability that a price in sector k is reset in any given period. Define the basket average adjustment rate by:

$$\bar{f} = \sum_{j=1}^{K} n_j\, f_j \quad\Longrightarrow\quad \bar{\alpha} = 1 - \bar{f}. \tag{B-35}$$

Let $T = \{\text{readjusted}, \text{trend}\}$ be the set of possible price types, and let $\Omega = \{1, \ldots, K\}$ index the universe of sectors, of which sector k is a subset. We posit a joint probability measure π on $T \times \Omega$, which, when conditioned on sector k, yields the distribution $P(T = t|k)$.

Representativeness statistic. By construction, the probability that a randomly chosen price that belongs to sector k is an adjusted price is

$$P(\text{adjusted}|k) = f_k, \qquad P(\text{adjusted}|\text{basket}) = \bar{f}$$

Thus the *representativeness* of an adjusted price for sector k given comparison group Ω is defined as the likelihood ratio:

$$R_k = \frac{P(\text{adjusted}|k)}{P(\text{adjusted}|\text{basket})} = \frac{f_k}{\bar{f}}, \qquad R'_k = \frac{P(\text{trend}|k)}{P(\text{trend}|\text{basket})} = \frac{\alpha_k}{\bar{\alpha}}. \tag{B-36}$$

When R_k is larger, a Bayesian agent is more certain that an observed price adjustment stems from sector k rather than from the broader universe Ω. Accordingly, the agent's distorted adjustment probability for price type $t \in T$ in sector k is:

$$\hat{f}_k = f_k \frac{h(R_k)}{f_k h(R_k) + \alpha_k h(R'_k)}, \tag{B-37}$$

where $h(\cdot)$ is a weakly increasing function. We term the resulting pair $(\hat{f}_k, \hat{\alpha}_k)$ the stereotype for sector k. Sectors with higher objective adjustment frequencies f_k receive correspondingly greater distorted weights. Choosing different forms for h embeds additional assumptions about how representativeness biases recall; here, we employ a representativeness-based discounting rule rather than a rank-based heuristic.

Functional form of the discounting function. Bordalo et al. (2016) propose representative-based discounting when the type space is small, which is precisely our setting. Here, agents assign continuously increasing weights to types with greater representativeness. We let h be a smooth, strictly positive function, and for tractability assume

$$h(x) = x^{\theta}, \quad \theta \geq 0, \tag{B-38}$$

so that θ governs the strength of the bias: when $\theta = 0$, $h \equiv 1$ and no distortion arises.

From discounting to distorted weights. Moving from discounting to distorted weights, the BCGS framework combines sampling bias with this stereotype adjustment to yield:

$$\tilde{n}_k = n_k \frac{\hat{f}_k}{\sum_{k'=1}^{K} n_{k'} \hat{f}_{k'}}.$$

Substituting (B-38) and using $f_k = 1 - \alpha_k$ (with $\bar{f} = 1 - \bar{\alpha}$) recover exactly the main-text expression for $\tilde{n}_k$:

$$\tilde{n}_k = \frac{\frac{f_k \left(\frac{f_k}{\bar{f}}\right)^{\theta}}{\alpha_k \left(\frac{\alpha_k}{\bar{\alpha}}\right)^{\theta} + f_k \left(\frac{f_k}{\bar{f}}\right)^{\theta}}}{\sum_{k'=1}^{K} n_{k'} \frac{f_{k'} \left(\frac{f_{k'}}{\bar{f}}\right)^{\theta}}{\alpha_{k'} \left(\frac{\alpha_{k'}}{\bar{\alpha}}\right)^{\theta} + f_{k'} \left(\frac{f_{k'}}{\bar{f}}\right)^{\theta}}} n_k. \tag{B-39}$$

Discussion of limiting cases. Examining edge cases illuminates the bias mechanics. With $\theta = 0$, we have $\hat{f}_k = f_k$ and

$$\tilde{n}_k = n_k \frac{f_k}{\sum_{k'=1}^{K} n_{k'} f_{k'}},$$

so only sampling bias operates. As $\theta \to \infty$, the sector with the largest representativeness ratio $R_k = f_k/\bar{f}$ monopolizes perceived weight. Intermediate θ values let us calibrate how strongly agents overemphasize high-flexibility sectors.

B.1.7
Welfare

This section decomposes salience-based inefficiencies into the three sufficient statistics that summarize welfare: the aggregate gap $x_{c,t}$, the dispersion of sectoral gaps $\sum_k n_k x_{c_k,t}^2$, and within-sector price dispersion $(\pi_{k,t} - \nu_k \pi_{k,t-1})^2$.

Because agents aggregate with $\tilde{n}_k$, the perceived indices $(\tilde{P}_t, \tilde{\pi}_t)$ replace (P_t, π_t) in three places. First, in the Euler equation, the perceived real rate increases the volatility of $x_{c,t}$. Second, in sectoral demand for consumption and intermediates, perceived relative prices with elasticity η misallocate spending across sectors, widening $\sum_k n_k x_{c_k,t}^2$. Third, in price setting, perceived marginal costs with within-sector elasticity θ and stickiness α_k increase dispersion across firms.

The intratemporal condition translates these misperceptions into a labor wedge. Its aggregate component shifts total hours, loading onto $x_{c,t}$, while its cross-sector component tilts hours across k, raising $\sum_k n_k x_{c_k,t}^2$. Input–output linkages with share δ propagate both channels through costs and markups, amplifying dispersion.

Aggregate gap channel: $x_{c,t}^2$. The Euler equation discounts with the perceived real rate:

$$x_{c,t} = \mathbb{E}_t x_{c,t+1} - (i_t - \mathbb{E}_t \tilde{\pi}_{t+1}) + (\mathbb{E}_t \gamma_{t+1} - \gamma_t).$$

When $\tilde{n}_k$ overweights flexible (more volatile) sectors, $\mathbb{E}_t \tilde{\pi}_{t+1}$ becomes too volatile relative to the CPI. The perceived real rate swings more, consumption reacts too much, and $V[x_{c,t}]$ rises. This raises the $x_{c,t}^2$ term in both welfare functions.

In our calibration, the welfare loss attributed to aggregate shocks is lower when policy responds to $\tilde{\pi}_t$ (Fig. B.2) for all values of θ. However, the dispersion cost in the sticky block dominates and increases even more steeply with θ under $\tilde{\pi}_t$ targeting. In addition, Figure B.1 shows that the price-dispersion component is the primary driver of welfare losses. Overall, we find no evidence supporting headline weights through expectations channels. Aggregate gap losses remain second order relative to dispersion.[4]

[4]See Dietrich (2024) for a formal two-sector bounded-attention model where headline targeting can dominate if expectations overweight non-core volatility.

Cross-sector misallocation: $\sum_k n_k x_{c_k,t}^2$. Sectoral demand is based on the perceived relative-price benchmark:

$$x_{c_k,t} = x_{c_k,t-1} + \Delta d_{k,t} + \Delta x_{c,t} - \eta(\pi_{k,t} - \tilde{\pi}_t).$$

Because $\tilde{\pi}_t$ tilts toward high-reset sectors, the benchmark used to compare sectoral prices is distorted. This leads households to misperceive relative inflation and shift expenditure toward sectors that only appear cheap, widening the dispersion of sectoral gaps $x_{c_k,t}$ and raising $\sum_k n_k x_{c_k,t}^2$.[5] Two factors amplify this effect: (i) a higher across-sector elasticity η, and (ii) a smaller δ.

Within-sector price dispersion: $(\pi_{k,t} - \nu_k \pi_{k,t-1})^2$. Firms set reset prices from perceived marginal costs, which depend on $\tilde{P}_t$ and $\tilde{\pi}_t$. When $\tilde{n}_k$ tilts toward flexible sectors, perceived costs become noisier, reset prices move more, and

$$\pi_{k,t} - \nu_k \pi_{k,t-1}$$

is more volatile. The welfare weight

$$\theta^2 \frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}$$

makes this especially costly in sticky sectors (high α_k). Indexation $\nu_k > 0$ preserves dispersion over time, increasing its contribution. A higher within-sector elasticity θ further amplifies the shock.

Labor-wedge channel. Efficiency requires MRS = MPL in true units and equalization across sectors:

$$\frac{W_{k,t}}{P_t} = \mathrm{MPL}_{k,t}, \qquad \frac{W_{k,t}}{P_t} = \frac{W_{k',t}}{P_t}.$$

Households, however, set hours from the perceived real wage:

$$\frac{W_{k,t}}{\tilde{P}_t} = \omega_k H_{k,t}^{\varphi} C_t.$$

Multiplying by $\tilde{P}_t/P_t$ delivers the implied MRS in true units:

$$\frac{W_{k,t}}{P_t} = \omega_k H_{k,t}^{\varphi} C_t \left(\frac{\tilde{P}_t}{P_t}\right),$$

[5] This term disappears in the simplified model with an economy-wide labor market and no roundabout input use.

where $\tilde{P}_t/P_t$ is the salience factor. The wedge is therefore

$$\psi_{k,t} \equiv \frac{W_{k,t}}{P_t} - \omega_k H_{k,t}^{\varphi} C_t = \omega_k H_{k,t}^{\varphi} C_t \Big(\frac{\tilde{P}_t}{P_t} - 1 \Big),$$

a pure misperception term that scales the MRS whenever $\tilde{P}_t \neq P_t$.

Two components follow. First, the aggregate wedge $\bar{\psi}_t \equiv \sum_k n_k \psi_{k,t}$ distorts total hours and raises $x_{c,t}^2$. Second, the cross-sector wedge $\psi_{k,t} - \bar{\psi}_t$ tilts hours across sectors, widening $\sum_k n_k x_{c_k,t}^2$ under segmented labor markets. In the simplified case with a single labor market and $\delta = 0$, only the aggregate component survives.

Because $\psi_{k,t}$ scales with C_t and $H_{k,t}^{\varphi}$, shocks that move activity amplify its impact on gaps. With $\delta > 0$, misallocated hours also reweight intermediates across suppliers, raising costs and prices and reinforcing the within-sector dispersion channel.

Intuition for the labor-hours mapping and where $\tilde{P}_t$ bites. Start from the sectoral hours identity. A firm in sector k requires labor to meet its own final demand $C_{k,t}(i)$ and to supply intermediates $\int Z_{k',k,t}(i', i), di'$ to other sectors. With roundabout technology, hours scale inversely with productivity and with the perceived real wage:

$$H_{k,t}(i) \propto \left(\frac{W_{k,t}}{\tilde{P}_t} \right)^{-\delta} \Big[C_{k,t}(i) + \sum_{k'} \int Z_{k',k,t}(i', i)\, di' \Big],$$

Thus $\tilde{P}_t$ enters directly in the cost term.

Aggregating over i and using Dixit-Stiglitz demand gives

$$C_{k,t}(i) \propto \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(\frac{P_{k,t}}{\tilde{P}_t} \right)^{-\eta} C_t,$$
$$Z_{k',k,t}(i', i) \propto \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(\frac{P_{k,t}}{\tilde{P}_t} \right)^{-\eta} Z_{k',t}(i').$$

Two economic forces follow: (i) The term $\Big(P_{k,t}/\tilde{P}_t \Big)^{-\eta}$ acts as the perceived relative price of the k-bundle. If $\tilde{P}_t$ understates (overstates) the true aggregate, the sector appears more (less) expensive, shifting final and intermediate demand with elasticity η. This reallocates expenditure and input sourcing across sectors, altering $C_{k,t}$ and $\sum_{k'} Z_{k',k,t}$ and changing labor demand; (ii) Cost share channel via δ. With intermediate share δ, the cost-minimizing ratio of intermediates to labor is

$$\frac{Z_{k,t}(i)}{H_{k,t}(i)} \propto \frac{W_{k,t}}{\tilde{P}_t}.$$

Misperceiving the deflator therefore shifts the shadow real wage that governs the labor-intermediate tradeoff, tilting labor demand even if quantities were unchanged.

Combining these channels and log-linearizing yields the sectoral hours condition:

$$h_{k,t} = d_{k,t} - a_t - a_{k,t} - \delta(w_{k,t} - \tilde{p}_t) - \eta(p_{k,t} - \tilde{p}_t) + (1-\delta)c_t + \delta z_t + r_{k,t},$$

which makes the two wedges explicit: (a) Labor-cost wedge: $-(w_{k,t} - \tilde{p}_t)$, weighted by δ, from choosing labor in perceived rather than true real units; (b) Relative-price wedge: $-(p_{k,t} - \tilde{p}_t)$, weighted by η, from allocating consumption and intermediates across sectors using the perceived aggregate.

The term

$$r_{k,t} \equiv \ln\left(\frac{1}{n_k}\int (P_{k,t}(i)/P_{k,t})^{-\theta} di\right)$$

captures within-sector dispersion: more relative-price heterogeneity means more hours per unit of the sectoral composite.

Finally, substituting the household intratemporal condition links hours to gaps:

$$x_{h_k,t} = \frac{1}{1+\varphi\delta}\left[\varphi\delta x_{c,t} + x_{c_k,t} + r_{k,t}\right].$$

Thus the average misperception component maps into the aggregate gap $x_{c,t}$ through the perceived real wage and the labor–intermediate mix. The sector-specific component maps into $x_{c_k,t}$ through perceived relative prices with elasticity η. The dispersion term $r_{k,t}$ adds labor demand even when gaps are fixed. These three objects are precisely the sufficient statistics that enter the quadratic welfare loss.

B.1.7.1 Results

This section evaluates interest-rate rules using a quadratic welfare loss that penalizes three familiar NK inefficiencies: (i) within-sector price dispersion from staggered pricing; (ii) aggregate slack; and (iii) cross-sector misallocation.

Quadratic loss and decomposition. We evaluate policies with a quadratic welfare criterion that has three components: price dispersion across firms, volatility of the aggregate output (consumption) gap, and sectoral misallocation. Because the loss includes only squared terms, welfare depends only on the unconditional variances of these variables. In a linear setting, each structural shock contributes independently to those variances, so total welfare can be additively decomposed. We report welfare shares by loss component and by shock class: aggregate, sectoral demand, and sectoral productivity.[6]

Welfare losses are measured in consumption-equivalent units relative to the efficient allocation:

$$\mathcal{L} = \sum_{k=1}^{K} n_k \frac{\lambda_{\pi_k}}{2} \mathrm{Var}[\pi_{k,t} - \nu_k \pi_{k,t-1}] + \frac{\lambda_c}{2} \mathrm{Var}[x_{c,t}] + \sum_{k=1}^{K} n_k \frac{\lambda_{c_k}}{2} \mathrm{Var}[x_{c_k,t}],$$

where $x_{c,t}$ is the aggregate output gap, $x_{c_k,t}$ is the sectoral gap, and $\pi_{k,t}$ is sectoral inflation. The welfare weights $(\lambda_c, \lambda_{\pi_k}, \lambda_{c_k})$ follow the standard quadratic approximation.[7]

All welfare loss curves slope upward and are concave. Higher θ raises losses, but at a diminishing rate.[8] The ranking of rules is stable for $\theta \in [0, 2]$. As θ rises, agents give more weight to flexible price categories in intertemporal decisions, which shifts aggregate demand and amplifies volatility.[9] Larger departures from rationality therefore lead to greater welfare losses.

Figure B.1 also shows the decomposition of losses across terms. Price dispersion, tied directly to the stickiness principle, dominates. Note that responding to perceived inflation in the rule is substantially more costly than targeting headline or core.

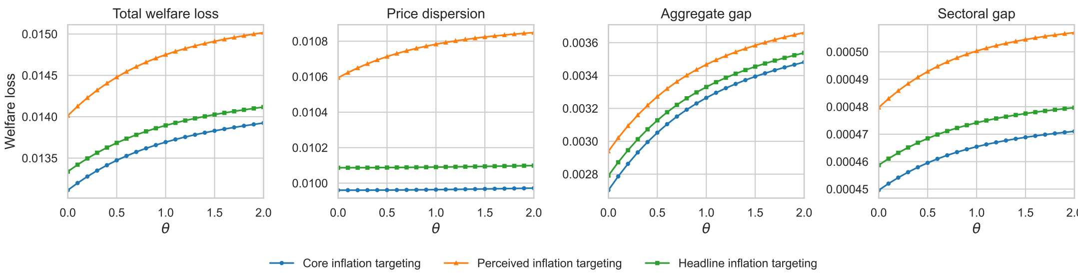
[6]In practice, we use Dynare's unconditional variances of the target variables and its shock by shock variance decompositions.

[7]See Woodford (2003) and Galí (2015). A full derivation appears in Appendix B.1.7.2. Behavioral agents are assumed to share the same welfare criterion as rational agents.

[8]Because the Stereotypes model already puts excess weight on flexible price sectors relative to $\bar{f}$, further increases in θ add only incremental distortion.

[9]A similar expectations channel is highlighted in Dietrich (2024).

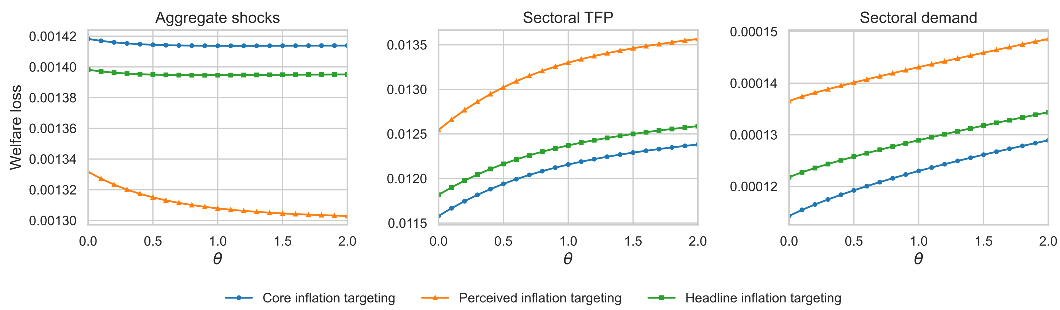
Figure B.1: Welfare losses shares across terms as functions of θ: Output gap, price dispersion, and sectoral output gaps.



Note: Price-dispersion weights scale with $\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}$, so rigid sectors dominate. Perceived inflation activates multiple distortion channels that interact with nominal rigidities and production linkages, while the potential non-core stabilization from responding to $\tilde{\pi}_t$ is only second order relative to the dominant dispersion and misallocation losses. See Appendix B.1.7 for details.

Productivity shocks dominate because they directly move marginal costs and sectoral inflation, compounding dispersion in sticky sectors. Productivity shocks in Financial Services (#14) and Health Care (#10), the stickiest sectors, account for more than half of baseline welfare losses. Gasoline (#7) also contributes due to frequent resets and high indexation that spread volatility over time, but its overall weight is modest (see Figure B.3).

Figure B.2: Welfare losses shares across shocks: Aggregate shocks, sectoral demand shocks, and sectoral productivity shocks.



Sectors Health (10) and Financial Services (14) dominate welfare losses. The dispersion term in the welfare loss loads sector k according to

$$n_k \frac{\epsilon^2}{1+\varphi\delta} \underbrace{\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}}_{\text{Calvo compounding}} V[\pi_{k,t} - \nu_k \pi_{k,t-1}]$$

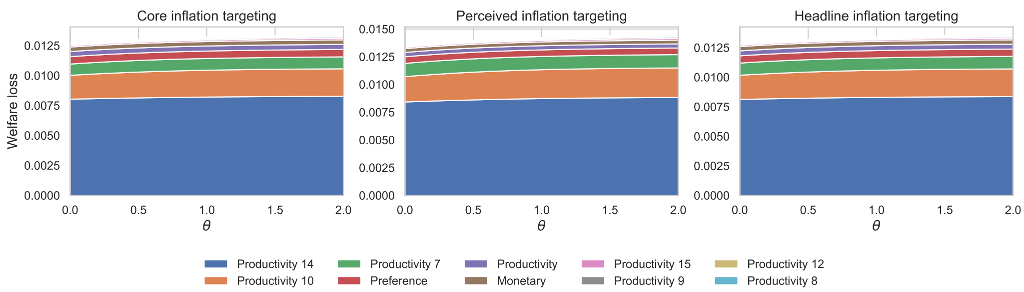
where the Calvo factor strongly penalizes rigid sectors.[10]

[10]For rigid sectors the factor $\alpha_k/(1-\alpha_k)$ is large. This mirrors the classic Aoki (2001) two-sector result: welfare prioritizes stabilizing inflation where nominal rigidities are largest;

Sectors Health (10) and Financial Services (14) combine three features: (i) very high nominal rigidity ($\alpha_{10} = 0.857$, $\alpha_{14} = 0.781$), which makes the Calvo weight large; (ii) sizable expenditure shares ($n_{10} = 15.7\%$, $n_{14} = 8.1\%$); and (iii) high productivity volatility ($\sigma_{a,14} = 42.8$, $\sigma_{a,10} = 8.0$). This triad ensures that any inflation variance in these sectors is extremely costly, so their productivity shocks account for a disproportionate welfare share across θ and across model variants.

Our framework does not assign sectors upstream or downstream roles as in Rubbo (2023). With roundabout production ($\delta > 0$) and a common CES composite of intermediates, each sector's output is split between final demand and inputs in the same proportions ($n_k D_{k,t}$). In this setting, large consumption sectors are also large input suppliers. This makes Health (10) and Financial Services (14) especially important: their high price rigidity raises dispersion costs, and their size means that shocks and slow-moving prices in these sectors spread through the input-cost index into other sectors' costs. As a result, size and rigidity alone are enough to place these sectors at the center of welfare outcomes.

Figure B.3: Ranking of welfare losses shares across shocks.



Notes: Health (#10) and Financial Services (#14) lead due to high stickiness and volatile/persistent productivity; Gasoline (#7) appears due to high $\sigma_{a,7}$ and high indexation ν_7, which spreads inflation innovations through cost spillovers.

Why sector 7 (Gasoline) appears among top shocks and why it disappears when $\delta = 0$. Sector 7 (Gasoline) is almost fully flexible ($\alpha_7 \simeq 0.003$), so its own price dispersion has little direct welfare weight. Its role comes indirectly. With roundabout production ($\delta > 0$ as the intermediate input share)[11], and a

targeting sticky-price (core) inflation implements that principle. See Eusepi, Hobijn and Tambalotti (2011) for a multi-sector implementation where optimally weighted inflation indices (CONDI) approximate the Ramsey allocation.

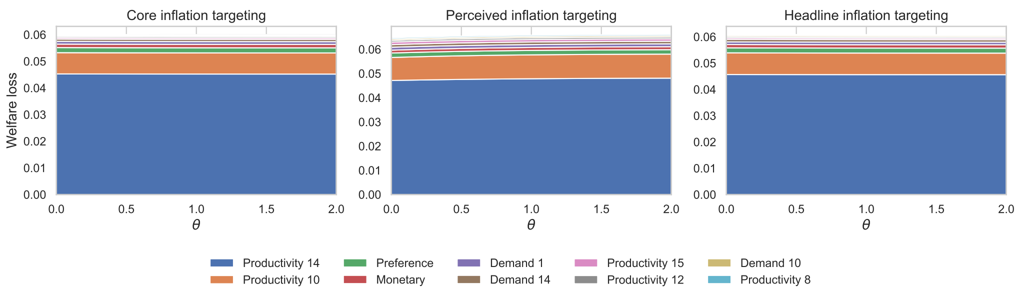
[11]In the second-order welfare approximation, the derivative of the coefficient multiplying the aggregate output gap $x_{c,t}^2$ is

$$\lambda_c'(\delta) = 2(1+\varphi)\varphi\left(1 + \frac{1}{(1+\varphi\delta)^2}\right) > 0,$$

common CES composite of intermediates, a productivity shock in gasoline, given its high volatility ($\sigma_{a,7} = 23.6$) and indexation ($\nu_7 = 0.51$), passes fully into P_7 and raises other sectors' marginal costs[12]. Oil-type productivity shocks in a flexible sector also force policy to adjust the output gap to contain inflation, adding gap and misallocation losses elsewhere.

The cross-sector term scales with substitution elasticities: higher elasticities magnify demand reallocation toward mispriced sectors. With our across-sector demand elasticity around $\eta \approx 0.6$, this amplification is moderate but nonzero, yet strong enough, given gasoline's network reach, to place it among the top welfare-relevant shocks. When intermediates are shut down ($\delta = 0$), the input-cost channel disappears, cross-sector wedges collapse, and productivity shocks in gasoline drop out of the main contributors (see Figure B.4).

Figure B.4: Ranking of welfare losses shares across shocks ($\delta = 0$).



Note: With $\delta = 0$ (no roundabout production), cost spillovers from flexible to stickier sectors vanish, so welfare losses are driven primarily by shocks in the rigid-price sectors.

and the second derivative is

$$\lambda_c''(\delta) = -\frac{4(1+\varphi)\varphi^2}{(1+\varphi\delta)^3} < 0.$$

Thus the welfare weight on the aggregate gap is increasing and concave in δ, with $\lambda_c(0) = 0$ and $\lambda_c(1) = 2\varphi(2+\varphi)$. Intuitively, stronger IO linkages raise the cost of aggregate deviations because shocks propagate through the common intermediate bundle. When $\delta = 0$, this channel shuts down and the aggregate-gap penalty vanishes. At the same time, sectoral-gap losses remain, reflecting misallocation induced by segmented labor markets. In Appendix B.2 we show that with an economy-wide labor market, sectoral gaps drop out of the welfare approximation, since cross-sector misallocations are entirely eliminated.

[12]Rubbo (2023) show that this creates cross-sector wedges between sticky prices and network-adjusted productivities, which her welfare criterion penalizes even if the originating sector is flexible.

B.1.7.2
Proofs

Proposition B.1 *Up to a second-order approximation around the flexible price equilibrium, the household utility is given by:*

$$-\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}_t\Bigg[\theta^2\sum_{k=1}^{K}\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}n_k(\pi_{k,\tau}-\nu_k\pi_{k,\tau-1})^2$$
$$+\frac{2(1+\varphi)\varphi\delta(2+\varphi\delta)}{1+\varphi\delta}x_{c,\tau}^2+\frac{1+\varphi}{1+\varphi\delta}\sum_{k=1}^{K}n_k x_{c_k,\tau}^2\Bigg]+t.i.p,$$

where $x_{c,t}\equiv c_t-c_t^n$, $x_{c_k,t}\equiv c_{k,t}-c_{k,t}^n$ and t.i.p represents terms that are not influenced by policy decisions.

Proof. Define the period utility $u_t\equiv u(C_t,H_{1,t},\ldots,H_{K,t})$ as:

$$u_t=\ln C_t-\sum_{k=1}^{K}\omega_k\frac{H_{k,t}^{1+\varphi}}{1+\varphi},$$

where $u_t^n=u(C_t^n,H_{1,t}^n\ldots,H_{K,t}^n)$ is its value on the flexible prices equilibrium. We approximate logged consumption and sectoral labor as:

$$\frac{C_t-C_t^n}{C_t^n}\approx x_{c,t}+\frac{1}{2}x_{c,t}^2$$
$$\frac{H_{k,t}-H_{k,t}^n}{H_{k,t}^n}\approx x_{h_k,t}+\frac{1}{2}x_{h_k,t}^2$$

A second-order Taylor expansion of u_t around our flexible prices equilibrium gives us:

$$u_t-u_t^n\approx u_C C_t^n\frac{C_t-C_t^n}{C_t^n}+\sum_{k=1}^{K}u_{H_k}H_{k,t}^n\frac{H_{k,t}-H_{k,t}^n}{H_{k,t}^n}+\frac{1}{2}u_{CC}(C_t^n)^2\left(\frac{C_t-C_t^n}{C_t^n}\right)^2$$
$$+\frac{1}{2}\sum_{k=1}^{K}u_{H_kH_k}(H_{k,t}^n)^2\left(\frac{H_{k,t}-H_{k,t}^n}{H_{k,t}^n}\right)^2$$
$$\approx u_C C_t^n\left(x_{c,t}+\frac{1}{2}x_{c,t}^2\right)+\sum_{k=1}^{K}u_{H_k}H_{k,t}^n\left(x_{h_k,t}+\frac{1}{2}x_{h_k,t}^2\right)$$
$$+\frac{1}{2}u_{CC}(C_t^n)^2x_{c,t}^2+\frac{1}{2}\sum_{k=1}^{K}u_{H_kH_k}(H_{k,t}^n)^2x_{h_k,t}^2.$$

Log preferences implies[13]*:*

$$u_t - u_t^n \approx x_{c,t} + \sum_{k=1}^{K} u_{H_k} H_{k,t}^n \left(x_{h_k,t} + \frac{1 + \frac{u_{H_k H_k}}{u_{H_k}} H_{k,t}^n}{2} x_{h_k,t}^2 \right)$$
$$\approx x_{c,t} - \sum_{k=1}^{K} n_k \left(x_{h_k,t} + \frac{1+\varphi}{2} x_{h_k,t}^2 \right)$$

Recall that:

$$\begin{aligned}
H_{k,t} &= \int_{\mathcal{I}_k} H_{k,t}(i) di \\
&= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_{k,t}}{\tilde{P}_t} \right)^{-\delta} \int_{\mathcal{I}_k} \left(C_{k,t}(i) + \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',k,t}(i', i) di' \right) di \\
&= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_{k,t}}{\tilde{P}_t} \right)^{-\delta} \int_{\mathcal{I}_k} \left(\frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(C_{k,t} + \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',k,t}(i') di' \right) \right) di \\
&= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_{k,t}}{\tilde{P}_t} \right)^{-\delta} \int_{\mathcal{I}_k} \left(D_{k,t} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(\frac{P_{k,t}}{\tilde{P}_t} \right)^{-\eta} \left(C_t + \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',t}(i') di' \right) \right) di \\
&= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_{k,t}}{\tilde{P}_t} \right)^{-\delta} D_{k,t} \left(\frac{P_{k,t}}{\tilde{P}_t} \right)^{-\eta} (C_t + Z_t) \int_{\mathcal{I}_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} di.
\end{aligned}$$

Therefore:

$$h_{k,t} = d_{k,t} - a_t - a_{k,t} - \delta(w_{k,t} - \tilde{p}_t) - \eta(p_{k,t} - \tilde{p}_t) + (1-\delta)c_t + \delta z_t + r_{k,t},$$

where $r_{k,t} \equiv \ln\left(\frac{1}{n_k} \int_{\mathcal{I}_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} di \right)$*. Solving for* $w_{k,t} - \tilde{p}_t$ *and* $p_{k,t} - \tilde{p}_t$*:*

$$h_{k,t} = \frac{1}{1+\varphi\delta} \left[\varphi\delta c_t + c_{k,t} - a_{k,t} - \frac{1+\varphi\delta}{1-\delta} a_t - \frac{(1+\varphi)\delta}{1-\delta} \bar{a}_t + r_{k,t} \right].$$

Solving for the labor gap:

$$x_{h_k,t} = \frac{1}{1+\varphi\delta} \left[\varphi\delta x_{c,t} + x_{c_k,t} + r_{k,t} \right],$$

where $r_{k,t}^n = 0$*. Now we express the sectoral price-dispersion term* $r_{k,t}$ *as a simple quadratic in relative prices. We define* $q_{ik} \equiv p_{k,t}(i) - p_{k,t}$*, where* $\int q_{ik} di = 0$ *and*

$$e^{-\theta q_{ik}} = 1 - \theta q_{ik} + \frac{\theta^2}{2} q_{ik}^2 + O(q_{ik}^3).$$

[13] We normalize the flexible price labor supply $(H_k/n_k)^\varphi = 1$, scaling all remaining quadratic terms by the same factor.

Therefore:

$$
\begin{aligned}
r_{k,t} &\approx \ln\left(\frac{1}{n_k}\int_{\mathcal{I}_k}\left[1-\theta q_{ik}+\frac{\theta^2}{2}q_{ik}^2\right]di\right)\\
&\approx \ln\left(1+\frac{1}{n_k}\int_{\mathcal{I}_k}\frac{\theta^2}{2}q_{ik}^2 di\right)\\
&\approx \frac{\theta^2}{2}V_{ik}[p_{k,t}(i)],
\end{aligned}
$$

where $V_{ik}[p_{k,t}(i)] \equiv \frac{1}{n_k}\int_{\mathcal{I}_k}(p_{k,t}(i)-\bar{p}_{k,t})^2 di$ *and* $p_{k,t} \approx \bar{p}_{k,t} \equiv \frac{1}{n_k}\int_{\mathcal{I}_k} p_{k,t}(i)di$*, up to a first order approximation. Combining all the pieces together:*

$$
\begin{aligned}
u_t - u_t^n \approx x_{c,t} &- \frac{1}{1+\varphi\delta}\sum_{k=1}^{K} n_k\left[\varphi\delta x_{c,t}+x_{c_k,t}+\frac{\theta^2}{2}V_{ik}[p_{k,t}(i)]\right]\\
&- \frac{1+\varphi}{2(1+\varphi\delta)^2}\sum_{k=1}^{K} n_k\left[\varphi\delta x_{c,t}+x_{c_k,t}+\frac{\theta^2}{2}V_{ik}[p_{k,t}(i)]\right]^2\\
&= -\frac{\theta^2}{2(1+\varphi\delta)}\sum_{k=1}^{K} n_k V_{ik}[p_{k,t}(i)] - \frac{(1+\varphi)\varphi\delta(2+\varphi\delta)}{(1+\varphi\delta)^2}x_{c,t}^2\\
&- \frac{1+\varphi}{2(1+\varphi\delta)^2}\sum_{k=1}^{K} n_k x_{c_k,t}^2
\end{aligned}
$$

where the (squared) dispersion term vanishes as it is fourth order, and cross terms are third order and can be ignored. We approximate the terms involving price dispersion as a function of inflation. The distribution of sectoral prices at date t *evolves according to the Calvo–indexation scheme:*

$$
\begin{aligned}
\bar{p}_{k,t}-\bar{p}_{k,t-1} &= \frac{1}{n_k}\int_{\mathcal{I}_k}(p_{k,t}(i)-\bar{p}_{k,t-1})di\\
&= \alpha_k[\bar{p}_{k,t-1}+\nu_k\pi_{k,t-1}-\bar{p}_{k,t-1}]+(1-\alpha_k)[p_{k,t}^*-\bar{p}_{k,t-1}]\\
&= \alpha_k\nu_k\pi_{k,t-1}+(1-\alpha_k)(p_{k,t}^*-\bar{p}_{k,t-1})\\
&\equiv \pi_{k,t}.
\end{aligned}
$$

We define the dispersion measure $\Delta_{k,t}$ *as the cross-sectional variance of* *log prices around the new average:*

$$\begin{aligned}
\Delta_{k,t} \equiv V_{ik}\Big[p_{k,t}(i)\Big] &= \frac{1}{n_k}\int_{\mathcal{I}_k}\Big(p_{k,t}(i)-\bar{p}_{k,t}\Big)^2 di \\
&= \frac{1}{n_k}\int_{\mathcal{I}_k}\Big(p_{k,t}(i)-\bar{p}_{k,t-1}\Big)^2 di - \pi_{k,t}^2 \\
&= \alpha_k\frac{1}{n_k}\int_{\mathcal{I}_k}\Big(p_{k,t-1}(i)+\nu_k\pi_{k,t-1}-\bar{p}_{k,t-1}\Big)^2 di + (1-\alpha_k)\Big(p^*_{k,t}-\bar{p}_{k,t-1}\Big)^2 - \pi_{k,t}^2 \\
&= \alpha_k\Delta_{k,t-1} + \alpha_k\nu_k^2\pi_{k,t-1}^2 + (1-\alpha_k)(p^*_{k,t}-p_{k,t-1})^2 - \pi_{k,t}^2 \\
&= \alpha_k\Delta_{k,t-1} + \frac{\alpha_k}{1-\alpha_k}(\pi_{k,t}-\nu_k\pi_{k,t-1})^2,
\end{aligned}$$

where we used

$$p^*_{k,t}-\bar{p}_{k,t-1} = \frac{\alpha_k}{1-\alpha_k}(\pi_{k,t}-\nu_k\pi_{k,t-1})$$

and dropped terms beyond second order.

We solve forward, starting from a small initial degree of price dispersion $\Delta_{k,-1}$*, which is independent of policy:*

$$\begin{aligned}
\Delta_{k,t} &\approx \alpha_k^{t+1}\Delta_{k,-1} + \frac{\alpha_k}{1-\alpha_k}\sum_{s=0}^{t}\alpha_k^{t-s}\tilde{\pi}_{k,s}^2 \\
&= \frac{\alpha_k}{1-\alpha_k}\sum_{s=0}^{t}\alpha_k^{t-s}\tilde{\pi}_{k,s}^2 + t.i.p,
\end{aligned}$$

where $\tilde{\pi}_{k,t} \equiv \pi_{k,t} - \nu_k\pi_{k,t-1}$*. We take the discounted value of these values over all periods* $\tau \geq t$*:*

$$\begin{aligned}
\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Delta_{k,\tau} &\approx \frac{\alpha_k}{1-\alpha_k}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\sum_{s=0}^{\tau}\alpha_k^{\tau-s}\tilde{\pi}_{k,s}^2 + t.i.p \\
&= \frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\tilde{\pi}_{k,\tau}^2 + t.i.p
\end{aligned}$$

Hence:

$$\begin{aligned}
\sum_{\tau=t}^{\infty}\beta^{\tau-t}(u_\tau-u_\tau^n) &\approx -\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Bigg[\frac{\theta^2}{1+\varphi\delta}\sum_{k=1}^{K}V_{ik}[p_{k,\tau}(i)] + \frac{2(1+\varphi)\varphi\delta(2+\varphi\delta)}{(1+\varphi\delta)^2}x_{c,\tau}^2 \\
&\quad + \frac{1+\varphi}{2(1+\varphi\delta)^2}\sum_{k=1}^{K}n_k x_{c_k,\tau}^2\Bigg] + t.i.p \\
&\approx -\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Bigg[\frac{\theta^2}{1+\varphi\delta}\sum_{k=1}^{K}\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}n_k\tilde{\pi}_{k,\tau}^2 \\
&\quad + \frac{2(1+\varphi)\varphi\delta(2+\varphi\delta)}{(1+\varphi\delta)^2}x_{c,\tau}^2 + \frac{1+\varphi}{(1+\varphi\delta)^2}\sum_{k=1}^{K}n_k x_{c_k,\tau}^2\Bigg] + t.i.p
\end{aligned}$$

■

B.2
Simplified model

This section presents a stripped-down version of the model under three restrictions: (i) price indexation is eliminated ($\nu_k = 0$); (ii) roundabout input-output linkages are removed ($\delta = 0$), so firms use only labor and no intermediate inputs; and (iii) sectoral labor markets are replaced with a single aggregate labor market. Agents continue to form perceptions using the distorted aggregate price index $\tilde{P}_t$, but with labor-only production, perceived and true marginal costs coincide.

Without indexation, the New Keynesian Phillips curve becomes fully forward-looking, as lagged inflation terms disappear. Removing roundabout production eliminates all intermediate-input terms $(Z, z_t, Z_{k,t})$, so the resource constraint simplifies to $Y_t = C_t$, and sectoral technology reduces to a linear form, $Y_{k,t}(i) = A_t A_{k,t} H_{k,t}(i)$. This also removes the equation $w_t - \tilde{p}_t = z_t - h_t$ from the equilibrium system.

With an economy-wide labor market, there is only one aggregate wage W_t and total hours H_t, replacing sector-specific wages $W_{k,t}$ and labor inputs $H_{k,t}$. This changes the dynamics of marginal costs and therefore the Phillips curve in equilibrium. Specifically, the curve becomes:

$$\begin{aligned}\pi_{k,t} = &\frac{\nu_k}{1+\beta\nu_k}\pi_{k,t-1} + \frac{\beta}{1+\beta\nu_k}\mathbb{E}_t[\pi_{k,t+1}] \\ &+\frac{(1-\alpha_k)(1-\alpha_k\beta)}{\alpha_k(1+\beta\nu_k)}\left\{\frac{1}{\eta}c_{k,t} + \left[\frac{(1-\delta)[(1-\delta)\varphi+1]}{1+\delta\varphi} - \frac{1}{\eta}\right]c_t \right. \\ &\left. +\frac{(1-\delta)\delta\varphi}{1+\delta\varphi}z_t - \frac{1+\varphi}{1+\delta\varphi}a_t - a_{k,t} - \frac{(1-\delta)\varphi}{1+\delta\varphi}\bar{a}_t - \frac{1}{\eta}d_{k,t}\right\}\end{aligned} \tag{B-40}$$

Given these restrictions, the welfare problem simplifies considerably.[14] With labor-only production and a single labor market, the intratemporal condition equates the marginal rate of substitution across all uses of labor. This eliminates sector-specific wage wedges that would otherwise generate costly cross-sector misallocations. As a result, the second-order welfare approximation depends only on two forces: (i) price dispersion arising from nominal rigidities and indexation, captured by the sectoral Calvo term $\sum_k n_k \frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}(\pi_{k,t} - \nu_k\pi_{k,t-1})^2$, and (ii) aggregate slack, summarized by the consumption gap $x_{c,t}^2$.

The Phillips curve in (B-40) shows the transmission. With $\nu_k = 0$ and $\delta = 0$, lagged inflation terms vanish and intermediate-input channels drop out,

[14]See Section B.2.1.

so inflation dynamics depend directly on $(c_{k,t}, c_t)$ through marginal costs that coincide with perceived costs.

B.2.1 Proofs

The proposition below formalizes welfare losses in the simplified model, setting $\nu_k = \delta = 0$, and derives closed-form welfare weights as functions of deep parameters. In contrast to the general multisector case, sectoral gaps drop out of the welfare approximation, since cross-sector misallocations are entirely eliminated.

Proposition B.2 *Consider the simplified multisector model with an economy-wide labor market. Up to a second-order approximation around the flexible-price equilibrium, household utility takes the form:*

$$-\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\mathbb{E}_t\left[\frac{\theta^2}{1+\varphi\delta}\sum_{k=1}^{K}\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}n_k(\pi_{k,\tau}-\nu_k\pi_{k,\tau-1})^2+(1+\varphi)x_{c,\tau}^2\right] +t.i.p,$$

where $x_{c,t} \equiv c_t - c_t^n$ and t.i.p represents terms that are not influenced by policy decisions.

Proof. Define the period utility $u_t \equiv u(C_t, H_t)$ as:

$$u_t = \ln C_t - \frac{H_t^{1+\varphi}}{1+\varphi},$$

where $u_t^n = u(C_t^n, H_t^n)$ is its value on the flexible prices equilibrium. We approximate logged consumption and sectoral labor as:

$$\frac{C_t - C_t^n}{C_t^n} \approx x_{c,t} + \frac{1}{2}x_{c,t}^2$$
$$\frac{H_t - H_t^n}{H_t^n} \approx x_{h,t} + \frac{1}{2}x_{h,t}^2$$

A second-order Taylor expansion of u_t around our flexible prices equilibrium *gives us:*

$$\begin{aligned} u_t - u_t^n &\approx u_C C_t^n \frac{C_t - C_t^n}{C_t^n} + u_H H_t^n \frac{H_t - H_t^n}{H_t^n} + \frac{1}{2} u_{CC} (C_t^n)^2 \left(\frac{C_t - C_t^n}{C_t^n} \right)^2 \\ &+ \frac{1}{2} u_{HH} (H_t^n)^2 \left(\frac{H_t - H_t^n}{H_t^n} \right)^2 \\ &\approx u_C C_t^n \left(x_{c,t} + \frac{1}{2} x_{c,t}^2 \right) + u_H H_t^n \left(x_{h,t} + \frac{1}{2} x_{h,t}^2 \right) \\ &+ \frac{1}{2} u_{CC} (C_t^n)^2 x_{c,t}^2 + \frac{1}{2} u_{HH} (H_t^n)^2 x_{h,t}^2 . \end{aligned}$$

Log preferences implies[15]*:*

$$\begin{aligned} u_t - u_t^n &\approx x_{c,t} + u_H H_t^n \left(x_{h,t} + \frac{1 + \frac{u_{HH}}{u_H} H_t^n}{2} x_{h,t}^2 \right) \\ &\approx x_{c,t} - \left(x_{h,t} + \frac{1+\varphi}{2} x_{h,t}^2 \right) \end{aligned}$$

Recall that sectoral labor demand is given by:

$$\begin{aligned} H_{k,t} &= \int_{\mathcal{I}_k} H_{k,t}(i) di \\ &= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_t}{\tilde{P}_t} \right)^{-\delta} \int_{\mathcal{I}_k} \left(C_{k,t}(i) + \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',k,t}(i', i) di' \right) di \\ &= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_t}{\tilde{P}_t} \right)^{-\delta} \int_{\mathcal{I}_k} \left(\frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(C_{k,t} + \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',k,t}(i') di' \right) \right) di \\ &= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_t}{\tilde{P}_t} \right)^{-\delta} \int_{\mathcal{I}_k} \left(D_{k,t} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} \left(\frac{P_{k,t}}{\tilde{P}_t} \right)^{-\eta} \left(C_t + \sum_{k'=1}^{K} \int_{\mathcal{I}_{k'}} Z_{k',t}(i') di' \right) \right) di \\ &= \frac{1}{A_t A_{k,t}} \left(\frac{\delta}{1-\delta} \frac{W_t}{\tilde{P}_t} \right)^{-\delta} D_{k,t} \left(\frac{P_{k,t}}{\tilde{P}_t} \right)^{-\eta} (C_t + Z_t) \int_{\mathcal{I}_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} di. \end{aligned}$$

Therefore:

$$h_{k,t} = d_{k,t} - a_t - a_{k,t} - \delta(w_t - \tilde{p}_t) - \eta(p_{k,t} - \tilde{p}_t) + (1-\delta) c_t + \delta z_t + r_{k,t},$$

where $r_{k,t} \equiv \ln \left(\frac{1}{n_k} \int_{\mathcal{I}_k} \left(\frac{P_{k,t}(i)}{P_{k,t}} \right)^{-\theta} di \right)$*. Solving for* $w_t - \tilde{p}_t$ *and* $p_{k,t} - \tilde{p}_t$*:*

$$h_{k,t} = \frac{1}{1+\varphi\delta} \left[\varphi \delta c_t + c_{k,t} - a_{k,t} - \frac{1+\varphi\delta}{1-\delta} a_t - \frac{(1+\varphi)\delta}{1-\delta} \bar{a}_t + r_{k,t} \right].$$

[15]We normalize the flexible price labor supply $H^{\varphi} = 1$, scaling all remaining quadratic terms by the same factor.

Solving for the labor gap:

$$x_{h_k,t} = \frac{1}{1+\varphi\delta}\left[\varphi\delta x_{c,t} + x_{c_k,t} + r_{k,t}\right],$$

where $r^n_{k,t} = 0$. *Aggregating over* k*:*

$$x_{h,t} = x_{c,t} + \frac{1}{1+\varphi\delta}\sum_{k=1}^{K} n_k r_{k,t}$$

Now we express the sectoral price-dispersion term $r_{k,t}$ *as a simple quadratic in relative prices. We define* $q_{ik} \equiv p_{k,t}(i) - p_{k,t}$, *where* $\int q_{ik} di = 0$ *and*

$$e^{-\theta q_{ik}} = 1 - \theta q_{ik} + \frac{\theta^2}{2} q_{ik}^2 + O(q_{ik}^3).$$

Therefore:

$$\begin{aligned}
r_{k,t} &\approx \ln\left(\frac{1}{n_k}\int_{\mathcal{I}_k}\left[1 - \theta q_{ik} + \frac{\theta^2}{2}q_{ik}^2\right] di\right) \\
&\approx \ln\left(1 + \frac{1}{n_k}\int_{\mathcal{I}_k}\frac{\theta^2}{2}q_{ik}^2 di\right) \\
&\approx \frac{\theta^2}{2} V_{ik}[p_{k,t}(i)],
\end{aligned}$$

where $V_{ik}[p_{k,t}(i)] \equiv \frac{1}{n_k}\int_{\mathcal{I}_k}(p_{k,t}(i) - \bar{p}_{k,t})^2 di$ *and* $p_{k,t} \approx \bar{p}_{k,t} \equiv \frac{1}{n_k}\int_{\mathcal{I}_k} p_{k,t}(i) di$, *up to a first order approximation. Combining all the pieces together:*

$$\begin{aligned}
u_t - u_t^n &\approx x_{c,t} - \left[x_{c,t} + \frac{1}{1+\varphi\delta}\bar{r}_t + \frac{1+\varphi}{2}\left(x_{c,t} + \frac{1}{1+\varphi\delta}\bar{r}_t\right)^2\right] \\
&= -\frac{\theta^2}{2(1+\varphi\delta)}\sum_{k=1}^{K} n_k V_{ik}[p_{k,t}(i)] - \frac{1+\varphi}{2}x_{c,t}^2
\end{aligned}$$

where the (squared) dispersion term vanishes as it is fourth order, and cross terms are third order and can be ignored. We approximate the terms involving price dispersion as a function of inflation. The distribution of sectoral prices at date t *evolves according to the Calvo–indexation scheme:*

$$\begin{aligned}
\bar{p}_{k,t} - \bar{p}_{k,t-1} &= \frac{1}{n_k}\int_{\mathcal{I}_k}(p_{k,t}(i) - \bar{p}_{k,t-1}) di \\
&= \alpha_k[\bar{p}_{k,t-1} + \nu_k \pi_{k,t-1} - \bar{p}_{k,t-1}] + (1-\alpha_k)[p^*_{k,t} - \bar{p}_{k,t-1}] \\
&= \alpha_k \nu_k \pi_{k,t-1} + (1-\alpha_k)(p^*_{k,t} - \bar{p}_{k,t-1}) \\
&\equiv \pi_{k,t}.
\end{aligned}$$

We define the dispersion measure $\Delta_{k,t}$ as the cross-sectional variance of log prices around the new average:

$$\begin{aligned}
\Delta_{k,t} \equiv V_{ik}\Big[p_{k,t}(i)\Big] &= \frac{1}{n_k}\int_{\mathcal{I}_k}\Big(p_{k,t}(i) - \bar{p}_{k,t}\Big)^2 di \\
&= \frac{1}{n_k}\int_{\mathcal{I}_k}\Big(p_{k,t}(i) - \bar{p}_{k,t-1}\Big)^2 di - \pi_{k,t}^2 \\
&= \alpha_k \frac{1}{n_k}\int_{\mathcal{I}_k}\Big(p_{k,t-1}(i) + \nu_k\pi_{k,t-1} - \bar{p}_{k,t-1}\Big)^2 di + (1-\alpha_k)\Big(p_{k,t}^* - \bar{p}_{k,t-1}\Big)^2 - \pi_{k,t}^2 \\
&= \alpha_k\Delta_{k,t-1} + \alpha_k\nu_k^2\pi_{k,t-1}^2 + (1-\alpha_k)(p_{k,t}^* - p_{k,t-1})^2 - \pi_{k,t}^2 \\
&= \alpha_k\Delta_{k,t-1} + \frac{\alpha_k}{1-\alpha_k}(\pi_{k,t} - \nu_k\pi_{k,t-1})^2,
\end{aligned}$$

where we used

$$p_{k,t}^* - \bar{p}_{k,t-1} = \frac{\alpha_k}{1-\alpha_k}(\pi_{k,t} - \nu_k\pi_{k,t-1})$$

and dropped terms beyond second order.

We solve forward, starting from a small initial degree of price dispersion $\Delta_{k,-1}$, which is independent of policy:

$$\begin{aligned}
\Delta_{k,t} &\approx \alpha_k^{t+1}\Delta_{k,-1} + \frac{\alpha_k}{1-\alpha_k}\sum_{s=0}^{t}\alpha_k^{t-s}\tilde{\pi}_{k,s}^2 \\
&= \frac{\alpha_k}{1-\alpha_k}\sum_{s=0}^{t}\alpha_k^{t-s}\tilde{\pi}_{k,s}^2 + t.i.p,
\end{aligned}$$

where $\tilde{\pi}_{k,t} \equiv \pi_{k,t} - \nu_k\pi_{k,t-1}$. We take the discounted value of these values over all periods $\tau \geq t$:

$$\begin{aligned}
\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Delta_{k,\tau} &\approx \frac{\alpha_k}{1-\alpha_k}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\sum_{s=0}^{\tau}\alpha_k^{\tau-s}\tilde{\pi}_{k,s}^2 + t.i.p \\
&= \frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\tilde{\pi}_{k,\tau}^2 + t.i.p
\end{aligned}$$

Hence:

$$\begin{aligned}
\sum_{\tau=t}^{\infty}\beta^{\tau-t}(u_\tau - u_\tau^n) &\approx -\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\left[\frac{\theta^2}{1+\varphi\delta}\sum_{k=1}^{K}V_{ik}[p_{k,\tau}(i)] + (1+\varphi)x_{c,\tau}^2\right] t.i.p \\
&\approx -\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\left[\frac{\theta^2}{1+\varphi\delta}\sum_{k=1}^{K}\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}n_k\tilde{\pi}_{k,\tau}^2 + (1+\varphi)x_{c,\tau}^2\right] + t.i.p
\end{aligned}$$

■

B.3 Figures

Figure B.5: Cumulative absolute errors for the correlation between 1-yr ahead expected inflation and sectoral inflation over the past 4 quarters across models estimated using the interest rate, sectoral inflation, and sectoral consumption growth as observables.

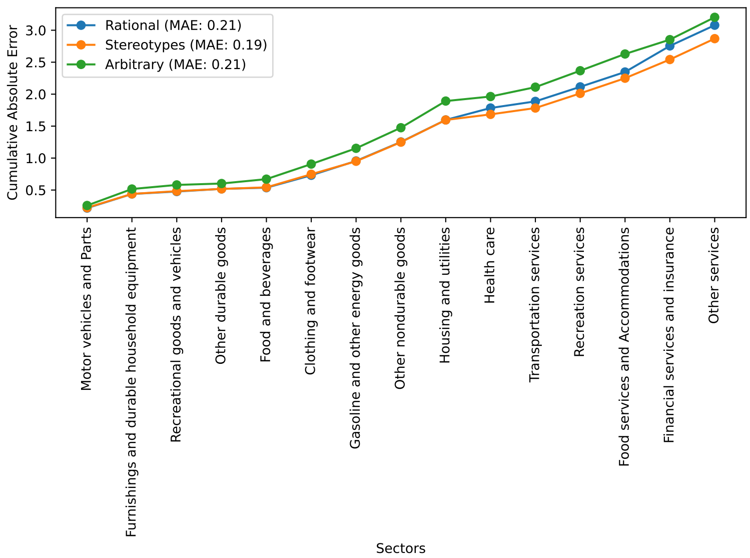


Figure B.6: Cumulative absolute errors for the correlation between 1-yr ahead expected inflation and sectoral inflation over the past 4 quarters across models estimated using the interest rate, sectoral inflation, sectoral consumption growth, and expected inflation from the Michigan Survey of Consumers as observables.

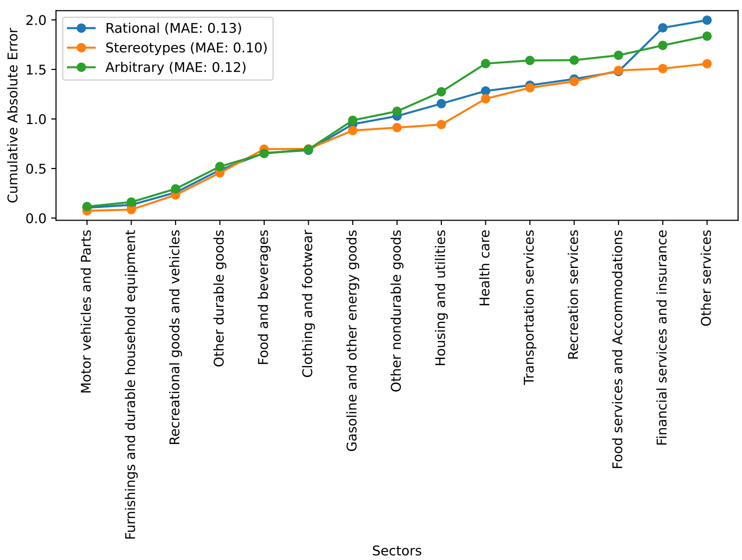


Figure B.7: Cumulative absolute errors for the correlation between 1-yr ahead expected inflation and sectoral inflation over the past 4 quarters across models estimated using the interest rate, sectoral inflation, sectoral consumption growth, and both perceived and expected inflation from the Michigan Survey of Consumers as observables.

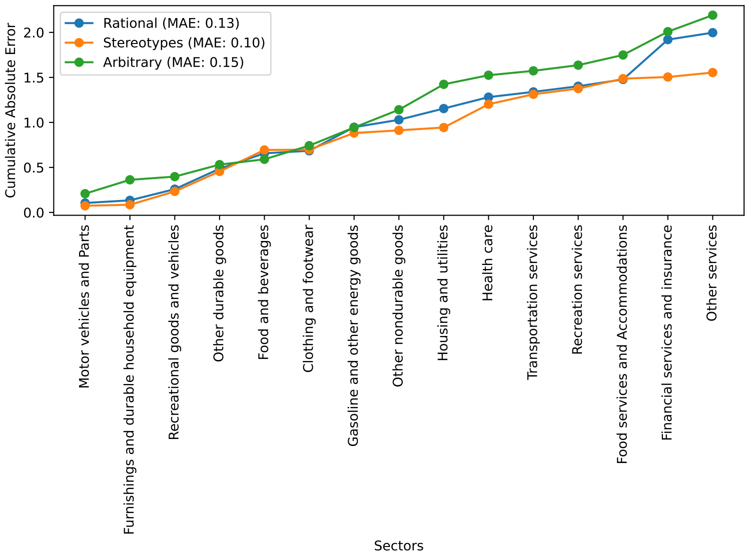


Figure B.8: This figure presents the potential scale reduction factors (PSRF) for the Rational, Arbitrary, and Stereotypes models estimated using the interest rate, sectoral inflation, and sectoral consumption growth as observables. PSRF values below 1.05 indicate acceptable parameter convergence, with those below 1.01 signalling strong convergence.

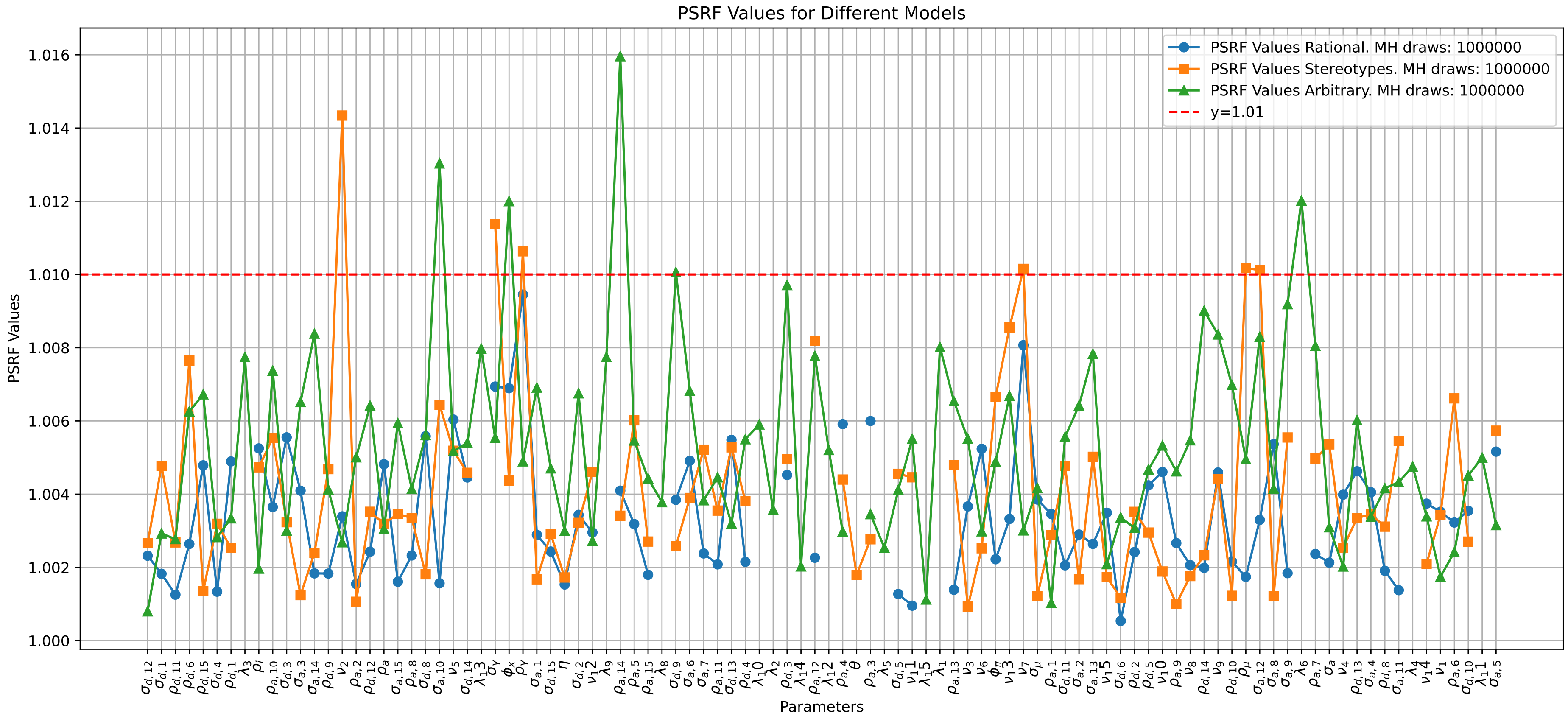


Figure B.9: This figure presents the potential scale reduction factors (PSRF) for the Rational, Arbitrary, and Stereotypes models estimated using the interest rate, sectoral inflation, sectoral consumption growth, and expected inflation from the Michigan Survey of Consumers as observables. PSRF values below 1.05 indicate acceptable parameter convergence, with those below 1.01 signalling strong convergence.

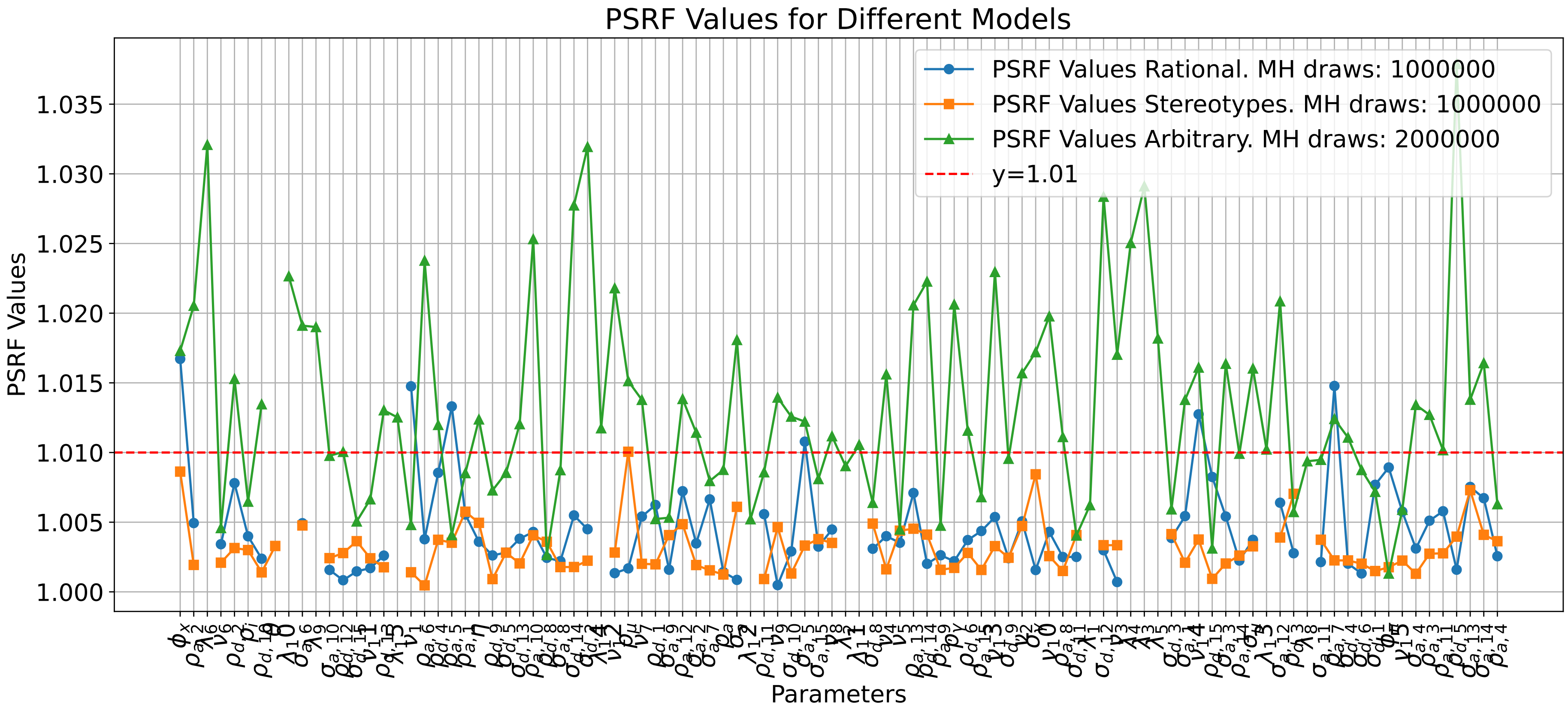


Figure B.10: This figure presents the potential scale reduction factors (PSRF) for the Rational, Arbitrary, and Stereotypes models estimated using the interest rate, sectoral inflation, sectoral consumption growth, and both perceived and expected inflation from the Michigan Survey of Consumers as observables. PSRF values below 1.05 indicate acceptable parameter convergence, with those below 1.01 signalling strong convergence.

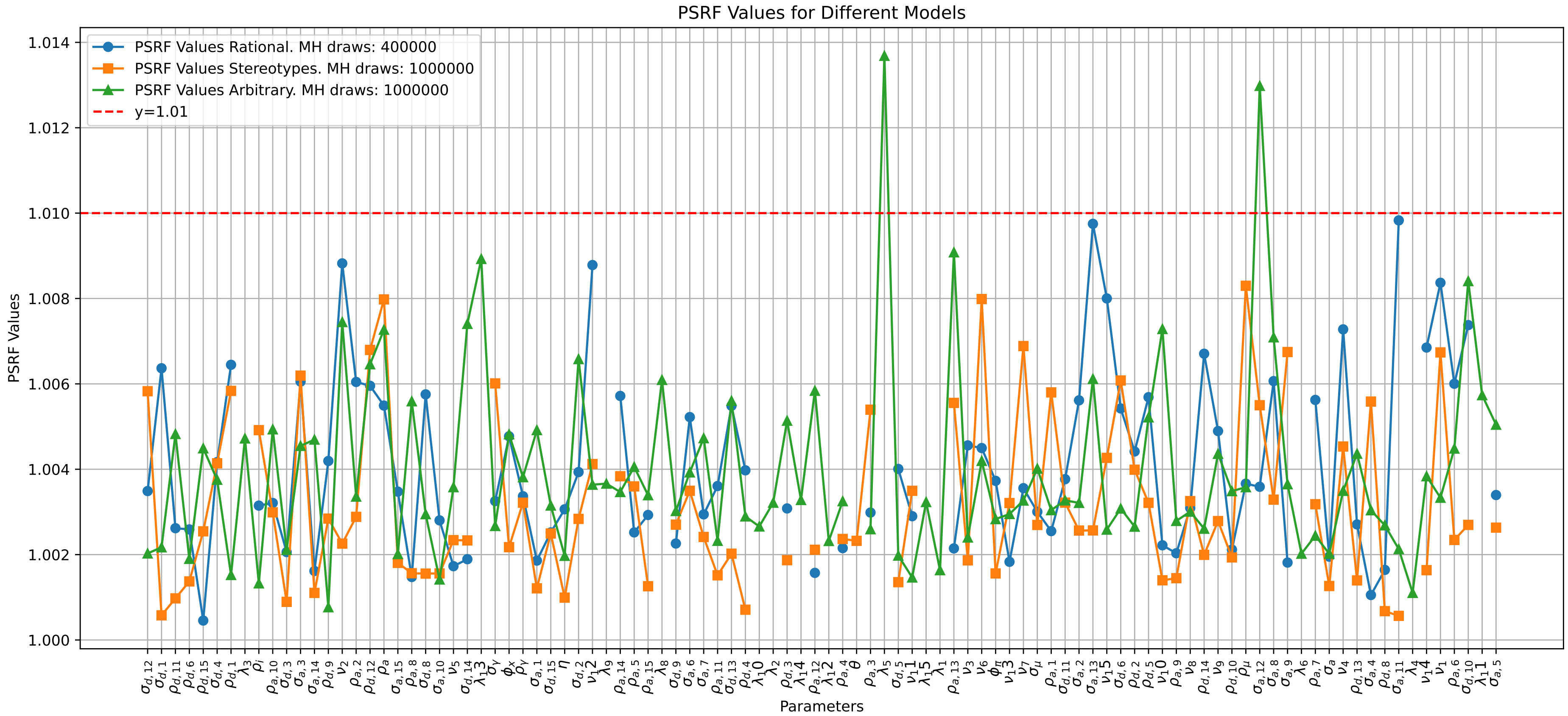


Figure B.11: Smoothed estimates of the 1-year expected inflation, obtained without using survey belief data. The series is adjusted for seasonality and expressed as deviations from its mean.

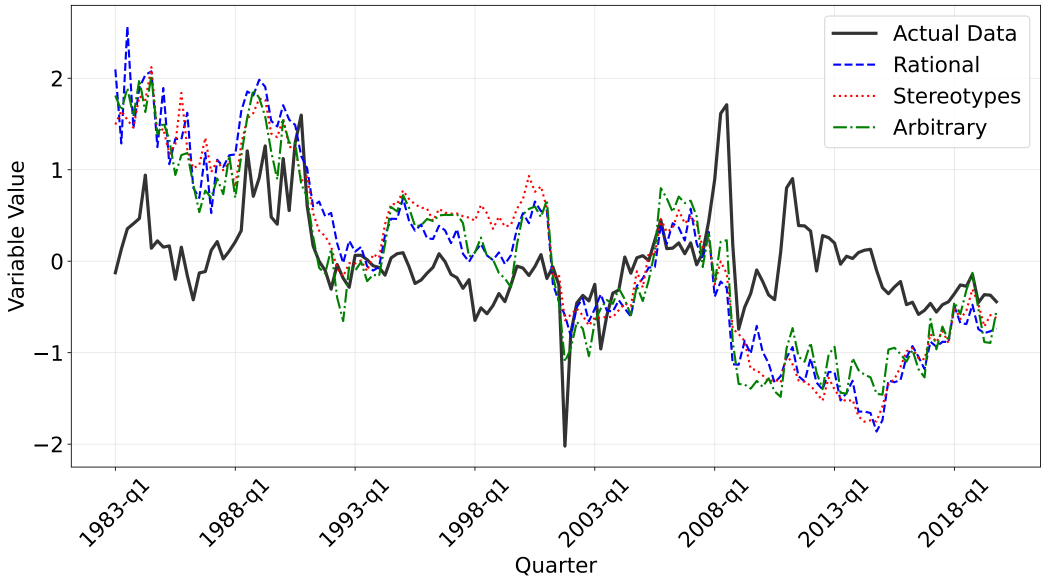


Figure B.12: Smoothed estimates of the perceived inflation over the past year, obtained without using survey belief data. The series is adjusted for seasonality and expressed as deviations from its mean.

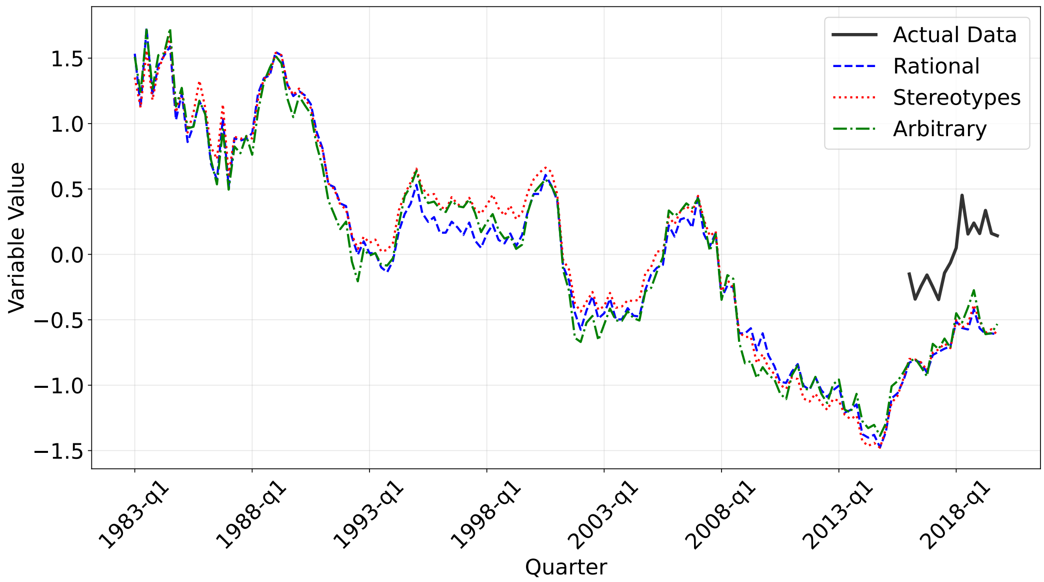


Figure B.13: Smoothed estimates of the perceived inflation over the past year, obtained using survey belief data (expected and perceived inflation). The series is adjusted for seasonality and expressed as deviations from its mean.

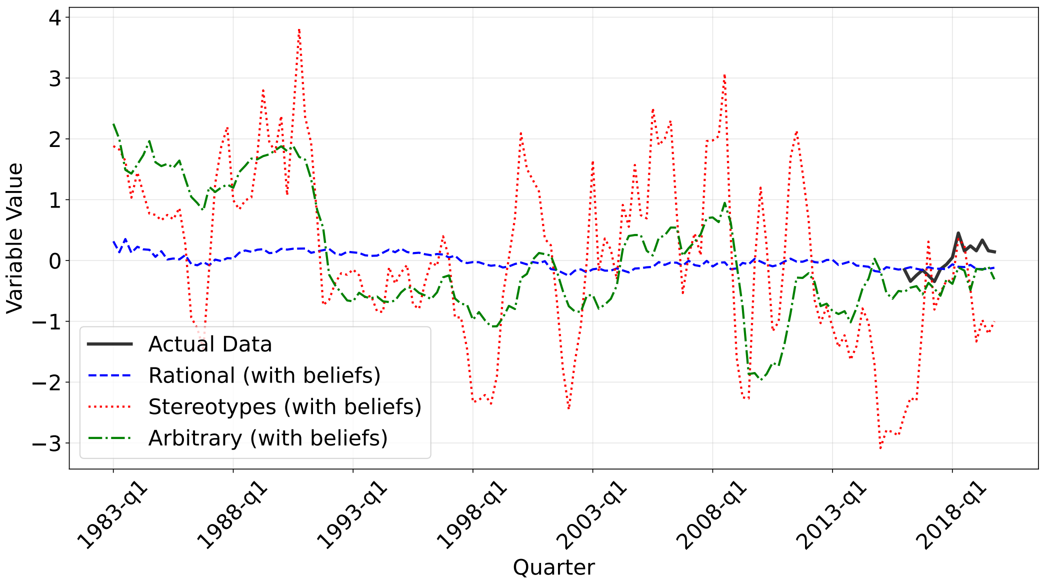
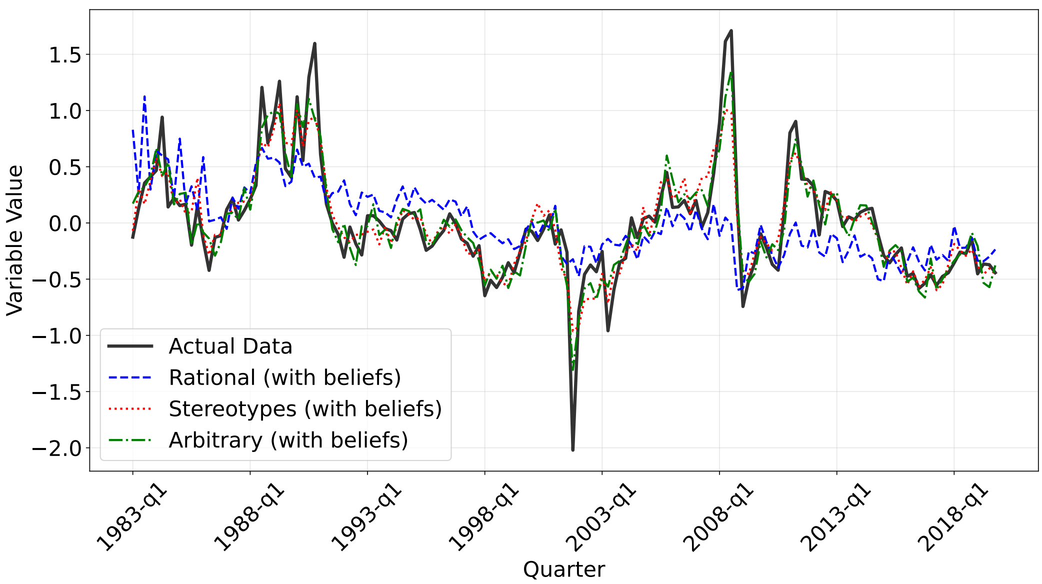


Figure B.14: Smoothed estimates of the 1-yr ahead expected inflation, obtained using survey belief data (expected inflation). The series is adjusted for seasonality and expressed as deviations from its mean.



B.4 Tables

Table B.1: Sector-level parameters, shares, and shock processes (posterior medians).

Sector	n_k	$\tilde{n}_k$	α_k	ν_k	$\sigma_{a,k}$	$\sigma_{d,k}$
1. Motor vehicles and Parts	4.6	7.6	0.212	0.87	4.8	18.4
2. Furnishings and durable equipment	2.4	1.9	0.484	0.12	4.0	4.8
3. Recreational goods and vehicles	1.8	1.2	0.564	0.24	4.8	6.8
4. Other durable goods	1.3	0.8	0.551	0.09	6.4	6.4
5. Food and beverages	9.0	11.1	0.327	0.32	2.8	2.8
6. Clothing and footwear	3.3	4.1	0.331	0.12	4.0	3.6
7. Gasoline and other energy goods	4.2	17.9	0.003	0.51	23.6	–
8. Other nondurable goods	7.5	5.1	0.541	0.13	3.6	2.8
9. Housing and utilities	19.6	32.8	0.212	0.87	1.6	2.8
10. Health care	15.7	2.4	0.857	0.02	8.0	2.8
11. Transportation services	3.4	3.6	0.375	0.14	4.0	4.4
12. Recreation services	3.7	1.3	0.727	0.04	6.8	3.6
13. Food services and Accommodations	6.7	3.8	0.599	0.15	2.8	3.6
14. Financial services and insurance	8.1	2.1	0.781	0.01	42.8	6.0
15. Other services	9.0	4.3	0.645	0.09	4.0	3.6

Note: Standard deviations are multiplied by 400 for comparability with annualized data. Quarterly price-adjustment frequencies $(1-\alpha_k)$ are taken from Nakamura and Steinsson (2008).

Table B.2: This table shows the estimated expenditure shares by sector for the Rational, Arbitrary, and Stereotypes models using the interest rate, sectoral inflation, and sectoral consumption growth as observables.

	Perceived expenditure shares		
Sector	Rational	Arbitrary	Stereotypes
Motor vehicles and Parts	0.0456	0.0054	0.0779
Furnishings and durable equipment	0.0241	0.0082	0.0183
Recreational goods and vehicles	0.0182	0.0051	0.0106
Other durable goods	0.0127	0.0074	0.0077
Food and beverages	0.0897	0.0099	0.1093
Clothing and footwear	0.0332	0.0051	0.0400
Gasoline and other energy goods	0.0419	0.0015	0.2013
Other nondurable goods	0.0748	0.0096	0.0470
Housing and utilities	0.1959	0.0076	0.3345
Health care	0.1565	0.0081	0.0183
Transportation services	0.0335	0.0069	0.0355
Recreation services	0.0368	0.0154	0.0107
Food services and Accommodations	0.0665	0.8828	0.0339
Financial services and insurance	0.0810	0.0045	0.0171
Other services	0.0897	0.0225	0.0380

Table B.3: This table shows the estimated expenditure shares by sector for the Rational, Arbitrary, and Stereotypes models using the interest rate, sectoral inflation, sectoral consumption growth, and expected inflation from the Michigan Survey of Consumers as observables.

	Perceived expenditure shares		
Sector	Rational	Arbitrary	Stereotypes
Motor vehicles and Parts	0.0456	0.0026	0.0763
Furnishings and durable equipment	0.0241	0.0014	0.0195
Recreational goods and vehicles	0.0182	0.0014	0.0116
Other durable goods	0.0127	0.0027	0.0084
Food and beverages	0.0897	0.0021	0.1109
Clothing and footwear	0.0332	0.0013	0.0406
Gasoline and other energy goods	0.0419	0.0003	0.1779
Other nondurable goods	0.0748	0.0018	0.0511
Housing and utilities	0.1959	0.0015	0.3278
Health care	0.1565	0.0013	0.0243
Transportation services	0.0335	0.0015	0.0366
Recreation services	0.0368	0.0032	0.0127
Food services and Accommodations	0.0665	0.9761	0.0377
Financial services and insurance	0.0810	0.0011	0.0211
Other services	0.0897	0.0015	0.0433

Table B.4: This table shows the estimated expenditure shares by sector for the Rational, Arbitrary, and Stereotypes models using the interest rate, sectoral inflation, sectoral consumption growth, and both perceived and expected inflation from the Michigan Survey of Consumers as observables.

	Perceived expenditure shares		
Sector	Rational	Arbitrary	Stereotypes
Motor vehicles and Parts	0.0456	0.0049	0.0764
Furnishings and durable equipment	0.0241	0.0080	0.0195
Recreational goods and vehicles	0.0182	0.1561	0.0116
Other durable goods	0.0127	0.0029	0.0084
Food and beverages	0.0897	0.0036	0.1109
Clothing and footwear	0.0332	0.0045	0.0406
Gasoline and other energy goods	0.0419	0.0007	0.1788
Other nondurable goods	0.0748	0.0030	0.0510
Housing and utilities	0.1959	0.4370	0.3280
Health care	0.1565	0.0020	0.0241
Transportation services	0.0335	0.0047	0.0365
Recreation services	0.0368	0.0048	0.0126
Food services and Accommodations	0.0665	0.3619	0.0376
Financial services and insurance	0.0810	0.0027	0.0210
Other services	0.0897	0.0033	0.0431

Table B.5: This table shows the prior means and standard deviations alongside the posterior medians and 5–95 confidence intervals for the Rational model estimated using the interest rate, sectoral inflation, and sectoral consumption growth as observables.

	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
η	Gamma	2.000	2.000	0.682	0.618	0.746
ρ_i	Beta	0.700	0.150	0.774	0.725	0.820
ρ_γ	Beta	0.700	0.150	0.970	0.953	0.986

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
ρ_μ	Beta	0.700	0.150	0.092	0.045	0.141
ρ_a	Beta	0.700	0.150	0.992	0.984	0.999
ϕ_π	Normal	2.500	0.500	2.851	2.400	3.337
ϕ_x	Normal	0.500	0.300	0.191	-0.202	0.579
ν_1	Beta	0.500	0.200	0.865	0.723	0.982
$\rho_{a,1}$	Beta	0.700	0.150	0.936	0.903	0.969
ν_2	Beta	0.500	0.200	0.105	0.017	0.206
$\rho_{a,2}$	Beta	0.700	0.150	0.969	0.947	0.991
ν_3	Beta	0.500	0.200	0.227	0.066	0.400
$\rho_{a,3}$	Beta	0.700	0.150	0.984	0.972	0.996
ν_4	Beta	0.500	0.200	0.088	0.014	0.177
$\rho_{a,4}$	Beta	0.700	0.150	0.978	0.960	0.995
ν_5	Beta	0.500	0.200	0.214	0.050	0.394
$\rho_{a,5}$	Beta	0.700	0.150	0.967	0.942	0.991
ν_6	Beta	0.500	0.200	0.127	0.021	0.254
$\rho_{a,6}$	Beta	0.700	0.150	0.963	0.938	0.988
ν_7	Beta	0.500	0.200	0.507	0.180	0.835
$\rho_{a,7}$	Beta	0.700	0.150	0.981	0.967	0.994
ν_8	Beta	0.500	0.200	0.109	0.019	0.211
$\rho_{a,8}$	Beta	0.700	0.150	0.971	0.948	0.992
ν_9	Beta	0.500	0.200	0.845	0.688	0.978
$\rho_{a,9}$	Beta	0.700	0.150	0.970	0.949	0.990
ν_{10}	Beta	0.500	0.200	0.025	0.003	0.052
$\rho_{a,10}$	Beta	0.700	0.150	0.968	0.949	0.986
ν_{11}	Beta	0.500	0.200	0.158	0.027	0.308
$\rho_{a,11}$	Beta	0.700	0.150	0.942	0.904	0.977
ν_{12}	Beta	0.500	0.200	0.043	0.006	0.092
$\rho_{a,12}$	Beta	0.700	0.150	0.790	0.699	0.877

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
ν_{13}	Beta	0.500	0.200	0.270	0.077	0.477
$\rho_{a,13}$	Beta	0.700	0.150	0.321	0.118	0.558
ν_{14}	Beta	0.500	0.200	0.015	0.002	0.033
$\rho_{a,14}$	Beta	0.700	0.150	0.894	0.875	0.912
ν_{15}	Beta	0.500	0.200	0.088	0.015	0.174
$\rho_{a,15}$	Beta	0.700	0.150	0.943	0.908	0.977
$\rho_{d,1}$	Beta	0.700	0.150	0.931	0.891	0.971
$\rho_{d,2}$	Beta	0.700	0.150	0.974	0.955	0.992
$\rho_{d,3}$	Beta	0.700	0.150	0.978	0.962	0.994
$\rho_{d,4}$	Beta	0.700	0.150	0.946	0.908	0.982
$\rho_{d,5}$	Beta	0.700	0.150	0.992	0.985	0.998
$\rho_{d,6}$	Beta	0.700	0.150	0.949	0.916	0.982
$\rho_{d,8}$	Beta	0.700	0.150	0.955	0.925	0.985
$\rho_{d,9}$	Beta	0.700	0.150	0.941	0.904	0.976
$\rho_{d,10}$	Beta	0.700	0.150	0.965	0.942	0.988
$\rho_{d,11}$	Beta	0.700	0.150	0.985	0.974	0.996
$\rho_{d,12}$	Beta	0.700	0.150	0.985	0.972	0.996
$\rho_{d,13}$	Beta	0.700	0.150	0.978	0.961	0.994
$\rho_{d,14}$	Beta	0.700	0.150	0.968	0.941	0.992
$\rho_{d,15}$	Beta	0.700	0.150	0.954	0.925	0.983
σ_{γ}	Inverse Gamma	0.010	0.500	0.038	0.021	0.062
σ_{a}	Inverse Gamma	0.010	0.500	0.005	0.004	0.005
σ_{μ}	Inverse Gamma	0.002	0.005	0.003	0.002	0.003
$\sigma_{a,1}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{a,2}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{a,3}$	Inverse Gamma	0.010	0.500	0.012	0.010	0.014
$\sigma_{a,4}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{a,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
$\sigma_{a,6}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.012
$\sigma_{a,7}$	Inverse Gamma	0.010	0.500	0.059	0.053	0.065
$\sigma_{a,8}$	Inverse Gamma	0.010	0.500	0.008	0.007	0.009
$\sigma_{a,9}$	Inverse Gamma	0.010	0.500	0.003	0.003	0.004
$\sigma_{a,10}$	Inverse Gamma	0.010	0.500	0.019	0.017	0.022
$\sigma_{a,11}$	Inverse Gamma	0.010	0.500	0.011	0.009	0.012
$\sigma_{a,12}$	Inverse Gamma	0.010	0.500	0.017	0.014	0.019
$\sigma_{a,13}$	Inverse Gamma	0.010	0.500	0.009	0.007	0.011
$\sigma_{a,14}$	Inverse Gamma	0.010	0.500	0.089	0.080	0.099
$\sigma_{a,15}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{d,1}$	Inverse Gamma	0.010	0.500	0.046	0.042	0.050
$\sigma_{d,2}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{d,3}$	Inverse Gamma	0.010	0.500	0.017	0.015	0.018
$\sigma_{d,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017
$\sigma_{d,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.007
$\sigma_{d,6}$	Inverse Gamma	0.010	0.500	0.009	0.009	0.010
$\sigma_{d,8}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,9}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,10}$	Inverse Gamma	0.010	0.500	0.007	0.007	0.008
$\sigma_{d,11}$	Inverse Gamma	0.010	0.500	0.011	0.010	0.012
$\sigma_{d,12}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,13}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,14}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{d,15}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010

Table B.6: This table shows the prior means and standard deviations alongside the posterior medians and 5–95 confidence intervals for the Arbitrary model estimated using the interest rate, sectoral inflation, and sectoral consumption growth as observables.

	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
η	Gamma	0.500	0.500	0.664	0.601	0.729
ρ_i	Beta	0.700	0.150	0.770	0.725	0.812
ρ_γ	Beta	0.700	0.150	0.969	0.952	0.986
ρ_μ	Beta	0.700	0.150	0.099	0.051	0.150
ρ_a	Beta	0.700	0.150	0.993	0.985	0.999
ϕ_π	Normal	2.500	0.200	2.684	2.406	2.960
ϕ_x	Normal	0.500	0.100	0.224	0.061	0.390
ν_1	Beta	0.500	0.200	0.865	0.725	0.982
$\rho_{a,1}$	Beta	0.700	0.150	0.935	0.902	0.969
ν_2	Beta	0.500	0.200	0.106	0.018	0.207
$\rho_{a,2}$	Beta	0.700	0.150	0.969	0.946	0.991
ν_3	Beta	0.500	0.200	0.228	0.067	0.399
$\rho_{a,3}$	Beta	0.700	0.150	0.984	0.972	0.996
ν_4	Beta	0.500	0.200	0.089	0.015	0.180
$\rho_{a,4}$	Beta	0.700	0.150	0.978	0.960	0.994
ν_5	Beta	0.500	0.200	0.213	0.048	0.393
$\rho_{a,5}$	Beta	0.700	0.150	0.967	0.943	0.991
ν_6	Beta	0.500	0.200	0.127	0.020	0.256
$\rho_{a,6}$	Beta	0.700	0.150	0.963	0.938	0.986
ν_7	Beta	0.500	0.200	0.508	0.176	0.834
$\rho_{a,7}$	Beta	0.700	0.150	0.977	0.961	0.991
ν_8	Beta	0.500	0.200	0.107	0.019	0.212
$\rho_{a,8}$	Beta	0.700	0.150	0.971	0.948	0.993
ν_9	Beta	0.500	0.200	0.846	0.688	0.976
$\rho_{a,9}$	Beta	0.700	0.150	0.970	0.948	0.990

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
ν_{10}	Beta	0.500	0.200	0.025	0.003	0.053
$\rho_{a,10}$	Beta	0.700	0.150	0.969	0.951	0.986
ν_{11}	Beta	0.500	0.200	0.162	0.031	0.314
$\rho_{a,11}$	Beta	0.700	0.150	0.942	0.905	0.978
ν_{12}	Beta	0.500	0.200	0.043	0.005	0.091
$\rho_{a,12}$	Beta	0.700	0.150	0.792	0.704	0.877
ν_{13}	Beta	0.500	0.200	0.294	0.085	0.508
$\rho_{a,13}$	Beta	0.700	0.150	0.297	0.112	0.507
ν_{14}	Beta	0.500	0.200	0.014	0.002	0.030
$\rho_{a,14}$	Beta	0.700	0.150	0.897	0.879	0.915
ν_{15}	Beta	0.500	0.200	0.087	0.015	0.174
$\rho_{a,15}$	Beta	0.700	0.150	0.944	0.910	0.978
λ_1	Normal	0.000	2.000	-0.578	-3.439	2.162
$\rho_{d,1}$	Beta	0.700	0.150	0.931	0.891	0.971
λ_2	Normal	0.000	2.000	-0.164	-3.205	2.795
$\rho_{d,2}$	Beta	0.700	0.150	0.974	0.956	0.992
λ_3	Normal	0.000	2.000	-0.628	-3.493	2.150
$\rho_{d,3}$	Beta	0.700	0.150	0.978	0.961	0.993
λ_4	Normal	0.000	2.000	-0.264	-3.243	2.715
$\rho_{d,4}$	Beta	0.700	0.150	0.945	0.908	0.982
λ_5	Normal	0.000	2.000	0.025	-3.263	3.263
$\rho_{d,5}$	Beta	0.700	0.150	0.992	0.985	0.998
λ_6	Normal	0.000	2.000	-0.644	-3.430	2.041
$\rho_{d,6}$	Beta	0.700	0.150	0.948	0.914	0.981
λ_8	Normal	0.000	2.000	-0.004	-3.109	3.141
$\rho_{d,8}$	Beta	0.700	0.150	0.956	0.926	0.985
λ_9	Normal	0.000	2.000	-0.236	-3.351	2.727
$\rho_{d,9}$	Beta	0.700	0.150	0.942	0.906	0.977

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
λ_{10}	Normal	0.000	2.000	-0.180	-3.145	2.671
$\rho_{d,10}$	Beta	0.700	0.150	0.964	0.940	0.988
λ_{11}	Normal	0.000	2.000	-0.331	-3.245	2.493
$\rho_{d,11}$	Beta	0.700	0.150	0.986	0.975	0.996
λ_{12}	Normal	0.000	2.000	0.466	-3.061	4.441
$\rho_{d,12}$	Beta	0.700	0.150	0.985	0.972	0.996
λ_{13}	Normal	0.000	2.000	4.516	0.017	7.452
$\rho_{d,13}$	Beta	0.700	0.150	0.976	0.958	0.993
λ_{14}	Normal	0.000	2.000	-0.771	-3.494	1.709
$\rho_{d,14}$	Beta	0.700	0.150	0.969	0.944	0.992
λ_{15}	Normal	0.000	2.000	0.847	-2.819	4.743
$\rho_{d,15}$	Beta	0.700	0.150	0.954	0.925	0.983
σ_{γ}	Inverse Gamma	0.010	0.500	0.036	0.020	0.060
σ_{a}	Inverse Gamma	0.010	0.500	0.005	0.004	0.005
σ_{μ}	Inverse Gamma	0.002	0.005	0.003	0.002	0.003
$\sigma_{a,1}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{a,2}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{a,3}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{a,4}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{a,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{a,6}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.012
$\sigma_{a,7}$	Inverse Gamma	0.010	0.500	0.059	0.054	0.065
$\sigma_{a,8}$	Inverse Gamma	0.010	0.500	0.008	0.007	0.009
$\sigma_{a,9}$	Inverse Gamma	0.010	0.500	0.003	0.003	0.004
$\sigma_{a,10}$	Inverse Gamma	0.010	0.500	0.020	0.017	0.022
$\sigma_{a,11}$	Inverse Gamma	0.010	0.500	0.011	0.009	0.012
$\sigma_{a,12}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.019
$\sigma_{a,13}$	Inverse Gamma	0.010	0.500	0.009	0.007	0.011

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
$\sigma_{a,14}$	Inverse Gamma	0.010	0.500	0.089	0.080	0.098
$\sigma_{a,15}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{d,1}$	Inverse Gamma	0.010	0.500	0.046	0.041	0.050
$\sigma_{d,2}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{d,3}$	Inverse Gamma	0.010	0.500	0.017	0.015	0.018
$\sigma_{d,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017
$\sigma_{d,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.007
$\sigma_{d,6}$	Inverse Gamma	0.010	0.500	0.009	0.009	0.010
$\sigma_{d,8}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,9}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,10}$	Inverse Gamma	0.010	0.500	0.007	0.007	0.008
$\sigma_{d,11}$	Inverse Gamma	0.010	0.500	0.011	0.010	0.012
$\sigma_{d,12}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,13}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,14}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{d,15}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010

Table B.7: This table shows the prior means and standard deviations alongside the posterior medians and 5–95 confidence intervals for the Stereotypes model estimated using the interest rate, sectoral inflation, and sectoral consumption growth as observables.

	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
η	Gamma	0.700	0.500	0.685	0.623	0.750
ρ_i	Beta	0.700	0.150	0.764	0.714	0.812
ρ_γ	Beta	0.700	0.150	0.970	0.953	0.986
ρ_μ	Beta	0.700	0.150	0.090	0.044	0.137
ρ_a	Beta	0.700	0.150	0.990	0.981	0.998

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
ϕ_π	Normal	2.500	0.500	2.916	2.467	3.401
ϕ_x	Normal	0.500	0.300	0.072	-0.119	0.265
ν_1	Beta	0.500	0.200	0.867	0.726	0.982
$\rho_{a,1}$	Beta	0.700	0.150	0.934	0.901	0.968
ν_2	Beta	0.500	0.200	0.107	0.017	0.213
$\rho_{a,2}$	Beta	0.700	0.150	0.970	0.947	0.991
ν_3	Beta	0.500	0.200	0.223	0.061	0.395
$\rho_{a,3}$	Beta	0.700	0.150	0.984	0.972	0.996
ν_4	Beta	0.500	0.200	0.088	0.015	0.177
$\rho_{a,4}$	Beta	0.700	0.150	0.978	0.960	0.995
ν_5	Beta	0.500	0.200	0.208	0.047	0.382
$\rho_{a,5}$	Beta	0.700	0.150	0.966	0.941	0.990
ν_6	Beta	0.500	0.200	0.122	0.021	0.246
$\rho_{a,6}$	Beta	0.700	0.150	0.962	0.937	0.986
ν_7	Beta	0.500	0.200	0.513	0.177	0.830
$\rho_{a,7}$	Beta	0.700	0.150	0.981	0.968	0.994
ν_8	Beta	0.500	0.200	0.111	0.020	0.215
$\rho_{a,8}$	Beta	0.700	0.150	0.971	0.947	0.992
ν_9	Beta	0.500	0.200	0.848	0.691	0.977
$\rho_{a,9}$	Beta	0.700	0.150	0.969	0.948	0.989
ν_{10}	Beta	0.500	0.200	0.026	0.004	0.055
$\rho_{a,10}$	Beta	0.700	0.150	0.970	0.952	0.988
ν_{11}	Beta	0.500	0.200	0.158	0.029	0.307
$\rho_{a,11}$	Beta	0.700	0.150	0.942	0.906	0.979
ν_{12}	Beta	0.500	0.200	0.043	0.005	0.089
$\rho_{a,12}$	Beta	0.700	0.150	0.792	0.704	0.878
ν_{13}	Beta	0.500	0.200	0.261	0.071	0.470
$\rho_{a,13}$	Beta	0.700	0.150	0.331	0.126	0.575

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		Prior			Posterior	
	Type	Mean	Std. Dev	Median	5%	95%
ν_{14}	Beta	0.500	0.200	0.016	0.002	0.033
$\rho_{a,14}$	Beta	0.700	0.150	0.900	0.880	0.919
ν_{15}	Beta	0.500	0.200	0.088	0.014	0.175
$\rho_{a,15}$	Beta	0.700	0.150	0.942	0.906	0.977
$\rho_{d,1}$	Beta	0.700	0.150	0.931	0.890	0.971
$\rho_{d,2}$	Beta	0.700	0.150	0.974	0.956	0.992
$\rho_{d,3}$	Beta	0.700	0.150	0.978	0.961	0.993
$\rho_{d,4}$	Beta	0.700	0.150	0.947	0.909	0.983
$\rho_{d,5}$	Beta	0.700	0.150	0.992	0.985	0.998
$\rho_{d,6}$	Beta	0.700	0.150	0.950	0.917	0.981
$\rho_{d,8}$	Beta	0.700	0.150	0.955	0.924	0.984
$\rho_{d,9}$	Beta	0.700	0.150	0.940	0.903	0.976
$\rho_{d,10}$	Beta	0.700	0.150	0.965	0.942	0.988
$\rho_{d,11}$	Beta	0.700	0.150	0.985	0.974	0.996
$\rho_{d,12}$	Beta	0.700	0.150	0.985	0.972	0.996
$\rho_{d,13}$	Beta	0.700	0.150	0.978	0.960	0.994
$\rho_{d,14}$	Beta	0.700	0.150	0.967	0.941	0.991
$\rho_{d,15}$	Beta	0.700	0.150	0.955	0.926	0.983
θ	Gamma	0.500	0.500	0.418	0.000	1.262
σ_{γ}	Inverse Gamma	0.010	0.500	0.038	0.021	0.063
σ_a	Inverse Gamma	0.010	0.500	0.005	0.004	0.006
σ_{μ}	Inverse Gamma	0.002	0.005	0.003	0.002	0.003
$\sigma_{a,1}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{a,2}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{a,3}$	Inverse Gamma	0.010	0.500	0.012	0.010	0.013
$\sigma_{a,4}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{a,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{a,6}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.012

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
$\sigma_{a,7}$	Inverse Gamma	0.010	0.500	0.059	0.053	0.064
$\sigma_{a,8}$	Inverse Gamma	0.010	0.500	0.008	0.007	0.009
$\sigma_{a,9}$	Inverse Gamma	0.010	0.500	0.003	0.003	0.004
$\sigma_{a,10}$	Inverse Gamma	0.010	0.500	0.019	0.017	0.022
$\sigma_{a,11}$	Inverse Gamma	0.010	0.500	0.011	0.009	0.012
$\sigma_{a,12}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.019
$\sigma_{a,13}$	Inverse Gamma	0.010	0.500	0.009	0.007	0.010
$\sigma_{a,14}$	Inverse Gamma	0.010	0.500	0.089	0.079	0.098
$\sigma_{a,15}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{d,1}$	Inverse Gamma	0.010	0.500	0.046	0.042	0.050
$\sigma_{d,2}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{d,3}$	Inverse Gamma	0.010	0.500	0.017	0.015	0.018
$\sigma_{d,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017
$\sigma_{d,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.007
$\sigma_{d,6}$	Inverse Gamma	0.010	0.500	0.009	0.009	0.010
$\sigma_{d,8}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,9}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,10}$	Inverse Gamma	0.010	0.500	0.007	0.007	0.008
$\sigma_{d,11}$	Inverse Gamma	0.010	0.500	0.011	0.010	0.012
$\sigma_{d,12}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,13}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,14}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{d,15}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010

Table B.8: This table shows the prior means and standard deviations alongside the posterior medians and 5–95 confidence intervals for the Rational model estimated using the interest rate, perceived inflation (measured over the past four quarters from the Michigan Survey of Consumers), expected inflation (measured over the next four quarters from the Michigan Survey of Consumers), sectoral inflation, and sectoral consumption growth as observables.

		Prior			Posterior	
	Mean	Std. Dev	Median	5%	95%	
η	Gamma	0.500	0.500	0.675	0.613	0.738
ρ_i	Beta	0.700	0.150	0.856	0.834	0.878
ρ_γ	Beta	0.700	0.150	0.887	0.871	0.904
ρ_μ	Beta	0.700	0.150	0.106	0.051	0.164
ρ_a	Beta	0.700	0.150	0.991	0.982	0.998
ϕ_π	Normal	2.500	0.200	3.043	2.769	3.311
ϕ_x	Normal	0.500	0.100	0.587	0.429	0.743
ν_1	Beta	0.500	0.200	0.868	0.727	0.982
$\rho_{a,1}$	Beta	0.700	0.150	0.942	0.905	0.981
ν_2	Beta	0.500	0.200	0.112	0.017	0.217
$\rho_{a,2}$	Beta	0.700	0.150	0.971	0.949	0.993
ν_3	Beta	0.500	0.200	0.217	0.056	0.385
$\rho_{a,3}$	Beta	0.700	0.150	0.989	0.978	0.998
ν_4	Beta	0.500	0.200	0.086	0.014	0.172
$\rho_{a,4}$	Beta	0.700	0.150	0.979	0.961	0.995
ν_5	Beta	0.500	0.200	0.249	0.069	0.451
$\rho_{a,5}$	Beta	0.700	0.150	0.969	0.950	0.988
ν_6	Beta	0.500	0.200	0.130	0.020	0.258
$\rho_{a,6}$	Beta	0.700	0.150	0.966	0.936	0.994
ν_7	Beta	0.500	0.200	0.514	0.180	0.841
$\rho_{a,7}$	Beta	0.700	0.150	0.973	0.964	0.984
ν_8	Beta	0.500	0.200	0.120	0.019	0.236
$\rho_{a,8}$	Beta	0.700	0.150	0.975	0.949	0.996

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		Prior			Posterior	
	Mean	Std. Dev	Median	5%	95%	
ν_9	Beta	0.500	0.200	0.864	0.719	0.982
$\rho_{a,9}$	Beta	0.700	0.150	0.961	0.929	0.991
ν_{10}	Beta	0.500	0.200	0.026	0.003	0.057
$\rho_{a,10}$	Beta	0.700	0.150	0.975	0.957	0.992
ν_{11}	Beta	0.500	0.200	0.150	0.028	0.296
$\rho_{a,11}$	Beta	0.700	0.150	0.951	0.922	0.982
ν_{12}	Beta	0.500	0.200	0.044	0.006	0.093
$\rho_{a,12}$	Beta	0.700	0.150	0.767	0.674	0.859
ν_{13}	Beta	0.500	0.200	0.336	0.114	0.571
$\rho_{a,13}$	Beta	0.700	0.150	0.281	0.110	0.480
ν_{14}	Beta	0.500	0.200	0.013	0.002	0.029
$\rho_{a,14}$	Beta	0.700	0.150	0.871	0.845	0.898
ν_{15}	Beta	0.500	0.200	0.087	0.016	0.174
$\rho_{a,15}$	Beta	0.700	0.150	0.946	0.916	0.976
$\rho_{d,1}$	Beta	0.700	0.150	0.934	0.895	0.973
$\rho_{d,2}$	Beta	0.700	0.150	0.974	0.956	0.992
$\rho_{d,3}$	Beta	0.700	0.150	0.978	0.961	0.994
$\rho_{d,4}$	Beta	0.700	0.150	0.944	0.906	0.980
$\rho_{d,5}$	Beta	0.700	0.150	0.992	0.985	0.998
$\rho_{d,6}$	Beta	0.700	0.150	0.950	0.917	0.981
$\rho_{d,8}$	Beta	0.700	0.150	0.955	0.924	0.984
$\rho_{d,9}$	Beta	0.700	0.150	0.941	0.905	0.978
$\rho_{d,10}$	Beta	0.700	0.150	0.965	0.942	0.988
$\rho_{d,11}$	Beta	0.700	0.150	0.985	0.974	0.996
$\rho_{d,12}$	Beta	0.700	0.150	0.985	0.972	0.996
$\rho_{d,13}$	Beta	0.700	0.150	0.978	0.961	0.994
$\rho_{d,14}$	Beta	0.700	0.150	0.969	0.944	0.992
$\rho_{d,15}$	Beta	0.700	0.150	0.956	0.927	0.985

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		Prior			Posterior	
	Mean	Std. Dev	Median	5%	95%	
σ_{γ}	Inverse Gamma	0.010	0.500	0.017	0.015	0.020
σ_{a}	Inverse Gamma	0.010	0.500	0.005	0.004	0.006
σ_{μ}	Inverse Gamma	0.002	0.005	0.002	0.002	0.002
$\sigma_{a,1}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{a,2}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{a,3}$	Inverse Gamma	0.010	0.500	0.012	0.010	0.013
$\sigma_{a,4}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{a,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{a,6}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.012
$\sigma_{a,7}$	Inverse Gamma	0.010	0.500	0.059	0.053	0.064
$\sigma_{a,8}$	Inverse Gamma	0.010	0.500	0.008	0.007	0.009
$\sigma_{a,9}$	Inverse Gamma	0.010	0.500	0.003	0.003	0.004
$\sigma_{a,10}$	Inverse Gamma	0.010	0.500	0.019	0.017	0.022
$\sigma_{a,11}$	Inverse Gamma	0.010	0.500	0.011	0.009	0.012
$\sigma_{a,12}$	Inverse Gamma	0.010	0.500	0.017	0.014	0.020
$\sigma_{a,13}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.011
$\sigma_{a,14}$	Inverse Gamma	0.010	0.500	0.093	0.083	0.103
$\sigma_{a,15}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{d,1}$	Inverse Gamma	0.010	0.500	0.046	0.041	0.050
$\sigma_{d,2}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{d,3}$	Inverse Gamma	0.010	0.500	0.017	0.015	0.018
$\sigma_{d,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017
$\sigma_{d,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.007
$\sigma_{d,6}$	Inverse Gamma	0.010	0.500	0.009	0.009	0.010
$\sigma_{d,8}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,9}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,10}$	Inverse Gamma	0.010	0.500	0.007	0.007	0.008
$\sigma_{d,11}$	Inverse Gamma	0.010	0.500	0.011	0.010	0.012

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		Prior			Posterior	
	Mean	Std. Dev	Median	5%	95%	
$\sigma_{d,12}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,13}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,14}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{d,15}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010

Table B.9: This table shows the prior means and standard deviations alongside the posterior medians and 5–95 confidence intervals for the Arbitrary model estimated using the interest rate, perceived inflation (measured over the past four quarters from the Michigan Survey of Consumers), expected inflation (measured over the next four quarters from the Michigan Survey of Consumers), sectoral inflation, and sectoral consumption growth as observables.

		Prior			Posterior	
	Type	Mean	Std. Dev	Median	5%	95%
η	Gamma	0.500	0.500	0.664	0.601	0.726
ρ_i	Beta	0.700	0.150	0.831	0.795	0.863
ρ_γ	Beta	0.700	0.150	0.928	0.913	0.943
ρ_μ	Beta	0.700	0.150	0.109	0.051	0.170
ρ_a	Beta	0.700	0.150	0.840	0.800	0.999
ϕ_π	Normal	2.500	0.200	3.012	2.751	3.273
ϕ_x	Normal	0.500	0.100	-0.022	-0.136	0.243
ν_1	Beta	0.500	0.200	0.870	0.732	0.982
$\rho_{a,1}$	Beta	0.700	0.150	0.947	0.913	0.982
ν_2	Beta	0.500	0.200	0.111	0.017	0.219
$\rho_{a,2}$	Beta	0.700	0.150	0.959	0.927	0.989
ν_3	Beta	0.500	0.200	0.166	0.034	0.321
$\rho_{a,3}$	Beta	0.700	0.150	0.983	0.970	0.995
ν_4	Beta	0.500	0.200	0.090	0.014	0.177
$\rho_{a,4}$	Beta	0.700	0.150	0.970	0.947	0.992
ν_5	Beta	0.500	0.200	0.313	0.086	0.559

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
$\rho_{a,5}$	Beta	0.700	0.150	0.965	0.942	0.987
ν_6	Beta	0.500	0.200	0.132	0.020	0.264
$\rho_{a,6}$	Beta	0.700	0.150	0.968	0.944	0.990
ν_7	Beta	0.500	0.200	0.511	0.187	0.838
$\rho_{a,7}$	Beta	0.700	0.150	0.959	0.943	0.975
ν_8	Beta	0.500	0.200	0.128	0.024	0.246
$\rho_{a,8}$	Beta	0.700	0.150	0.954	0.918	0.987
ν_9	Beta	0.500	0.200	0.860	0.713	0.980
$\rho_{a,9}$	Beta	0.700	0.150	0.981	0.965	0.995
ν_{10}	Beta	0.500	0.200	0.025	0.004	0.053
$\rho_{a,10}$	Beta	0.700	0.150	0.961	0.937	0.984
ν_{11}	Beta	0.500	0.200	0.151	0.026	0.293
$\rho_{a,11}$	Beta	0.700	0.150	0.962	0.927	0.991
ν_{12}	Beta	0.500	0.200	0.042	0.005	0.089
$\rho_{a,12}$	Beta	0.700	0.150	0.857	0.736	0.948
ν_{13}	Beta	0.500	0.200	0.133	0.023	0.266
$\rho_{a,13}$	Beta	0.700	0.150	0.949	0.553	0.993
ν_{14}	Beta	0.500	0.200	0.014	0.002	0.028
$\rho_{a,14}$	Beta	0.700	0.150	0.826	0.787	0.908
ν_{15}	Beta	0.500	0.200	0.092	0.016	0.184
$\rho_{a,15}$	Beta	0.700	0.150	0.947	0.912	0.980
λ_1	Normal	0.000	2.000	0.048	-2.896	2.953
$\rho_{d,1}$	Beta	0.700	0.150	0.930	0.889	0.971
λ_2	Normal	0.000	2.000	0.542	-2.651	3.326
$\rho_{d,2}$	Beta	0.700	0.150	0.974	0.956	0.992
λ_3	Normal	0.000	2.000	3.515	-0.619	4.996
$\rho_{d,3}$	Beta	0.700	0.150	0.976	0.958	0.992
λ_4	Normal	0.000	2.000	-0.481	-3.268	2.177

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
$\rho_{d,4}$	Beta	0.700	0.150	0.945	0.909	0.982
λ_5	Normal	0.000	2.000	-0.255	-3.189	2.675
$\rho_{d,5}$	Beta	0.700	0.150	0.992	0.985	0.998
λ_6	Normal	0.000	2.000	-0.031	-2.969	2.797
$\rho_{d,6}$	Beta	0.700	0.150	0.948	0.914	0.981
λ_8	Normal	0.000	2.000	-0.441	-3.287	2.220
$\rho_{d,8}$	Beta	0.700	0.150	0.956	0.926	0.985
λ_9	Normal	0.000	2.000	4.544	-1.286	6.072
$\rho_{d,9}$	Beta	0.700	0.150	0.953	0.919	0.986
λ_{10}	Normal	0.000	2.000	-0.846	-3.459	1.559
$\rho_{d,10}$	Beta	0.700	0.150	0.964	0.940	0.988
λ_{11}	Normal	0.000	2.000	0.011	-2.936	2.896
$\rho_{d,11}$	Beta	0.700	0.150	0.985	0.974	0.996
λ_{12}	Normal	0.000	2.000	0.026	-3.182	2.988
$\rho_{d,12}$	Beta	0.700	0.150	0.984	0.971	0.996
λ_{13}	Normal	0.000	2.000	4.356	2.912	7.075
$\rho_{d,13}$	Beta	0.700	0.150	0.976	0.956	0.994
λ_{14}	Normal	0.000	2.000	-0.557	-3.183	1.871
$\rho_{d,14}$	Beta	0.700	0.150	0.968	0.943	0.992
λ_{15}	Normal	0.000	2.000	-0.341	-3.122	2.296
$\rho_{d,15}$	Beta	0.700	0.150	0.954	0.925	0.983
σ_γ	Inverse Gamma	0.010	0.500	0.022	0.017	0.027
σ_a	Inverse Gamma	0.010	0.500	0.005	0.004	0.005
σ_μ	Inverse Gamma	0.002	0.005	0.002	0.002	0.003
$\sigma_{a,1}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{a,2}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{a,3}$	Inverse Gamma	0.010	0.500	0.012	0.010	0.013
$\sigma_{a,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
$\sigma_{a,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.009
$\sigma_{a,6}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.012
$\sigma_{a,7}$	Inverse Gamma	0.010	0.500	0.060	0.054	0.066
$\sigma_{a,8}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{a,9}$	Inverse Gamma	0.010	0.500	0.004	0.003	0.004
$\sigma_{a,10}$	Inverse Gamma	0.010	0.500	0.020	0.017	0.023
$\sigma_{a,11}$	Inverse Gamma	0.010	0.500	0.011	0.009	0.012
$\sigma_{a,12}$	Inverse Gamma	0.010	0.500	0.015	0.013	0.019
$\sigma_{a,13}$	Inverse Gamma	0.010	0.500	0.006	0.005	0.009
$\sigma_{a,14}$	Inverse Gamma	0.010	0.500	0.100	0.083	0.114
$\sigma_{a,15}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{d,1}$	Inverse Gamma	0.010	0.500	0.046	0.041	0.050
$\sigma_{d,2}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{d,3}$	Inverse Gamma	0.010	0.500	0.017	0.015	0.018
$\sigma_{d,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017
$\sigma_{d,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.007
$\sigma_{d,6}$	Inverse Gamma	0.010	0.500	0.009	0.009	0.010
$\sigma_{d,8}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,9}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,10}$	Inverse Gamma	0.010	0.500	0.007	0.007	0.008
$\sigma_{d,11}$	Inverse Gamma	0.010	0.500	0.011	0.010	0.012
$\sigma_{d,12}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,13}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,14}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{d,15}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010

Table B.10: This table shows the prior means and standard deviations alongside the posterior medians and 5–95 confidence intervals for the Stereotypes model estimated using the interest rate, perceived inflation (measured over the past four quarters from the Michigan Survey of Consumers), expected inflation (measured over the next four quarters from the Michigan Survey of Consumers), sectoral inflation, and sectoral consumption growth as observables.

	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
η	Gamma	0.700	0.500	0.678	0.616	0.742
ρ_i	Beta	0.700	0.150	0.858	0.832	0.885
ρ_γ	Beta	0.700	0.150	0.934	0.918	0.950
ρ_μ	Beta	0.700	0.150	0.172	0.097	0.246
ρ_a	Beta	0.700	0.150	0.813	0.780	0.844
ϕ_π	Normal	2.500	0.500	3.480	2.994	4.004
ϕ_x	Normal	0.500	0.300	0.469	0.305	0.634
ν_1	Beta	0.500	0.200	0.866	0.721	0.981
$\rho_{a,1}$	Beta	0.700	0.150	0.945	0.912	0.977
ν_2	Beta	0.500	0.200	0.118	0.021	0.231
$\rho_{a,2}$	Beta	0.700	0.150	0.956	0.924	0.987
ν_3	Beta	0.500	0.200	0.235	0.067	0.415
$\rho_{a,3}$	Beta	0.700	0.150	0.983	0.970	0.995
ν_4	Beta	0.500	0.200	0.086	0.014	0.176
$\rho_{a,4}$	Beta	0.700	0.150	0.970	0.947	0.991
ν_5	Beta	0.500	0.200	0.322	0.112	0.541
$\rho_{a,5}$	Beta	0.700	0.150	0.976	0.958	0.994
ν_6	Beta	0.500	0.200	0.117	0.020	0.234
$\rho_{a,6}$	Beta	0.700	0.150	0.971	0.950	0.991
ν_7	Beta	0.500	0.200	0.511	0.185	0.834
$\rho_{a,7}$	Beta	0.700	0.150	0.979	0.967	0.991
ν_8	Beta	0.500	0.200	0.131	0.026	0.249
$\rho_{a,8}$	Beta	0.700	0.150	0.955	0.921	0.987

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
ν_9	Beta	0.500	0.200	0.874	0.739	0.982
$\rho_{a,9}$	Beta	0.700	0.150	0.978	0.960	0.994
ν_{10}	Beta	0.500	0.200	0.024	0.003	0.051
$\rho_{a,10}$	Beta	0.700	0.150	0.962	0.939	0.985
ν_{11}	Beta	0.500	0.200	0.142	0.024	0.278
$\rho_{a,11}$	Beta	0.700	0.150	0.964	0.938	0.988
ν_{12}	Beta	0.500	0.200	0.043	0.005	0.090
$\rho_{a,12}$	Beta	0.700	0.150	0.793	0.702	0.887
ν_{13}	Beta	0.500	0.200	0.146	0.029	0.276
$\rho_{a,13}$	Beta	0.700	0.150	0.932	0.885	0.978
ν_{14}	Beta	0.500	0.200	0.014	0.002	0.030
$\rho_{a,14}$	Beta	0.700	0.150	0.796	0.764	0.827
ν_{15}	Beta	0.500	0.200	0.091	0.016	0.179
$\rho_{a,15}$	Beta	0.700	0.150	0.934	0.894	0.972
$\rho_{d,1}$	Beta	0.700	0.150	0.938	0.899	0.977
$\rho_{d,2}$	Beta	0.700	0.150	0.975	0.957	0.993
$\rho_{d,3}$	Beta	0.700	0.150	0.979	0.963	0.994
$\rho_{d,4}$	Beta	0.700	0.150	0.945	0.909	0.982
$\rho_{d,5}$	Beta	0.700	0.150	0.992	0.985	0.998
$\rho_{d,6}$	Beta	0.700	0.150	0.949	0.915	0.981
$\rho_{d,8}$	Beta	0.700	0.150	0.955	0.925	0.984
$\rho_{d,9}$	Beta	0.700	0.150	0.940	0.903	0.976
$\rho_{d,10}$	Beta	0.700	0.150	0.958	0.933	0.983
$\rho_{d,11}$	Beta	0.700	0.150	0.985	0.974	0.996
$\rho_{d,12}$	Beta	0.700	0.150	0.984	0.971	0.996
$\rho_{d,13}$	Beta	0.700	0.150	0.976	0.958	0.994
$\rho_{d,14}$	Beta	0.700	0.150	0.973	0.950	0.994
$\rho_{d,15}$	Beta	0.700	0.150	0.958	0.930	0.985

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
θ	Gamma	0.500	0.500	0.219	0.000	0.700
σ_γ	Inverse Gamma	0.010	0.500	0.030	0.023	0.037
σ_a	Inverse Gamma	0.010	0.500	0.005	0.004	0.006
σ_μ	Inverse Gamma	0.002	0.005	0.002	0.002	0.003
$\sigma_{a,1}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{a,2}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{a,3}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.014
$\sigma_{a,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017
$\sigma_{a,5}$	Inverse Gamma	0.010	0.500	0.007	0.007	0.008
$\sigma_{a,6}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{a,7}$	Inverse Gamma	0.010	0.500	0.059	0.053	0.065
$\sigma_{a,8}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{a,9}$	Inverse Gamma	0.010	0.500	0.004	0.003	0.004
$\sigma_{a,10}$	Inverse Gamma	0.010	0.500	0.020	0.017	0.023
$\sigma_{a,11}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.012
$\sigma_{a,12}$	Inverse Gamma	0.010	0.500	0.017	0.014	0.020
$\sigma_{a,13}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.007
$\sigma_{a,14}$	Inverse Gamma	0.010	0.500	0.107	0.095	0.119
$\sigma_{a,15}$	Inverse Gamma	0.010	0.500	0.010	0.009	0.011
$\sigma_{d,1}$	Inverse Gamma	0.010	0.500	0.046	0.041	0.050
$\sigma_{d,2}$	Inverse Gamma	0.010	0.500	0.012	0.011	0.013
$\sigma_{d,3}$	Inverse Gamma	0.010	0.500	0.017	0.015	0.018
$\sigma_{d,4}$	Inverse Gamma	0.010	0.500	0.016	0.014	0.017
$\sigma_{d,5}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.007
$\sigma_{d,6}$	Inverse Gamma	0.010	0.500	0.009	0.009	0.010
$\sigma_{d,8}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,9}$	Inverse Gamma	0.010	0.500	0.007	0.006	0.008
$\sigma_{d,10}$	Inverse Gamma	0.010	0.500	0.007	0.007	0.008

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	Prior			Posterior		
	Type	Mean	Std. Dev	Median	5%	95%
$\sigma_{d,11}$	Inverse Gamma	0.010	0.500	0.011	0.010	0.012
$\sigma_{d,12}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,13}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010
$\sigma_{d,14}$	Inverse Gamma	0.010	0.500	0.015	0.014	0.017
$\sigma_{d,15}$	Inverse Gamma	0.010	0.500	0.009	0.008	0.010

C
Appendix of Flexible Prices and the Unanchoring of Inflation Expectations

C.1
The Undetermined Coefficients Solution

C.1.1
Baseline Equilibrium

We use the definition of relative prices and the guessed solution for T_t to get:

$$rp_{1,t} = \tilde{n}_2[\alpha_5 T_{t-1} + (\gamma_1 - \gamma_3)a_{1,t} + (\gamma_2 - \gamma_4)a_{2,t} + (\gamma_{i,1} - \gamma_{i,2})\varphi_t] \tag{C-1}$$

$$rp_{2,t} = -\tilde{n}_1[\alpha_5 T_{t-1} + (\gamma_1 - \gamma_3)a_{1,t} + (\gamma_2 - \gamma_4)a_{2,t} + (\gamma_{i,1} - \gamma_{i,2})\varphi_t] \tag{C-2}$$

Substituting the solutions for sectoral inflation rates, relative prices, and consumption into the sectoral Phillips curve and Euler equation, and equating coefficients on T_{t-1} in each of the resulting equations yields:

$$\alpha_1 = \xi_1[(1+\varphi)\alpha_3 - (1+\varphi\eta)\tilde{n}_2(1+\alpha_1-\alpha_2)] + \beta\alpha_1(1+\alpha_1-\alpha_2) \tag{C-3}$$

$$\alpha_2 = \xi_2[(1+\varphi)\alpha_3 + (1+\varphi\eta)\tilde{n}_1(1+\alpha_1-\alpha_2)] + \beta\alpha_2(1+\alpha_1-\alpha_2) \tag{C-4}$$

$$\alpha_3(1+\alpha_1-\alpha_2)-\alpha_3 = \tau_1 n_1\alpha_1+\tau_2 n_2\alpha_2+\lambda_x\alpha_3-(\tilde{n}_1\alpha_1+\tilde{n}_2\alpha_2)(1+\alpha_1-\alpha_2) \tag{C-5}$$

We can solve the above equations for the elasticities $\{\alpha_1, \alpha_2, \alpha_3\}$. Equating coefficients on $a_{1,t}$ yields:

$$\gamma_1 = \xi_1[(1+\varphi)\gamma_5-(1+\varphi\eta)\tilde{n}_2(\gamma_1-\gamma_3)-(1+\varphi)]+\beta[\gamma_1\rho_1+\alpha_1(\gamma_1-\gamma_3)] \tag{C-6}$$

$$\gamma_3 = \xi_2[(1+\varphi)\gamma_5 + (1+\varphi\eta)\tilde{n}_1(\gamma_1-\gamma_3)] + \beta[\gamma_3\rho_1 + \alpha_2(\gamma_1-\gamma_3)] \tag{C-7}$$

$$\begin{aligned}\gamma_5\rho_1 - \gamma_5 + \alpha_3(\gamma_1-\gamma_3) &= \tau_1 n_1\gamma_1 + \tau_2 n_2\gamma_3 + \lambda_x\gamma_5 \\ &-[(\tilde{n}_1\gamma_1 + \tilde{n}_2\gamma_3)\rho_1 + (\tilde{n}_1\alpha_1 + \tilde{n}_2\alpha_2)(\gamma_1-\gamma_3)]\end{aligned} \tag{C-8}$$

Given solutions for $\{\alpha_1, \alpha_2, \alpha_3\}$, this system can be solved for $\{\gamma_1, \gamma_3, \gamma_5\}$. Symmetrically, we can equate coefficients on $a_{2,t}$ and get:

$$\gamma_2 = \xi_1[(1+\varphi)\gamma_6 - (1+\varphi\eta)\tilde{n}_2(\gamma_2-\gamma_4)] + \beta[\gamma_2\rho_2 + \alpha_1(\gamma_2-\gamma_4)] \tag{C-9}$$

$$\gamma_4 = \xi_2[(1+\varphi)\gamma_6+(1+\varphi\eta)\tilde{n}_1(\gamma_2-\gamma_4)-(1+\varphi)]+\beta[\gamma_4\rho_2+\alpha_2(\gamma_2-\gamma_4)] \tag{C-10}$$

$$\gamma_6\rho_2 - \gamma_6 + \alpha_3(\gamma_2 - \gamma_4) = \tau_1 n_1 \gamma_2 + \tau_2 n_2 \gamma_4 + \lambda_x \gamma_6$$
$$-[(\tilde{n}_1\gamma_2 + \tilde{n}_2\gamma_4)\rho_2 + (\tilde{n}_1\alpha_1 + \tilde{n}_2\alpha_2)(\gamma_2 - \gamma_4)] \tag{C-11}$$

Lastly, equating coefficients on φ_t yields a system for $\{\gamma_{i,1}, \gamma_{i,2}, \gamma_{i,3}\}$, given the solutions for $\{\alpha_1, \alpha_2, \alpha_3\}$:

$$\gamma_{i,1} = \xi_1[(1+\varphi)\gamma_{i,3} - (1+\varphi\eta)\tilde{n}_2(\gamma_{i,1} - \gamma_{i,2})] + \beta[\gamma_{i,1}\rho + \alpha_1(\gamma_{i,1} - \gamma_{i,2})] \tag{C-12}$$

$$\gamma_{i,2} = \xi_2[(1+\varphi)\gamma_{i,3} + (1+\varphi\eta)\tilde{n}_1(\gamma_{i,1} - \gamma_{i,2})] + \beta[\gamma_{i,2}\rho + \alpha_2(\gamma_{i,1} - \gamma_{i,2})] \tag{C-13}$$

$$\gamma_{i,3}\rho - \gamma_{i,3} + \alpha_3(\gamma_{i,1} - \gamma_{i,2}) = 1 + \tau_1 n_1 \gamma_{i,1} + \tau_2 n_2 \gamma_{i,2} + \lambda_x \gamma_{i,3}$$
$$-[(\tilde{n}_1\gamma_{i,1} + \tilde{n}_2\gamma_{i,2})\rho + (\tilde{n}_1\alpha_1 + \tilde{n}_2\alpha_2)(\gamma_{i,1} - \gamma_{i,2})] \tag{C-14}$$

C.1.2 Households' Anchoring Equilibrium

Substitute the conjectured coefficients into Equation 4-23 to obtain a system for the elasticities $\alpha_3, \gamma_5, \gamma_6, \gamma_{i,3}, \gamma_{\pi,3}$. Because the state is persistent, the solution requires model-consistent forecasts of T_t. We compute forecasts for T_{t+h} recursively, and define S_T as

$$\begin{aligned}
S_T &\equiv \hat{E}_t\left[\sum_{h=0}^{\infty}\beta^h T_{t+h-1}\right] \\
&= T_{t-1} + \hat{E}_t\left[\sum_{h=1}^{\infty}\beta^h T_{t+h-1}\right] \\
&= T_{t-1} + \hat{E}_t\left[\sum_{h=0}^{\infty}\beta^{h+1} T_{t+h}\right] \\
&= T_{t-1} + \beta S_T^*,
\end{aligned}$$

where

$$\begin{aligned}
S_T^* &\equiv \hat{E}_t\left[\sum_{h=0}^{\infty}\beta^h T_{t+h}\right] \\
&= \sum_{h=0}^{\infty}\beta^h\left[\alpha_5^h T_t + \sum_{m=1}^{h}\alpha_5^{h-m}\hat{E}_t[\Delta_{t+m}]\right] \\
&= \frac{T_t}{1-\beta\alpha_5} + \sum_{h=0}^{\infty}\beta^h\sum_{m=1}^{h}\alpha_5^{h-m}\hat{E}_t[\Delta_{t+m}] \\
&= \frac{T_t}{1-\beta\alpha_5} + \sum_{h=1}^{\infty}\beta^h\hat{E}_t[\Delta_{t+h}]\sum_{h=0}^{\infty}(\beta\alpha_5)^h \\
&= \frac{1}{1-\beta\alpha_5}\left[T_t + \sum_{h=1}^{\infty}\beta^h\hat{E}_t[\Delta_{t+h}]\right]
\end{aligned}$$

and

$$\Delta_{t+h} \equiv (\gamma_1 - \gamma_3)a_{1,t+h} + (\gamma_2 - \gamma_4)a_{2,t+h} + (\gamma_{i,1} - \gamma_{i,2})\varphi_{t+h} + (\gamma_{\pi,1} - \gamma_{\pi,2})\bar{\pi}_{t+h}$$

This implies:

$$\begin{aligned} S_T &= \frac{T_{t-1}}{1-\beta\alpha_5} + \frac{\beta(\gamma_1-\gamma_3)}{(1-\beta\alpha_5)(1-\beta\rho_1)}a_{1,t} + \frac{\beta(\gamma_2-\gamma_4)}{(1-\beta\alpha_5)(1-\beta\rho_2)}a_{2,t} \\ &+ \frac{\beta(\gamma_{i,1}-\gamma_{i,2})}{(1-\beta\alpha_5)(1-\beta\rho)}\varphi_t + \frac{\beta(\gamma_{\pi,1}-\gamma_{\pi,2})}{(1-\beta\alpha_5)(1-\beta)}\bar{\pi}_t \\ &\equiv C_T^T T_{t-1} + C_1^T a_{1,t} + C_2^T a_{2,t} + C_\varphi^T \varphi_t + C_\pi^T \bar{\pi}_t, \end{aligned}$$

for $|\alpha_5| < 1$,[1] the prefactor $(1-\beta\alpha_5)^{-1}$ is the discounted geometric sum of α_5-propagations. Each shock contributes a double-geometric term: T_{t+h} scales with α_5^h, the shock follows ρ_k^h, and the entire path is discounted by β^h. The perceived inflation target enters with unit persistence: once it shifts, agents expect it to remain at the new level. Similarly,

$$S_T^* \equiv \hat{E}_t\left[\sum_{h=0}^{\infty}\beta^h T_{t+h}\right] = \beta^{-1}(S_T - T_{t-1})$$

We also compute the following quantities:

$$\begin{aligned} S_c &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}c_\tau\right] \\ &= \alpha_3 S_T + \frac{\gamma_5}{1-\beta\rho_1}a_{1,t} + \frac{\gamma_6}{1-\beta\rho_2}a_{2,t} + \frac{\gamma_{i,3}}{1-\beta\rho}\varphi_t + \frac{\gamma_{\pi,3}}{1-\beta}\bar{\pi}_t \\ &= \alpha_3 C_T^T T_{t-1} + \left(\frac{\gamma_5}{1-\beta\rho_1} + \alpha_3 C_1^T\right)a_{1,t} + \left(\frac{\gamma_6}{1-\beta\rho_2} + \alpha_3 C_2^T\right)a_{2,t} \\ &+ \left(\frac{\gamma_{i,3}}{1-\beta\rho} + \alpha_3 C_\varphi^T\right)\varphi_t + \left(\frac{\gamma_{\pi,3}}{1-\beta} + \alpha_3 C_\pi^T\right)\bar{\pi}_t \\ &\equiv C_T^c T_{t-1} + C_1^c a_{1,t} + C_2^c a_{2,t} + C_\varphi^c \varphi_t + C_\pi^c \bar{\pi}_t \end{aligned}$$

[1]We assume $\alpha_5 \neq \rho_1, \rho_2, \rho$.

$$
\begin{aligned}
S_{\pi_1} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\pi_{1,\tau}\right] \\
&= \alpha_1^B S_T + \frac{\gamma_1^B}{1-\beta\rho_1}a_{1,t} + \frac{\gamma_2^B}{1-\beta\rho_2}a_{2,t} + \frac{\gamma_{i,1}^B}{1-\beta\rho}\varphi_t + \frac{1}{1-\beta}\bar{\pi}_t \\
&= \alpha_1^B C_T^T T_{t-1} + \left(\frac{\gamma_1^B}{1-\beta\rho_1} + \alpha_1^B C_1^T\right)a_{1,t} + \left(\frac{\gamma_2^B}{1-\beta\rho_2} + \alpha_1^B C_2^T\right)a_{2,t} \\
&+ \left(\frac{\gamma_{i,1}^B}{1-\beta\rho} + \alpha_1^B C_\varphi^T\right)\varphi_t + \left(\frac{1}{1-\beta} + \alpha_1^B C_\pi^T\right)\bar{\pi}_t \\
&\equiv C_T^1 T_{t-1} + C_1^1 a_{1,t} + C_2^1 a_{2,t} + C_\varphi^1\varphi_t + C_\pi^1\bar{\pi}_t
\end{aligned}
$$

$$
\begin{aligned}
S_{\pi_2} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\pi_{2,\tau}\right] \\
&= \alpha_2^B S_T + \frac{\gamma_3^B}{1-\beta\rho_1}a_{1,t} + \frac{\gamma_4^B}{1-\beta\rho_2}a_{2,t} + \frac{\gamma_{i,2}^B}{1-\beta\rho}\varphi_t + \frac{1}{1-\beta}\bar{\pi}_t \\
&= \alpha_2^B C_T^T T_{t-1} + \left(\frac{\gamma_3^B}{1-\beta\rho_1} + \alpha_2^B C_1^T\right)a_{1,t} + \left(\frac{\gamma_4^B}{1-\beta\rho_2} + \alpha_2^B C_2^T\right)a_{2,t} \\
&+ \left(\frac{\gamma_{i,2}^B}{1-\beta\rho} + \alpha_2^B C_\varphi^T\right)\varphi_t + \left(\frac{1}{1-\beta} + \alpha_2^B C_\pi^T\right)\bar{\pi}_t \\
&\equiv C_T^2 T_{t-1} + C_1^2 a_{1,t} + C_2^2 a_{2,t} + C_\varphi^2\varphi_t + C_\pi^2\bar{\pi}_t
\end{aligned}
$$

$$
\begin{aligned}
S_\varphi &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\varphi_\tau\right] \\
&= \frac{1}{1-\beta\rho}\varphi_t \\
S'_{\pi_1} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\pi_{1,\tau+1}\right] \\
&= \beta^{-1}(S_{\pi_1} - \pi_{1,t}) \\
S'_{\pi_2} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}\beta^{\tau-t}\pi_{2,\tau+1}\right] \\
&= \beta^{-1}(S_{\pi_2} - \pi_{2,t})
\end{aligned}
$$

In the Anchoring-DW equilibrium, agents combine correct laws of motion with biased perceptions. They model exogenous shocks, aggregate consumption, and relative prices using the same linear rules as a rational agent. For sectoral inflation $\pi_{1,t}$ and $\pi_{2,t}$, however, they rely on the partial-information system implied by the Baseline-DW equilibrium $(\pi_{1,t}^B, \pi_{2,t}^B)$ while updating the perceived long-run mean $\bar{\pi}_t$. Substituting these perceived forecasts into the

Phillips curves and the Euler equation yields a linear system solved with the method of undetermined coefficients. In particular, c_t is linear in the states and the perceived target,

$$\begin{aligned}
c_t &= \alpha_3 T_{t-1} + \gamma_5 a_{1,t} + \gamma_6 a_{2,t} + \gamma_{i,3}\varphi_t + \gamma_{\pi,3}\bar{\pi}_t \\
&= (1-\beta(1+\lambda_x))S_c - \beta\tau_1 n_1 S_{\pi_1} - \beta\tau_2 n_2 S_{\pi_2} - \beta S_\varphi + \beta(\tilde{n}_1 S'_{\pi_1} + \tilde{n}_2 S'_{\pi_2}) \\
&- \frac{\beta}{1-\beta}(1-\tau_1 n_1 - \tau_2 n_2)\bar{\pi}_t \\
&= (1-\beta(1+\lambda_x))S_c + (\tilde{n}_1 - \beta\tau_1 n_1)S_{\pi_1} + (\tilde{n}_2 - \beta\tau_2 n_2)S_{\pi_2} - \tilde{n}_1\pi_{1,t} - \tilde{n}_2\pi_{2,t} \\
&- \beta S_\varphi - \frac{\beta}{1-\beta}(1-\tau_1 n_1 - \tau_2 n_2)\bar{\pi}_t \\
&= \left[(1-\beta(1+\lambda_x))C_T^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_T^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_T^2 - \tilde{n}_1\alpha_1 - \tilde{n}_2\alpha_2\right] T_{t-1} \\
&+ \left[(1-\beta(1+\lambda_x))C_1^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_1^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_1^2 - \tilde{n}_1\gamma_1 - \tilde{n}_2\gamma_3\right] a_{1,t} \\
&+ \left[(1-\beta(1+\lambda_x))C_2^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_2^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_2^2 - \tilde{n}_1\gamma_2 - \tilde{n}_2\gamma_4\right] a_{2,t} \\
&+ \left[(1-\beta(1+\lambda_x))C_\varphi^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_\varphi^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_\varphi^2 - \tilde{n}_1\gamma_{i,1} - \tilde{n}_2\gamma_{i,2} - \frac{\beta}{1-\beta\rho}\right] \varphi_t \\
&+ \Bigg[(1-\beta(1+\lambda_x))C_\pi^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_\pi^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_\pi^2 - \tilde{n}_1\gamma_{\pi,1} - \tilde{n}_2\gamma_{\pi,2} \\
&- \frac{\beta}{1-\beta}(1-\tau_1 n_1 - \tau_2 n_2)\Bigg] \bar{\pi}_t
\end{aligned}$$

Therefore, we have the following system of equations for $\{\alpha_3, \gamma_5, \gamma_6, \gamma_{i,3}, \gamma_{\pi,3}\}$:

$$\alpha_3 = (1-\beta(1+\lambda_x))C_T^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_T^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_T^2 - \tilde{n}_1\alpha_1 - \tilde{n}_2\alpha_2 \quad \text{(C-15)}$$

$$\gamma_5 = (1-\beta(1+\lambda_x))C_1^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_1^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_1^2 - \tilde{n}_1\gamma_1 - \tilde{n}_2\gamma_3 \quad \text{(C-16)}$$

$$\gamma_6 = (1-\beta(1+\lambda_x))C_2^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_2^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_2^2 - \tilde{n}_1\gamma_2 - \tilde{n}_2\gamma_4 \quad \text{(C-17)}$$

$$\gamma_{i,3} = (1-\beta(1+\lambda_x))C_\varphi^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_\varphi^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_\varphi^2 - \tilde{n}_1\gamma_{i,1} - \tilde{n}_2\gamma_{i,2} - \frac{\beta}{1-\beta\rho} \quad \text{(C-18)}$$

$$\gamma_{\pi,3} = (1-\beta(1+\lambda_x))C_\pi^c + (\tilde{n}_1 - \beta\tau_1 n_1)C_\pi^1 + (\tilde{n}_2 - \beta\tau_2 n_2)C_\pi^2 - \tilde{n}_1\gamma_{\pi,1} - \tilde{n}_2\gamma_{\pi,2} - \frac{\beta}{1-\beta}(1-\tau_1 n_1 - \tau_2 n_2) \quad \text{(C-19)}$$

where

$$C_T^T = \frac{1}{1-\beta\alpha_5}, \quad C_1^T = \frac{\beta(\gamma_1-\gamma_3)}{1-\beta\rho_1}C_T^T, \quad C_2^T = \frac{\beta(\gamma_2-\gamma_4)}{1-\beta\rho_2}C_T^T, \quad C_\varphi^T = \frac{\beta(\gamma_{i,1}-\gamma_{i,2})}{1-\beta\rho}C_T^T,$$
$$C_\pi^T = \frac{\beta(\gamma_{\pi,1}-\gamma_{\pi,2})}{1-\beta}C_T^T, \quad C_T^c = \alpha_3 C_T^T, \quad C_1^c = \frac{\gamma_5}{1-\beta\rho_1}+\alpha_3 C_1^T, \quad C_2^c = \frac{\gamma_6}{1-\beta\rho_2}+\alpha_3 C_2^T,$$
$$C_\varphi^c = \frac{\gamma_{i,3}}{1-\beta\rho}+\alpha_3 C_\varphi^T, \quad C_\pi^c = \frac{\gamma_{\pi,3}}{1-\beta}+\alpha_3 C_\pi^T, \quad C_T^1 = \alpha_1^B C_T^T, \quad C_1^1 = \frac{\gamma_1^B}{1-\beta\rho_1}+\alpha_1^B C_1^T,$$
$$C_2^1 = \frac{\gamma_2^B}{1-\beta\rho_2}+\alpha_1^B C_2^T, \quad C_\varphi^1 = \frac{\gamma_{i,1}^B}{1-\beta\rho}+\alpha_1^B C_\varphi^T, \quad C_\pi^1 = \frac{1}{1-\beta}+\alpha_1^B C_\pi^T, \quad C_T^2 = \alpha_2^B C_T^T,$$
$$C_1^2 = \frac{\gamma_3^B}{1-\beta\rho_1}+\alpha_2^B C_1^T, \quad C_2^2 = \frac{\gamma_4^B}{1-\beta\rho_2}+\alpha_2^B C_2^T, \quad C_\varphi^2 = \frac{\gamma_{i,2}^B}{1-\beta\rho}+\alpha_2^B C_\varphi^T,$$
$$C_\pi^2 = \frac{1}{1-\beta}+\alpha_2^B C_\pi^T$$

C.1.3 Firms' Anchoring Equilibrium

Now we substitute the conjectured values into Equation 4-24. We have an adjusted measure for S_T:

$$\begin{aligned} S_{T,k} &\equiv \hat{E}_t\left[\sum_{h=0}^{\infty}(\beta\,\theta_k)^h\,T_{t+h-1}\right] \\ &= T_{t-1} + \hat{E}_t\left[\sum_{h=1}^{\infty}(\beta\,\theta_k)^h\,T_{t+h-1}\right] \\ &= T_{t-1} + \beta\,\theta_k\,S_{T,k}^*, \end{aligned}$$

where

$$\begin{aligned} S_{T,k} &\equiv \hat{E}_t\left[\sum_{h=0}^{\infty}(\beta\,\theta_k)^h\,T_{t+h}\right] \\ &= \sum_{h=0}^{\infty}(\beta\,\theta_k)^h\left[\alpha_5^h\,T_t + \sum_{m=1}^{h}\alpha_5^{h-m}\hat{E}_t\left[\Delta_{t+m}\right]\right] \\ &= \frac{T_t}{1-\beta\theta_k\alpha_5} + \sum_{h=0}^{\infty}(\beta\,\theta_k)^h\sum_{m=1}^{h}\alpha_5^{h-m}\hat{E}_t\left[\Delta_{t+m}\right] \\ &= \frac{T_t}{1-\beta\theta_k\alpha_5} + \sum_{h=1}^{\infty}(\beta\theta_k)^h\hat{E}_t\left[\Delta_{t+h}\right]\sum_{j=0}^{\infty}(\beta\theta_k\alpha_5)^j \\ &= \frac{1}{1-\beta\theta_k\alpha_5}\left[T_t + \sum_{h=1}^{\infty}(\beta\theta_k)^h\hat{E}_t[\Delta_{t+h}]\right]. \end{aligned}$$

and

$$\Delta_{t+h} \equiv (\gamma_1-\gamma_3)a_{1,t+h} + (\gamma_2-\gamma_4)a_{2,t+h} + (\gamma_{i,1}-\gamma_{i,2})\varphi_{t+h} + (\gamma_{\pi,1}-\gamma_{\pi,2})\bar{\pi}_{t+h}.$$

This implies:

$$\begin{aligned}S_{T,k} &= \frac{T_{t-1}}{1-\beta\theta_k\alpha_5} + \frac{\beta\theta_k\left(\gamma_1-\gamma_3\right)}{\left(1-\beta\theta_k\alpha_5\right)\left(1-\beta\theta_k\rho_1\right)}a_{1,t} + \frac{\beta\theta_k\left(\gamma_2-\gamma_4\right)}{\left(1-\beta\theta_k\alpha_5\right)\left(1-\beta\theta_k\rho_2\right)}a_{2,t} \\ &+ \frac{\beta\theta_k\left(\gamma_{i,1}-\gamma_{i,2}\right)}{\left(1-\beta\theta_k\alpha_5\right)\left(1-\beta\theta_k\rho\right)}\varphi_t + \frac{\beta\theta_k\left(\gamma_{\pi,1}-\gamma_{\pi,2}\right)}{\left(1-\beta\theta_k\alpha_5\right)\left(1-\beta\theta_k\right)}\bar{\pi}_t \\ &\equiv C^T_{T,k}T_{t-1} + C^T_{1,k}a_{1,t} + C^T_{2,k}a_{2,t} + C^T_{\varphi,k}\varphi_t + C^T_{\pi,k}\bar{\pi}_t.\end{aligned}$$

Reflecting firms' discounting at rate $(\beta\theta_k)^h$, the prefactor $(1-\beta\theta_k\alpha_{5,k})^{-1}$ again comes from summing an infinite sequence of $\alpha_{5,k}$-propagations, each now discounted by $\beta\theta_k$. Each shock contributes a double-geometric term: T_{t+h} scales with $\alpha^h_{5,k}$, the shock follows ρ^h_k (for the relevant $\rho_{k,i}$), and the entire path is discounted by $(\beta\theta_k)^h$. Similarly,

$$S^*_{T,k} = \hat{E}_t\left[\sum_{h=0}^{\infty}(\beta\theta_k)^h T_{t+h}\right] = (\beta\theta_k)^{-1}\left(S_{T,k}-T_{t-1}\right).$$

We now define the present-value operators:

$$\begin{aligned}S_{c,k} &\equiv \hat{E}_t\left[\sum_{\tau=t}^{\infty}(\theta_k\beta)^{\tau-t}c_\tau\right] \\ &= \alpha_3 S_{T,k} + \frac{\gamma_5}{1-\theta_k\beta\rho_1}a_{1,t} + \frac{\gamma_6}{1-\theta_k\beta\rho_2}a_{2,t} + \frac{\gamma_{i,3}}{1-\theta_k\beta\rho}\varphi_t + \frac{\gamma_{\pi,3}}{1-\theta_k\beta}\bar{\pi}_t \\ &= \alpha_3 C^T_{T,k}T_{t-1} + \left(\frac{\gamma_5}{1-\theta_k\beta\rho_1} + \alpha_3 C^T_{1,k}\right)a_{1,t} + \left(\frac{\gamma_6}{1-\theta_k\beta\rho_2} + \alpha_3 C^T_{2,k}\right)a_{2,t} \\ &+ \left(\frac{\gamma_{i,3}}{1-\theta_k\beta\rho} + \alpha_3 C^T_{\varphi,k}\right)\varphi_t + \left(\frac{\gamma_{\pi,3}}{1-\theta_k\beta} + \alpha_3 C^T_{\pi,k}\right)\bar{\pi}_t \\ &\equiv C^c_{T,k}T_{t-1} + C^c_{1,k}a_{1,t} + C^c_{2,k}a_{2,t} + C^c_{\varphi,k}\varphi_t + C^c_{\pi,k}\bar{\pi}_t.\end{aligned}$$

$$\begin{aligned}S_{\pi_1,1} &\equiv \hat{E}_t\left[\sum_{\tau=t}^{\infty}(\theta_1\beta)^{\tau-t}\pi_{1,\tau}\right] \\ &= \alpha^B_1 S_{T,1} + \frac{\gamma^B_1}{1-\theta_1\beta\rho_1}a_{1,t} + \frac{\gamma^B_2}{1-\theta_1\beta\rho_2}a_{2,t} + \frac{\gamma^B_{i,1}}{1-\theta_1\beta\rho}\varphi_t + \frac{1}{1-\theta_1\beta}\bar{\pi}_t \\ &= \alpha^B_1\left(C^T_{T,1}T_{t-1} + C^T_{1,1}a_{1,t} + C^T_{2,1}a_{2,t} + C^T_{\varphi,1}\varphi_t + C^T_{\pi,1}\bar{\pi}_t\right) + \frac{\gamma^B_1}{1-\theta_1\beta\rho_1}a_{1,t} + \cdots \\ &\equiv C^1_{T,1}T_{t-1} + C^1_{1,1}a_{1,t} + C^1_{2,1}a_{2,t} + C^1_{\varphi,1}\varphi_t + C^1_{\pi,1}\bar{\pi}_t,\end{aligned}$$

$$
\begin{aligned}
S_{\pi_2,2} &\equiv \hat{E}_t\left[\sum_{\tau=t}^{\infty}(\theta_2\beta)^{\tau-t}\pi_{2,\tau}\right] \\
&= \alpha_2^B S_{T,2} + \frac{\gamma_3^B}{1-\theta_2\beta\rho_1}a_{1,t} + \frac{\gamma_4^B}{1-\theta_2\beta\rho_2}a_{2,t} + \frac{\gamma_{i,2}^B}{1-\theta_2\beta\rho}\varphi_t + \frac{1}{1-\theta_2\beta}\bar{\pi}_t \\
&= \alpha_2^B\left(C_{T,2}^T T_{t-1} + C_{1,2}^T a_{1,t} + C_{2,2}^T a_{2,t} + C_{\varphi,2}^T\varphi_t + C_{\pi,2}^T\bar{\pi}_t\right) + \frac{\gamma_3^B}{1-\theta_2\beta\rho_1}a_{1,t} + \cdots \\
&\equiv C_{T,2}^2 T_{t-1} + C_{1,2}^2 a_{1,t} + C_{2,2}^2 a_{2,t} + C_{\varphi,2}^2\varphi_t + C_{\pi,2}^2\bar{\pi}_t.
\end{aligned}
$$

$$
\begin{aligned}
S'_{\pi_1} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}(\theta_1\beta)^{\tau-t}\pi_{1,\tau+1}\right] \\
&= (\theta_1\beta)^{-1}(S_{\pi_1,1}-\pi_{1,t}) \\
S'_{\pi_2} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}(\theta_2\beta)^{\tau-t}\pi_{2,\tau+1}\right] \\
&= (\theta_2\beta)^{-1}(S_{\pi_2,2}-\pi_{2,t}) \\
S_{rp_1} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}(\theta_1\beta)^{\tau-t}rp_{1,\tau}\right] \\
&= \tilde{n}_2 S_{T,1}^* \\
S_{rp_2} &= \hat{E}_t\left[\sum_{\tau=t}^{\infty}(\theta_2\beta)^{\tau-t}rp_{2,\tau}\right] \\
&= -\tilde{n}_1 S_{T,2}^*
\end{aligned}
$$

We solve for the sector 1's Phillips curve:

$$
\begin{aligned}
\pi_{1,t} &= \alpha_1 T_{t-1} + \gamma_1 a_{1,t} + \gamma_2 a_{2,t} + \gamma_{i,1}\varphi_t + \gamma_{\pi,1}\bar{\pi}_t \\
&= \xi_1(1+\varphi)S_{c,1} - \xi_1(1+\varphi)\frac{1}{1-\theta_1\beta\rho_1}a_{1,t} - \xi_1(1+\varphi\eta)\tilde{n}_2 S'_{T,1} + (1-\theta_1)\beta S'_{\pi_1} \\
&- \frac{(1-\theta_1)\beta}{1-\theta_1\beta}\bar{\pi}_t \\
&= \left[\theta_1\xi_1(1+\varphi)C_{T,1}^c - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2(C_{T,1}^T-1) + (1-\theta_1)C_{T,1}^1\right]T_{t-1} \\
&+ \left[\theta_1\xi_1(1+\varphi)C_{1,1}^c - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C_{1,1}^T - \frac{\theta_1\xi_1(1+\varphi)}{1-\theta_1\beta\rho_1} + (1-\theta_1)C_{1,1}^1\right]a_{1,t} \\
&+ \left[\theta_1\xi_1(1+\varphi)C_{2,1}^c - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C_{2,1}^T + (1-\theta_1)C_{2,1}^1\right]a_{2,t} \\
&+ \left[\theta_1\xi_1(1+\varphi)C_{\varphi,1}^c - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C_{\varphi,1}^T + (1-\theta_1)C_{\varphi,1}^1\right]\varphi_t \\
&+ \left[\theta_1\xi_1(1+\varphi)C_{\pi,1}^c - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C_{\pi,1}^T - \frac{(1-\theta_1)\theta_1\beta}{1-\theta_1\beta} + (1-\theta_1)C_{\pi,1}^1\right]\bar{\pi}_t
\end{aligned}
$$

Therefore, we have the following system of equations for $\{\alpha_1, \gamma_1, \gamma_2, \gamma_{i,1}, \gamma_{\pi,1}\}$:

$$\alpha_1 = \theta_1\xi_1(1+\varphi)C^c_{T,1} - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2(C^T_{T,1}-1) + (1-\theta_1)C^1_{T,1} \tag{C-20}$$

$$\gamma_1 = \theta_1\xi_1(1+\varphi)C^c_{1,1} - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C^T_{1,1} - \frac{\theta_1\xi_1(1+\varphi)}{1-\theta_1\beta\rho_1} + (1-\theta_1)C^1_{1,1} \tag{C-21}$$

$$\gamma_2 = \theta_1\xi_1(1+\varphi)C^c_{2,1} - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C^T_{2,1} + (1-\theta_1)C^1_{2,1} \tag{C-22}$$

$$\gamma_{i,1} = \theta_1\xi_1(1+\varphi)C^c_{\varphi,1} - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C^T_{\varphi,1} + (1-\theta_1)C^1_{\varphi,1} \tag{C-23}$$

$$\gamma_{\pi,1} = \theta_1\xi_1(1+\varphi)C^c_{\pi,1} - \beta^{-1}\xi_1(1+\varphi\eta)\tilde{n}_2 C^T_{\pi,1} - \frac{(1-\theta_1)\theta_1\beta}{1-\theta_1\beta} + (1-\theta_1)C^1_{\pi,1} \tag{C-24}$$

where

$$C^T_{T,1} = \frac{1}{1-\theta_1\beta\alpha_5}, \quad C^T_{1,1} = \frac{\theta_1\beta(\gamma_1-\gamma_3)}{1-\theta_1\beta\rho_1}C^T_{T,1}, \quad C^T_{2,1} = \frac{\theta_1\beta(\gamma_2-\gamma_4)}{1-\theta_1\beta\rho_2}C^T_{T,1},$$
$$C^T_{\varphi,1} = \frac{\theta_1\beta(\gamma_{i,1}-\gamma_{i,2})}{1-\theta_1\beta\rho}C^T_{T,1}, \quad C^T_{\pi,1} = \frac{\theta_1\beta(\gamma_{\pi,1}-\gamma_{\pi,2})}{1-\theta_1\beta}C^T_{T,1}, \quad C^c_{T,1} = \alpha_3 C^T_{T,1},$$
$$C^c_{1,1} = \frac{\gamma_5}{1-\theta_1\beta\rho_1} + \alpha_3 C^T_{1,1}, \quad C^c_{2,1} = \frac{\gamma_6}{1-\theta_1\beta\rho_2} + \alpha_3 C^T_{2,1}, \quad C^c_{\varphi,1} = \frac{\gamma_{i,3}}{1-\theta_1\beta\rho} + \alpha_3 C^T_{\varphi,1},$$
$$C^c_{\pi,1} = \frac{\gamma_{\pi,3}}{1-\theta_1\beta} + \alpha_3 C^T_{\pi,1}, \quad C^1_{T,1} = \alpha^B_1 C^T_{T,1}, \quad C^1_{1,1} = \frac{\gamma^B_1}{1-\theta_1\beta\rho_1} + \alpha^B_1 C^T_{1,1},$$
$$C^1_{2,1} = \frac{\gamma^B_2}{1-\theta_1\beta\rho_2} + \alpha^B_1 C^T_{2,1}, \quad C^1_{\varphi,1} = \frac{\gamma^B_{i,1}}{1-\theta_1\beta\rho} + \alpha^B_1 C^T_{\varphi,1}, \quad C^1_{\pi,1} = \frac{1}{1-\theta_1\beta} + \alpha^B_1 C^T_{\pi,1}.$$

We solve for the sector 2's Phillips curve:

$$\begin{aligned}
\pi_{2,t} &= \alpha_2 T_{t-1} + \gamma_3 a_{1,t} + \gamma_4 a_{2,t} + \gamma_{i,2}\varphi_t + \gamma_{\pi,2}\bar{\pi}_t \\
&= \xi_2(1+\varphi)S_{c,2} - \xi_2(1+\varphi)\frac{1}{1-\theta_2\beta\rho_2}a_{2,t} + \xi_2(1+\varphi\eta)\tilde{n}_1 S'_{T,2} + (1-\theta_2)\beta S'_{\pi_2} \\
&- \frac{(1-\theta_2)\beta}{1-\theta_2\beta}\bar{\pi}_t \\
&= \left[\theta_2\xi_2(1+\varphi)C^c_{T,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1(C^T_{T,2}-1) + (1-\theta_2)C^2_{T,2}\right]T_{t-1} \\
&+ \left[\theta_2\xi_2(1+\varphi)C^c_{1,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{1,2} + (1-\theta_2)C^2_{1,2}\right]a_{1,t} \\
&+ \left[\theta_2\xi_2(1+\varphi)C^c_{2,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{2,2} - \frac{\theta_2\xi_2(1+\varphi)}{1-\theta_2\beta\rho_2} + (1-\theta_2)C^2_{2,2}\right]a_{2,t} \\
&+ \left[\theta_2\xi_2(1+\varphi)C^c_{\varphi,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{\varphi,2} + (1-\theta_2)C^2_{\varphi,2}\right]\varphi_t \\
&+ \left[\theta_2\xi_2(1+\varphi)C^c_{\pi,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{\pi,2} - \frac{(1-\theta_2)\theta_2\beta}{1-\theta_2\beta} + (1-\theta_2)C^2_{\pi,2}\right]\bar{\pi}_t
\end{aligned}$$

Therefore, we have the following system of equations for $\{\alpha_2, \gamma_3, \gamma_4, \gamma_{i,2}, \gamma_{\pi,2}\}$:

$$\alpha_2 = \theta_2\xi_2(1+\varphi)C^c_{T,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1(C^T_{T,2}-1) + (1-\theta_2)C^2_{T,2} \tag{C-25}$$

$$\gamma_3 = \theta_2\xi_2(1+\varphi)C^c_{1,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{1,2} + (1-\theta_2)C^2_{1,2} \tag{C-26}$$

$$\gamma_4 = \theta_2\xi_2(1+\varphi)C^c_{2,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{2,2} - \frac{\theta_2\xi_2(1+\varphi)}{1-\theta_2\beta\rho_2} + (1-\theta_2)C^2_{2,2} \quad \text{(C-27)}$$

$$\gamma_{i,2} = \theta_2\xi_2(1+\varphi)C^c_{\varphi,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{\varphi,2} + (1-\theta_2)C^2_{\varphi,2} \quad \text{(C-28)}$$

$$\gamma_{\pi,2} = \theta_2\xi_2(1+\varphi)C^c_{\pi,2} + \beta^{-1}\xi_2(1+\varphi\eta)\tilde{n}_1 C^T_{\pi,2} - \frac{(1-\theta_2)\theta_2\beta}{1-\theta_2\beta} + (1-\theta_2)C^2_{\pi,2} \quad \text{(C-29)}$$

where

$$C^T_{T,2} = \frac{1}{1-\theta_2\beta\alpha_5}, \quad C^T_{1,2} = \frac{\theta_2\beta(\gamma_1-\gamma_3)}{1-\theta_2\beta\rho_1}C^T_{T,2}, \quad C^T_{2,2} = \frac{\theta_2\beta(\gamma_2-\gamma_4)}{1-\theta_2\beta\rho_2}C^T_{T,2},$$
$$C^T_{\varphi,2} = \frac{\theta_2\beta(\gamma_{i,1}-\gamma_{i,2})}{1-\theta_2\beta\rho}C^T_{T,2}, \quad C^T_{\pi,2} = \frac{\theta_2\beta(\gamma_{\pi,1}-\gamma_{\pi,2})}{1-\theta_2\beta}C^T_{T,2}, \quad C^c_{T,2} = \alpha_3 C^T_{T,2},$$
$$C^c_{1,2} = \frac{\gamma_5}{1-\theta_2\beta\rho_1} + \alpha_3 C^T_{1,2}, \quad C^c_{2,2} = \frac{\gamma_6}{1-\theta_2\beta\rho_2} + \alpha_3 C^T_{2,2}, \quad C^c_{\varphi,2} = \frac{\gamma_{i,3}}{1-\theta_2\beta\rho} + \alpha_3 C^T_{\varphi,2},$$
$$C^c_{\pi,2} = \frac{\gamma_{\pi,3}}{1-\theta_2\beta} + \alpha_3 C^T_{\pi,2}, \quad C^2_{T,2} = \alpha^B_2 C^T_{T,2}, \quad C^2_{1,2} = \frac{\gamma^B_3}{1-\theta_2\beta\rho_1} + \alpha^B_2 C^T_{1,2},$$
$$C^2_{2,2} = \frac{\gamma^B_4}{1-\theta_2\beta\rho_2} + \alpha^B_2 C^T_{2,2}, \quad C^2_{\varphi,2} = \frac{\gamma^B_{i,2}}{1-\theta_2\beta\rho} + \alpha^B_2 C^T_{\varphi,2}, \quad C^2_{\pi,2} = \frac{1}{1-\theta_2\beta} + \alpha^B_2 C^T_{\pi,2}.$$

C.1.4 Empirical Verification of Coefficient Equivalence

Although we do not provide a formal proof, we verify numerically that the undetermined-coefficients solutions from the baseline model and from the anchoring model coincide for all coefficients on the states $X_t \equiv (T_{t-1}, a_{1,t}, a_{2,t}, \varphi_t)$, while the anchoring model features additional loadings on the perceived long-run inflation $\bar{\pi}_t$. Across an empirically relevant grid, the matched coefficients lie on the 45° line up to solver precision.

Parameter sampling. For each draw, we sample a parameter vector from independent uniforms over empirically plausible intervals, with buffers away from boundaries for numerical stability:

$$\theta_1 \in (0, 0.5), \quad \theta_2 \in (0.5, 1), \quad n_1 \in (0,1),\ n_2 = 1 - n_1,$$

$$\tilde{n}_1 \in (0,1), \quad \tilde{n}_2 = 1 - \tilde{n}_1, \quad \beta, \rho_1, \rho_2, \rho \in (0,1),$$

$$\varphi, \eta, \tau_1, \tau_2 \in (0,5), \quad \lambda_x \in (0,2).$$

We enforce standard stability restrictions (e.g., $|\alpha_5| < 1$, $|\rho_i| < 1$) and discard draws that violate them.

Solution routine. For each draw, we first solve the *Baseline* system to obtain

$$\{\alpha_1^B, \alpha_2^B, \alpha_3^B, \gamma_1^B, \gamma_2^B, \gamma_3^B, \gamma_4^B, \gamma_5^B, \gamma_6^B, \gamma_{i,1}^B, \gamma_{i,2}^B, \gamma_{i,3}^B\}.$$

We then use these values as starting guesses for the *Anchoring* system, which returns

$$\{\alpha_1, \alpha_2, \alpha_3, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_{i,1}, \gamma_{i,2}, \gamma_{i,3}, \gamma_{\pi,1}, \gamma_{\pi,2}, \gamma_{\pi,3}\}.$$

We retain draws only if both solves converge.

Equivalence diagnostics. Figure C.1 plots (α_i^B, α_i) and $(\gamma_\ell^B, \gamma_\ell)$ against the 45° line. In our runs, the maximal absolute discrepancy is $\mathcal{O}(10^{-7})$, which matches standard solver tolerances.

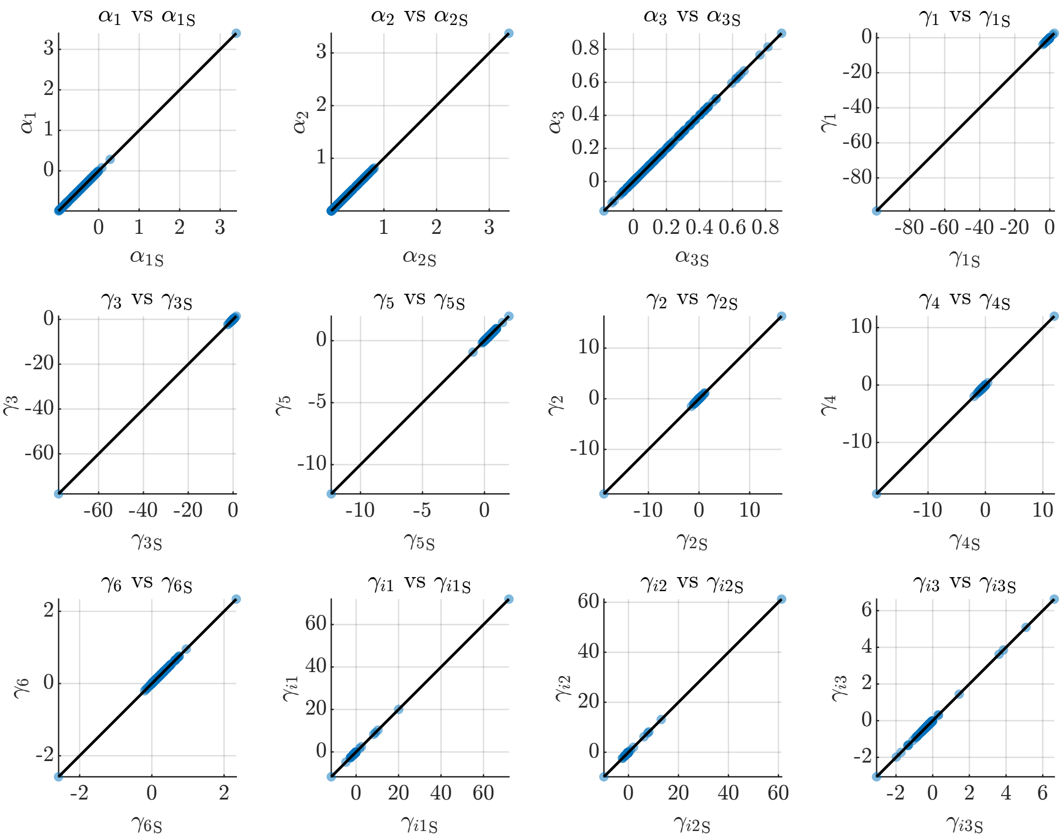


Figure C.1: Scatter plots of (α_i^B, α_i) and $(\gamma_\ell^B, \gamma_\ell)$ over parameter draws. Points lie on the 45° line, indicating numerical equivalence across the empirically relevant parameter region.

$\bar{\pi}_t$ loadings. The Baseline system does not identify $\{\gamma_{\pi,1}, \gamma_{\pi,2}, \gamma_{\pi,3}\}$. The Anchoring system does. Figure C.2 shows these coefficients across draws.

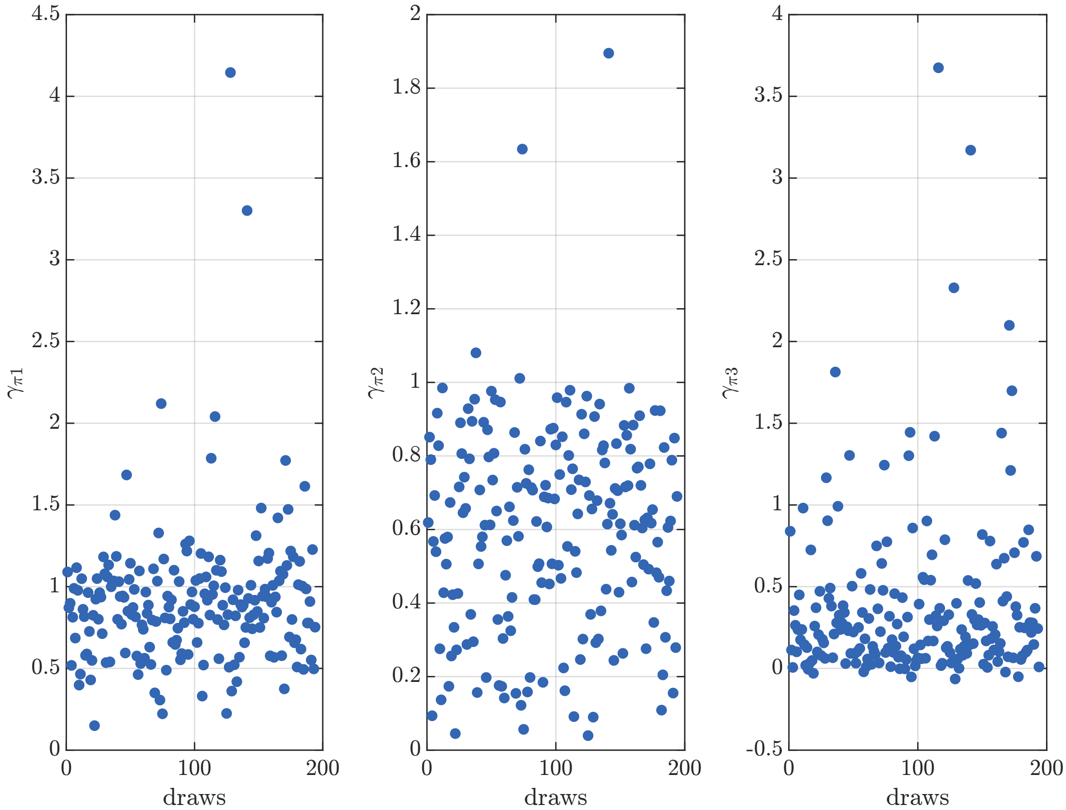


Figure C.2: Policy-rule coefficients $\gamma_{\pi,1}$, $\gamma_{\pi,2}$, and $\gamma_{\pi,3}$ across parameter draws. They are positive and not necessarily equal, as determined by the full system.

Economic intuition. The short-run mapping from the states X_t into marginal costs and inflation comes from three ingredients that are the same in both solves: Calvo pricing, sectoral demand, and a Taylor rule that reacts to current sectoral inflation and activity. In the Anchoring system, agents learn only the endpoint $\bar{\pi}_t$. A change in $\bar{\pi}_t$ acts like a common drift in the price level. It shifts the intercept of $\pi_{k,t}$ and c_t through expected real rates but does not change relative prices or the way marginal cost responds to X_t. Because the coefficients we compare are slopes with respect to X_t, they line up across systems. The extra terms $\gamma_{\pi,\cdot}\bar{\pi}_t$ capture the drift component that the Baseline system does not include. The equality of slopes can fail if agents also learn about the short-run inflation dynamics.

C.1.5
Proofs and Derivations

Forecast error decomposition. We report flexible vs. rigid shares in one-step-ahead perceived-CPI forecast errors. The one-step error is

$$f_t = \tilde{\pi}_t - \hat{E}_{t-1}[\tilde{\pi}_t]$$

Flexible vs. rigid sector contributions. Define

$$\begin{aligned} f_t^F &= \tilde{n}_1\Big[\gamma_1 a_{1,t} + \gamma_2 a_{2,t} + \gamma_{i,1}\varphi_t + (\gamma_{\pi,1}-1)\bar{\pi}_t + (\alpha_1 - \alpha_1^B)T_{t-1} \\ &\qquad - \gamma_1^B \rho_1 a_{1,t-1} - \gamma_2^B \rho_2 a_{2,t-1} - \gamma_{i,1}^B \rho \varphi_{t-1}\Big] \\ &= \tilde{n}_1\Big[(\gamma_{\pi,1}-1)\bar{\pi}_t + \gamma_1 \epsilon_{1,t} + \gamma_2 \epsilon_{2,t} + \gamma_{i,1}\epsilon_t\Big], \\ f_t^R &= \tilde{n}_2\Big[\gamma_3 a_{1,t} + \gamma_4 a_{2,t} + \gamma_{i,2}\varphi_t + (\gamma_{\pi,2}-1)\bar{\pi}_t + (\alpha_2 - \alpha_2^B)T_{t-1} \\ &\qquad - \gamma_3^B \rho_1 a_{1,t-1} - \gamma_4^B \rho_2 a_{2,t-1} - \gamma_{i,2}^B \rho \varphi_{t-1}\Big] \\ &= \tilde{n}_2\Big[(\gamma_{\pi,2}-1)\bar{\pi}_t + \gamma_3 \epsilon_{1,t} + \gamma_4 \epsilon_{2,t} + \gamma_{i,2}\epsilon_t\Big]. \end{aligned}$$

Then

$$f_t = f_t^F + f_t^R.$$

The flexible block loads relatively more on perceived CPI because agents overweight the flexible sector ($\tilde{n}_1 > n_1$). In anchored periods, this salience tilt helps flexible-price surprises dominate forecast errors. In unanchored windows, elevated nominal drift raises both blocks through their sectoral anchor wedges $(\gamma_{\pi,k}-1)\bar{\pi}_t$, with rigid prices becoming more visible but remaining secondary.

Direct accounting by source. Equivalently, the same forecast error can be written as the sum of five source contributions:

$$f_t = C_{1,t} + C_{2,t} + C_{\mathrm{MP},t} + C_{T,t} + C_{\mathrm{Anchor},t}$$

with

$$
\begin{aligned}
C_{1,t} &= \tilde{\gamma}_7 a_{1,t} - \tilde{\gamma}_7^B \rho_1 a_{1,t-1} = \tilde{\gamma}_7 \epsilon_{1,t} \\
C_{2,t} &= \tilde{\gamma}_8 a_{2,t} - \tilde{\gamma}_8^B \rho_2 a_{2,t-1} = \tilde{\gamma}_8 \epsilon_{2,t}, \\
C_{\mathrm{MP},t} &= \tilde{\gamma}_{i,4} \varphi_t - \tilde{\gamma}_{i,4}^B \rho \varphi_{t-1} = \tilde{\gamma}_{i,4} \epsilon_t, \\
C_{T,t} &= \left(\tilde{\alpha}_4 - \tilde{\alpha}_4^B\right) T_{t-1} = 0, \\
C_{\mathrm{Anchor},t} &= \left(\tilde{\gamma}_{\pi,4} - 1\right) \bar{\pi}_t.
\end{aligned}
$$

Here the salience-weighted coefficients are

$$
\tilde{\alpha}_4 = \tilde{n}_1 \alpha_1 + \tilde{n}_2 \alpha_2, \quad \tilde{\gamma}_7 = \tilde{n}_1 \gamma_1 + \tilde{n}_2 \gamma_3, \quad \tilde{\gamma}_8 = \tilde{n}_1 \gamma_2 + \tilde{n}_2 \gamma_4,
$$

$$
\tilde{\gamma}_{i,4} = \tilde{n}_1 \gamma_{i,1} + \tilde{n}_2 \gamma_{i,2}, \qquad \tilde{\gamma}_{\pi,4} = \tilde{n}_1 \gamma_{\pi,1} + \tilde{n}_2 \gamma_{\pi,2},
$$

and similarly for the B coefficients $\tilde{\alpha}_4^B, \tilde{\gamma}_7^B, \tilde{\gamma}_8^B, \tilde{\gamma}_{i,4}^B$. By construction, these five pieces add exactly to f_t each quarter. In our estimates, $C_{1,t}$ (sector 1 productivity) and $C_{\mathrm{MP},t}$ (policy) dominate in anchored regimes; in unanchored windows, $C_{\mathrm{Anchor},t}$ becomes comparably important, consistent with learning about the endpoint.

Why the nominal anchor dominates the switching threshold. Agents switch to constant-gain learning when the normalized distance between subjective and objective perceived-CPI forecasts exceeds a threshold. In our notation the (unnormalized) statistic is

$$
\begin{aligned}
\theta_t \equiv |A_\theta' m_t| = |&(\tilde{\gamma}_{\pi,4} - 1)\bar{\pi}_t + (\tilde{\alpha}_4 - \tilde{\alpha}_4^B) T_{t-1} + (\tilde{\gamma}_7 - \tilde{\gamma}_7^B)\rho_1\, a_{1,t-1} \\
&+ (\tilde{\gamma}_8 - \tilde{\gamma}_8^B)\rho_2\, a_{2,t-1} + (\tilde{\gamma}_{i,4} - \tilde{\gamma}_{i,4}^B)\rho\varphi_{t-1}| \\
= |&(\tilde{\gamma}_{\pi,4} - 1)\bar{\pi}_t| \\
= &\left| (\tilde{\gamma}_{\pi,4} - 1) \left[\bar{\pi}_0 + \sum_{\tau=0}^{t-1} k_\tau^{-1} f_\tau \right] \right|.
\end{aligned}
$$

The switching threshold depends solely on the nominal anchor, $\bar{\pi}_t$, with $(\tilde{\gamma}_{\pi,4} - 1)$ playing the same role as $(\Gamma - 1)$ in Carvalho et al. (2023). The parameter $\tilde{\gamma}_{\pi,4}$ captures the degree of self-referentiality. Moreover, the switching criterion is a function of past forecast errors, conditional on the initial conditions $\bar{\pi}_0$, f_0, and k_0. It can be expressed as a gain-weighted average of the entire history of past forecast errors.

Flexible vs. rigid sector contributions. Write

$$\begin{aligned}\theta_t^F &\equiv \tilde{n}_1\Big[(\gamma_{\pi,1}-1)\bar{\pi}_t + (\alpha_1-\alpha_1^B)T_{t-1} + (\gamma_1-\gamma_1^B)\rho_1 a_{1,t-1} + (\gamma_2-\gamma_2^B)\rho_2 a_{2,t-1} \\ &\qquad + (\gamma_{i,1}-\gamma_{i,1}^B)\rho\varphi_{t-1}\Big] \\ &= \tilde{n}_1(\gamma_{\pi,1}-1)\bar{\pi}_t, \\ \theta_t^R &\equiv \tilde{n}_2\Big[\gamma_{\pi,2}\bar{\pi}_t + (\alpha_2-\alpha_2^B)T_{t-1} + (\gamma_3-\gamma_3^B)\rho_1 a_{1,t-1} + (\gamma_4-\gamma_4^B)\rho_2 a_{2,t-1} \\ &\qquad + (\gamma_{i,2}-\gamma_{i,2}^B)\rho\varphi_{t-1}\Big] \\ &= \tilde{n}_2(\gamma_{\pi,2}-1)\bar{\pi}_t\end{aligned}$$

Then $\theta_t = |A'_\theta m_{t-1}| = |\theta_t^F + \theta_t^R|$. We define the aligned contribution of the flexible block as

$$s_{\theta,t}^F \equiv \operatorname{sgn}(A'_\theta m_t \theta_t^F)|\theta_t^F| = \begin{cases} \theta_t^F, & \text{if } A'_\theta m_t \theta_t^F \geq 0 \quad \text{(same direction)} \\ -\theta_t^F, & \text{if } A'_\theta m_t \theta_t^F < 0 \quad \text{(offsetting)}. \end{cases}$$

Analogously $s_{\theta,t}^R = \operatorname{sgn}(A'_\theta m_t)|\theta_t^R|$. Of course, these contributions depend on the size of the coefficients $\gamma_{\pi,1}$ and $\gamma_{\pi,2}$ and on the perceived inflation shares $\tilde{n}_1$ and $\tilde{n}_2$.

Stationarity of the perceived inflation target $\bar{\pi}_t$. We show that the perceived long run inflation target $\bar{\pi}_t$ is stationary in our two sector model under the same logic as Carvalho et al. (2023) henceforth AIE. We follow their steps and invoke their results.

Agents update the perceived target using the anchored learning rule

$$\bar{\pi}_{t+1} = \bar{\pi}_t + g_t[(\tilde{\gamma}_{\pi,4}-1)\bar{\pi}_t + \eta_t] \tag{C-30}$$

where g_t is the gain which is decreasing gain in the baseline and may be a small constant in episodes of unanchoring as in AIE and $\eta_t \equiv \gamma_1\epsilon_{1,t} + \gamma_2\epsilon_{2,t} + \gamma_{i,1}\epsilon_t$. This is the two sector analogue of AIE where the scalar feedback $(1-\gamma)\Gamma$ is replaced by the salience weighted pass through $\tilde{\gamma}_{\pi,4}$. With decreasing gain $g_t = t^{-1}$ AIE show that the stochastic difference equation admits the ODE approximation

$$\dot{\bar{\pi}} = (\tilde{\gamma}_{\pi,4}-1)\,\bar{\pi} \tag{C-31}$$

By AIE the ODE is globally stable whenever the feedback is strictly below one. In our notation this requires $\tilde{\gamma}_{\pi,4} < 1$.

With constant gain $g_t \equiv \bar{g} \in (0,1)$ the belief process is a linear process driven by the innovation in f_t:

$$\bar{\pi}_{t+1} = [1 + \bar{g}(\tilde{\gamma}_{\pi,4} - 1)]\,\bar{\pi}_t + \bar{g}\eta_t. \tag{C-32}$$

Let $\phi \equiv 1+\bar{g}(\tilde{\gamma}_{\pi,4} - 1)$. Then $\bar{\pi}_t$ is an AR(1) mean zero process if $\phi < 1$, which is the AIE condition with $(1-\gamma)\Gamma$ replaced by $\tilde{\gamma}_{\pi,4}$.

Present value operators and the shifting end point. As in AIE the PV operators inside the Phillips curve and Euler equation use the subjective shifting end point restriction

$$\lim_{T\to\infty} \hat{E}_t[\pi_T] = \bar{\pi}_t \tag{C-33}$$

which yields for perceived inflation

$$\hat{E}_t\left[\sum_{h=0}^{\infty} \beta^h \tilde{\pi}_{t+h}\right] = \frac{1}{1-\beta}\bar{\pi}_t + \text{PV of stationary terms} \tag{C-34}$$

This step is purely subjective and also mirrors AIE.

C.2 Welfare

In the flexible price equilibrium, we have $mc_{k,t} - p_{k,t} = 0$ for all $k = 1, \ldots, K$. This implies:

$$mc_{k,t} - p_{k,t} = (1+\varphi)(c_t^n - a_{k,t}) - \varphi\eta r p_{k,t}^n = 0 \tag{C-35}$$

Solving for both sectors:

$$(1+\varphi)(c_t^n - a_{1,t}) = \varphi\eta\tilde{n}_2 T_t^n \tag{C-36}$$

$$(1+\varphi)(c_t^n - a_{2,t}) = -\varphi\eta\tilde{n}_1 T_t^n \tag{C-37}$$

We solve for T_t^n:

$$T_t^n = \frac{1+\varphi}{\varphi\eta}(a_{2,t} - a_{1,t}) \tag{C-38}$$

Solving for c_t^n:

$$c_t^n = \tilde{n}_1 a_{1,t} + \tilde{n}_2 a_{2,t} \equiv \bar{a}_t \tag{C-39}$$

Solving for $c_{1,t}^n$ and $c_{2,t}^n$:

$$c_{1,t}^n = \bar{a}_t - \frac{1+\varphi}{\varphi}\tilde{n}_2(a_{2,t} - a_{1,t}) \tag{C-40}$$

$$c_{2,t}^n = \bar{a}_t + \frac{1+\varphi}{\varphi}\tilde{n}_1(a_{2,t} - a_{1,t}) \tag{C-41}$$

Therefore, these variables in the flexible price equilibrium are linear in the states $(a_{1,t}, a_{2,t})$ and the weights depend on φ, η, and $\tilde{n}_k$.

We show in Proposition C.1 that the period quadratic loss reduces to two components:

$$l_t = \sum_{k=1}^{2} n_k \left(\theta^2 \frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}\right) \pi_{k,t}^2 + (1+\varphi) \sum_{k=1}^{2} n_k x_{c_k,t}^2 \tag{C-42}$$

C.2.1 Proofs

Proposition C.1 *Up to a second-order approximation around the flexible price equilibrium, the household utility is given by:*

$$-\frac{1}{2}\sum_{\tau=t}^{\infty} \beta^{\tau-t}\mathbb{E}_t \left[\sum_{k=1}^{2} n_k \left(\theta^2 \frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}\right) \pi_{k,\tau}^2 + (1+\varphi) \sum_{k=1}^{2} n_k x_{c_k,\tau}^2\right] + t.i.p,$$

where $x_{c_k,t} \equiv c_{k,t} - c_{k,t}^n$ *and t.i.p represents terms that are not influenced by policy decisions.*

Proof. Define the period utility $u_t \equiv u(C_t, H_{1,t}, \ldots, H_{K,t})$ *as:*

$$u_t = \ln C_t - \frac{H_{1,t}^{1+\varphi}}{1+\varphi} - \frac{H_{2,t}^{1+\varphi}}{1+\varphi},$$

where $u_t^n = u(C_t^n, H_{1,t}^n, H_{2,t}^n)$ *is its value on the flexible prices equilibrium. Section B.1.7.2 shows that a second-order Taylor expansion of* u_t *around our flexible prices equilibrium gives us:*

$$u_t - u_t^n \approx x_{c,t} - \sum_{k=1}^{2} n_k \left(x_{h_k,t} + \frac{1+\varphi}{2} x_{h_k,t}^2\right)$$

Given that $Y_{k,t}(i) = C_{k,t}(i)$ *and*

$$\begin{aligned} H_{k,t} &= \int_{\mathcal{I}_k} H_{k,t}(i)di \\ &= \frac{1}{A_{k,t}} \int_{\mathcal{I}_k} C_{k,t}(i)di \\ &= \frac{1}{A_{k,t}} \int_{\mathcal{I}_k} \frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta} C_{k,t}di \\ &= \frac{1}{A_{k,t}} \left(\frac{P_{k,t}}{\tilde{P}_t}\right)^{-\eta} C_t \int_{\mathcal{I}_k} \frac{1}{n_k} \left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta} di. \end{aligned}$$

Therefore:

$$h_{k,t} = -a_{k,t} - \eta(p_{k,t} - \tilde{p}_t) + c_t + r_{k,t},$$

where $r_{k,t} \equiv \ln\left(\frac{1}{n_k}\int_{\mathcal{I}_k}\left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\theta} di\right)$. *Solving for* $p_{k,t} - \tilde{p}_t$*:*

$$h_{k,t} = c_{k,t} - a_{k,t} + r_{k,t}.$$

Solving for the labor gap:

$$x_{h_k,t} = x_{c_k,t} + r_{k,t},$$

where $r^n_{k,t} = 0$*. We express the sectoral price-dispersion term* $r_{k,t}$ *as:*

$$r_{k,t} \approx \frac{\theta^2}{2} V_{ik}[p_{k,t}(i)],$$

where $V_{ik}[p_{k,t}(i)] \equiv \frac{1}{n_k}\int_{\mathcal{I}_k}(p_{k,t}(i) - \bar{p}_{k,t})^2 di$ *and* $p_{k,t} \approx \bar{p}_{k,t} \equiv \frac{1}{n_k}\int_{\mathcal{I}_k} p_{k,t}(i)di$*, up to a first order approximation. Combining all the pieces together:*

$$u_t - u^n_t \approx -\frac{\theta^2}{2}\sum_{k=1}^{2} n_k V_{ik}[p_{k,t}(i)] - \frac{1+\varphi}{2}\sum_{k=1}^{2} n_k x^2_{c_k,t}$$

where the (squared) dispersion term vanishes as it is fourth order, and cross terms are third order and can be ignored. We define the dispersion measure $\Delta_{k,t}$ *as the cross-sectional variance of log prices around the new average:*

$$\begin{aligned}\Delta_{k,t} \equiv V_{ik}\Big[p_{k,t}(i)\Big] &= \frac{1}{n_k}\int_{\mathcal{I}_k}\Big(p_{k,t}(i) - \bar{p}_{k,t}\Big)^2 di \\ &= \frac{\alpha_k}{1-\alpha_k}\sum_{s=0}^{t}\alpha_k^{t-s}\pi^2_{k,s} + t.i.p\end{aligned}$$

We take the discounted value of these values over all periods $\tau \geq t$*:*

$$\sum_{\tau=t}^{\infty}\beta^{\tau-t}\Delta_{k,\tau} \approx \frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\pi^2_{k,\tau} + t.i.p$$

Hence:

$$\begin{aligned}\sum_{\tau=t}^{\infty}\beta^{\tau-t}(u_\tau - u^n_\tau) &\approx -\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\left[\theta^2\sum_{k=1}^{2}V_{ik}[p_{k,\tau}(i)] + (1+\varphi)\sum_{k=1}^{2}n_k x^2_{c_k,\tau}\right] + t.i.p \\ &\approx -\frac{1}{2}\sum_{\tau=t}^{\infty}\beta^{\tau-t}\left[\theta^2\sum_{k=1}^{2}\frac{\alpha_k}{(1-\alpha_k)(1-\alpha_k\beta)}n_k\pi^2_{k,\tau} + (1+\varphi)\sum_{k=1}^{2}n_k x^2_{c_k,\tau}\right] + t.i.p\end{aligned}$$

■

C.3 Model Summary and State-Space Representation

We first summarize the two-sector New Keynesian model with endogenous belief distortion and a switching gain. We then recast it in a state-space form suitable for estimation with a marginalized (Rao-Blackwellized) particle filter.

C.3.1 State Definition and Matrix Form

Linear Gaussian states. To apply a marginalized particle filter, we split the state into a nonlinear switching block and a linear-Gaussian block. Let $m_t = [\bar{\pi}_t \; T_{t-1} \; \xi_{t-1}]'$ denote the switching component and let ξ_t collect the linear-Gaussian states:

$$\xi_t = \begin{pmatrix} a_{1,t} \\ a_{2,t} \\ \varphi_t \end{pmatrix},$$

which evolve according to:

$$\xi_t = A_\xi \xi_{t-1} + S_\xi \boldsymbol{\varepsilon}_t, \tag{C-43}$$

where $\boldsymbol{\varepsilon}_t = (\epsilon_{1,t}, \epsilon_{2,t}, \epsilon_t)'$ are i.i.d. Gaussian shocks. The matrix A_ξ contains the AR(1) coefficients (e.g., ρ_1, ρ_2, ρ for $a_{1,t}, a_{2,t}, \varphi_t$). The matrix S_ξ includes the corresponding shock loadings $(\sigma_1, \sigma_2, \sigma)$.

Explicitly, for the AR(1) processes:

$$\begin{aligned} a_{1,t} &= \rho_1 a_{1,t-1} + \sigma_1 \epsilon_{1,t}, \\ a_{2,t} &= \rho_2 a_{2,t-1} + \sigma_2 \epsilon_{2,t}, \\ \varphi_t &= \rho \varphi_{t-1} + \sigma \epsilon_t. \end{aligned}$$

Then we have:

$$A_\xi = \begin{pmatrix} \rho_1 & 0 & 0 \\ 0 & \rho_2 & 0 \\ 0 & 0 & \rho \end{pmatrix}, \quad S_\xi = \begin{pmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma \end{pmatrix}$$

Nonlinear state equations. The inflation mean is estimated with the following recursive updating algorithm:

$$\bar{\pi}_t = \bar{\pi}_{t-1} + k_t^{-1} f_{t-1},$$

where the forecast error is given by:

$$\begin{aligned}
f_t &= \tilde{\pi}_t - \hat{E}_{t-1}[\tilde{\pi}_t] \\
&= \tilde{\alpha}_4 T_{t-1} + \tilde{\gamma}_7 a_{1,t} + \tilde{\gamma}_8 a_{2,t} + \tilde{\gamma}_{i,4}\varphi_t + \tilde{\gamma}_{\pi,4}\bar{\pi}_t - \bar{\pi}_t - \tilde{\alpha}_4^B T_{t-1} - \tilde{\gamma}_7^B \rho_1 a_{1,t-1} - \tilde{\gamma}_8^B \rho_2 a_{2,t-1} - \tilde{\gamma}_{i,4}^B \rho \varphi_{t-1} \\
&= A_f' \xi_t + B_f' m_t,
\end{aligned}$$

where

$$A_f = \begin{pmatrix} \tilde{\gamma}_7 \\ \tilde{\gamma}_8 \\ \tilde{\gamma}_{i,4} \end{pmatrix}, \quad B_f = \begin{pmatrix} \tilde{\gamma}_{\pi,4} - 1 \\ \tilde{\alpha}_4 - \tilde{\alpha}_4^B \\ -\tilde{\gamma}_7^B \rho_1 \\ -\tilde{\gamma}_8^B \rho_2 \\ -\tilde{\gamma}_{i,4}^B \rho \end{pmatrix}.$$

The evolution of the learning gain is directly tied to the relative distance of forecasts under the subjective ($\hat{E}_{t-1}\tilde{\pi}_t$) and objective ($\mathbb{E}_{t-1}\tilde{\pi}_t$) probability distributions:

$$k_t = \mathbb{I}(\theta_{t-1} \leq \bar{\theta})(k_{t-1} + 1) + (1 - \mathbb{I}(\theta_{t-1} \leq \bar{\theta}))\bar{g}^{-1},$$

where θ_{t-1} is given by

$$\begin{aligned}
\theta_{t-1} &= |\mathbb{E}_{t-2} f_{t-1}| / \sigma_f \\
&= |A_\theta' m_{t-1}| / \sigma_f,
\end{aligned}$$

where

$$A_\theta = \begin{pmatrix} \tilde{\gamma}_{\pi,4} - 1 \\ \tilde{\alpha}_4 - \tilde{\alpha}_4^B \\ (\tilde{\gamma}_7 - \tilde{\gamma}_7^B)\rho_1 \\ (\tilde{\gamma}_8 - \tilde{\gamma}_8^B)\rho_2 \\ (\tilde{\gamma}_{i,4} - \tilde{\gamma}_{i,4}^B)\rho \end{pmatrix},$$

and the forecast error volatility is given by

$$\sigma_f = \sqrt{\tilde{\gamma}_7^2\sigma_1^2 + \tilde{\gamma}_8^2\sigma_2^2 + \tilde{\gamma}_{i,4}^2\sigma^2}.$$

We define $\mathbb{I}(m_{t-1})$ as:

$$\mathbb{I}(m_{t-1}) = \begin{cases} 1, & \text{if } |A'_\theta m_{t-1}| \leq \bar{\theta}\sigma_f, \\ 0, & \text{otherwise.} \end{cases}$$

Rewriting the model with $f_{\bar{\pi}}$, f_T, and f_k. The nonlinear state can be rewritten as:

$$\begin{aligned} k_t &= f_k(m_{t-1}, k_{t-1}) \\ T_{t-1} &= f_T(m_{t-1}, k_{t-1}) + A_T(m_{t-1}, k_{t-1})\xi_{t-1} \\ \bar{\pi}_t &= \bar{\pi}_{t-1} + f_k(m_{t-1}, k_{t-1})^{-1}(A'_f\xi_{t-1} + B'_f m_{t-1}) \\ &\equiv f_{\bar{\pi}}(m_{t-1}, k_{t-1}) + A_{\bar{\pi}}(m_{t-1}, k_{t-1})\xi_{t-1} \end{aligned}$$

where

$$\begin{aligned} &f_k(m_{t-1}, k_{t-1}) = \mathbb{I}(m_{t-1})(k_{t-1} + 1) + [1 - \mathbb{I}(m_{t-1})]\bar{g}^{-1}, \\ &f_T(m_{t-1}, k_{t-1}) = \begin{pmatrix} \gamma_{\pi,1} - \gamma_{\pi,2} & \alpha_5 & 0_{1\times 3} \end{pmatrix} m_{t-1} \\ &A_T(m_{t-1}, k_{t-1}) = \begin{pmatrix} \gamma_1 - \gamma_3 & \gamma_2 - \gamma_4 & \gamma_{i,1} - \gamma_{i,2} \end{pmatrix} \\ &f_{\bar{\pi}}(m_{t-1}, k_{t-1}) = \bar{\pi}_{t-1} + f_k(m_{t-1}, k_{t-1})^{-1} B'_f m_{t-1} \\ &= f_k(m_{t-1}, k_{t-1})^{-1} \begin{pmatrix} f_k(m_{t-1}, k_{t-1}) + \tilde{\gamma}_{\pi,4} - 1 & \tilde{\alpha}_4 - \tilde{\alpha}_4^B & -\tilde{\gamma}_7^B\rho_1 & -\tilde{\gamma}_8^B\rho_2 & -\tilde{\gamma}_{i,4}^B\rho \end{pmatrix} m_{t-1} \\ &A_{\bar{\pi}}(m_{t-1}, k_{t-1}) = f_k(m_{t-1}, k_{t-1})^{-1} A'_f \end{aligned}$$

C.3.2 Measurement Equation

Given the data $y_1, \ldots, y_T$, the model observation equation is

$$y_t = h_{0,t} + h_{\bar{\pi},t}\bar{\pi}_t + H'_t\xi_t + R_t^{1/2}\epsilon_t^o, \tag{C-44}$$

where all vector and matrices are defined to be consistent with the timing of available data and $\boldsymbol{\epsilon}_t$ denotes observations errors.

We start from the given policy functions and the simplest possible defined observables:

$$
\begin{aligned}
\pi_{1,t}^{annual} &= \pi^* + 400\pi_{1,t} + \epsilon_{1,t}^o \\
\pi_{2,t}^{annual} &= \pi^* + 400\pi_{2,t} + \epsilon_{2,t}^o \\
\pi_{e,t}^{annual} &= \pi^* + 100\mathbb{E}_t[\tilde{\pi}_{t+1} + \tilde{\pi}_{t+2} + \tilde{\pi}_{t+3} + \tilde{\pi}_{t+4}] + \epsilon_{3,t}^o \\
\text{ffr}_t &= \pi^* + 400 i_t + \epsilon_{4,t}^o \\
\bar{\pi}_t^{annual} &= \pi^* + 400\bar{\pi}_t + \epsilon_{5,t}^o
\end{aligned}
$$

We compute agents' expected inflation for the next four quarters as:

$$
\begin{aligned}
&\mathbb{E}_t[\tilde{\pi}_{t+1} + \tilde{\pi}_{t+2} + \tilde{\pi}_{t+3} + \tilde{\pi}_{t+4}] = \tilde{\alpha}_4^B(\alpha_5 + \alpha_5^2 + \alpha_5^3 + \alpha_5^4)T_{t-1} \\
&+ \Big\{\tilde{\alpha}_4^B(\gamma_1 - \gamma_3)\Big[(1 + \rho_1 + \rho_1^2 + \rho_1^3) + \alpha_5(1 + \rho_1 + \rho_1^2) + \alpha_5^2(1 + \rho_1) + \alpha_5^3\Big] \\
&+ \tilde{\gamma}_7^B(\rho_1 + \rho_1^2 + \rho_1^3 + \rho_1^4)\Big\} a_{1,t} \\
&+ \Big\{\tilde{\alpha}_4^B(\gamma_2 - \gamma_4)\Big[(1 + \rho_2 + \rho_2^2 + \rho_2^3) + \alpha_5(1 + \rho_2 + \rho_2^2) + \alpha_5^2(1 + \rho_2) + \alpha_5^3\Big] \\
&+ \tilde{\gamma}_8^B(\rho_2 + \rho_2^2 + \rho_2^3 + \rho_2^4)\Big\} a_{2,t} \\
&+ \Big\{\tilde{\alpha}_4^B(\gamma_{i,1} - \gamma_{i,2})\Big[(1 + \rho + \rho^2 + \rho^3) + \alpha_5(1 + \rho + \rho^2) + \alpha_5^2(1 + \rho) + \alpha_5^3\Big] \\
&+ \tilde{\gamma}_{i,4}^B(\rho + \rho^2 + \rho^3 + \rho^4)\Big\} \varphi_t \\
&+ \Big[\tilde{\alpha}_4^B(\gamma_{\pi,1} - \gamma_{\pi,2})(4 + 3\alpha_5 + 2\alpha_5^2 + \alpha_5^3) + 4\Big] \bar{\pi}_t \\
&\equiv \tilde{\alpha}_{4,e}T_{t-1} + \tilde{\gamma}_{7,e}a_{1,t} + \tilde{\gamma}_{8,e}a_{2,t} + \tilde{\gamma}_{i,4,e}\varphi_t + \tilde{\gamma}_{\pi,4,e}\bar{\pi}_t
\end{aligned}
$$

Loadings on ffr_t are given by:

$$
\begin{aligned}
i_t &= (\tau_1 n_1 \alpha_1 + \tau_2 n_2 \alpha_2 + \lambda_x \alpha_3)T_{t-1} + (\tau_1 n_1 \gamma_1 + \tau_2 n_2 \gamma_3 + \lambda_x \gamma_5)a_{1,t} \\
&+ (\tau_1 n_1 \gamma_2 + \tau_2 n_2 \gamma_4 + \lambda_x \gamma_6)a_{2,t} + (\tau_1 n_1 \gamma_{i,1} + \tau_2 n_2 \gamma_{i,2} + \lambda_x \gamma_{i,3} + 1)\varphi_t \\
&+ (\tau_1 n_1 \gamma_{\pi,1} + \tau_2 n_2 \gamma_{\pi,2} + \lambda_x \gamma_{\pi,3})\bar{\pi}_t \\
&\equiv \alpha_{4,i}T_{t-1} + \gamma_{7,i}a_{1,t} + \gamma_{8,i}a_{2,t} + \gamma_{i,4,i}\varphi_t + \gamma_{\pi,4,i}\bar{\pi}_t
\end{aligned}
$$

We now write the full measurement equation for:

$$
y_t = \begin{pmatrix} \pi_{1,t}^{annual} \\ \pi_{2,t}^{annual} \\ \pi_{e,t}^{annual} \\ \text{ffr}_t \\ \bar{\pi}_t^{annual} \end{pmatrix}.
$$

We can write this as:

$$\begin{aligned} y_t &= h_{0,t} + h_{\bar{\pi},t}\bar{\pi}_t + H_t'\xi_t + R_t^{1/2}\epsilon_t^o \\ &= h_{0,t} + h_{y,t}m_t + H_t'\xi_t + R_t^{1/2}\epsilon_t^o \end{aligned}$$

where

$$h_{0,t} = \begin{pmatrix} \pi^* \\ \pi^* \\ \pi^* \\ \pi^* \\ \pi^* \end{pmatrix}, \quad h_{y,t} = 400\begin{pmatrix} \gamma_{\pi,1} & \alpha_1 & 0_{1\times 3} \\ \gamma_{\pi,2} & \alpha_2 & 0_{1\times 3} \\ \tilde{\gamma}_{\pi,4,e}/4 & \tilde{\alpha}_{4,e}/4 & 0_{1\times 3} \\ \gamma_{\pi,4,i} & \alpha_{4,i} & 0_{1\times 3} \\ 1 & 0 & 0_{1\times 3} \end{pmatrix},$$

$$H' = 400\begin{pmatrix} \gamma_1 & \gamma_2 & \gamma_{i,1} \\ \gamma_3 & \gamma_4 & \gamma_{i,2} \\ \tilde{\gamma}_{7,e}/4 & \tilde{\gamma}_{8,e}/4 & \tilde{\gamma}_{i,4,e}/4 \\ \gamma_{7,i} & \gamma_{8,i} & \gamma_{i,4,i} \\ 0 & 0 & 0 \end{pmatrix}, \quad R_t^{1/2} = \begin{pmatrix} \sigma_1^o & 0 & 0 & 0 & 0 \\ 0 & \sigma_2^o & 0 & 0 & 0 \\ 0 & 0 & \sigma_3^o & 0 & 0 \\ 0 & 0 & 0 & \sigma_4^o & 0 \\ 0 & 0 & 0 & 0 & \sigma_5^o \end{pmatrix}$$

where π^* is the mean inflation rate.

C.3.3 State-Space Representation

The Two-Sector New Keynesian model can be written as

$$\xi_t = A_\xi \xi_{t-1} + S_\xi \epsilon_t \tag{C-45}$$

$$k_t = f_k(m_{t-1}, k_{t-1}) \tag{C-46}$$

$$m_t = h_{m,t}(m_{t-1}, k_{t-1}) + A_{m,t}(m_{t-1}, k_{t-1})\xi_{t-1} \tag{C-47}$$

$$y_t = h_{0,t} + h_{y,t}m_t + H_t'\xi_t + R_t^{1/2}\epsilon_t^o \tag{C-48}$$

where

$$h_{m,t}(m_{t-1}, k_{t-1}) = \begin{pmatrix} f_{\bar{\pi}}(m_{t-1}, k_{t-1}) \\ f_T(m_{t-1}, k_{t-1}) \\ 0_{3\times 1} \end{pmatrix}, \quad A_{m,t}(m_{t-1}, k_{t-1}) = \begin{pmatrix} A_{\bar{\pi}}(m_{t-1}, k_{t-1}) \\ A_T(m_{t-1}, k_{t-1}) \\ I_3 \end{pmatrix}$$

C.4 Marginalized Particle Filter: Parameter Dependence and Workflow

We solve the model and cast it in a state-space form suitable for a marginalized particle filter (MPF). Let the deep parameters be

$$\theta = \{\rho_1, \rho_2, \rho, \beta, \xi_1, \xi_2, \lambda_x, \tau_1, \tau_2, n_1, n_2, \bar{\theta}, \bar{g}\}.$$

The undetermined-coefficients solution delivers policy coefficients $(\alpha_k, \gamma_k, \gamma_{\pi,k}, \gamma_{i,k}, \dots)$ for both equilibria (Baseline and Anchoring). These coefficients determine the linear or piecewise-linear objects used in filtering.

Because the policy coefficients depend on θ, each new draw requires: (i) solving the model by undetermined coefficients to obtain $(\alpha_i, \gamma_i, \dots)$ under the two equilibria, and (ii) rebuilding the state-space objects that depend on θ and on those coefficients,

$$f_\xi,\ A_\xi,\ S_\xi,\ h_m,\ A_m,\ H,\ \text{etc.}$$

Given these updates, we run the MPF to evaluate the likelihood $p(Y_T|\theta)$.

We target the factorization

$$p(\xi_t, [m_t, k_t]'|Y_t) = p\Big(\xi_t \mid [m_t, k_t]', Y_t\Big) \times p\Big([m_t, k_t]' \mid Y_t\Big),$$

that is, a Kalman update for the conditionally linear block ξ_t and a particle update for the nonlinear or switching block $[m_t, k_t]'$.

Algorithm (filtering step). This follows Schon and Gustafsson (2005) and Carvalho et al. (2023). Given data $\{y_t\}_{t=1}^T$:

Step 1: Initialization. Draw $m^i_{1|0}$ from a chosen prior, set $k^i_{1|0} = \bar{k}_0$ (or draw from $U(0, \bar{g}^{-1})$), and initialize the linear block with $\xi^i_{1|0}$ and covariance $P^i_{1|0}$. Each particle i encodes a hypothesis about the nonlinear/switching state; $P_{1|0}$ initializes the Kalman recursions.

Step 2: Importance weights. For $i = 1, \dots, N$,

$$q^i_t = p\left(y_t|m^i_{t|t-1}, \xi^i_{t|t-1}\right) = \mathcal{N}\left(h_{0,t} + h_{m,t} m^i_{t|t-1} + H'_t \xi^i_{t|t-1}, \Omega^i_t\right),$$

with $\Omega_t^i = H_t' P_{t|t-1}^i H_t + R_t$. Hence

$$q_t^i = w_{t-1}^i |\Omega_t^i|^{-1/2} \exp\left\{-\frac{1}{2}\epsilon_t^i{}' \, (\Omega_t^i)^{-1} \epsilon_t^i\right\}$$
$$\epsilon_t^i = y_t - h_{0,t} - h_{m,t} m_{t|t-1}^i - H_t' \xi_{t|t-1}^i$$

Normalize $\{q_t^i\}$ to obtain weights $\{w_t^i\}$.

Step 3: Resampling. Compute the effective sample size $ESS = 1/\sum_{j=1}^{N} \left(w_t^j\right)^2$. If $ESS < 0.75N$, resample with probabilities $\tilde{q}_t^j = q_t^j / \sum q_t^i$ and reset $w_t^i = 1/N$ for $i = 1, \ldots, N$. Otherwise, keep $w_t^i = \tilde{q}_t^i$. Resampling mitigates weight degeneracy.

Step 4: Linear (Kalman) measurement update for ξ_t. For $i = 1, \ldots, N$,

$$\xi_{t|t}^i = \xi_{t|t-1}^i + K_t \left(y_t - h_{0,t} - h_{m,t} m_{t|t}^i - H_t' \xi_{t|t-1}^i\right)$$
$$K_t = P_{t|t-1} H_t \Omega_t^{-1}$$
$$P_{t|t} = P_{t|t-1} - K_t H_t' P_{t|t-1}$$

Step 5: Nonlinear prediction (switch and propagate). Evaluate the indicator

$$\mathbb{I}(m_{t|t}^i) = \begin{cases} 1, & \text{if } \left|A_\theta' m_{t|t}^i\right| \leq \bar{\theta}\sigma^f, \\ 0, & \text{otherwise,} \end{cases}$$

and update the gain state

$$k_{t+1|t}^i = f_k(m_{t|t}^i, k_{t|t}^i)$$

Draw

$$m_{t+1|t}^i \sim \mathcal{N}\left(f_{m,t}(m_{t|t}^i, k_{t|t}^i) + A_{m,t}(m_{t|t}^i, k_{t|t}^i)\xi_{t|t}^i, N_t\right),$$

with $N_t = A_{m,t}(m_{t|t}^i, k_{t|t}^i) P_{t|t} A_{m,t}(m_{t|t}^i, k_{t|t}^i)'$. [2]

[2] We include ξ_{t-1} among the nonlinear states when it enters discrete switching rules. This promotes exact evaluation of threshold events at the particle level while preserving conditional Gaussianity of ξ_t.

Step 6: Linear prediction for ξ_{t+1}.

$$\tilde{\xi}^i_{t|t} = \xi^i_{t|t} + \tilde{K}^i_t\Big(m^i_{t+1|t} - f^i_m(m^i_{t|t}, k^i_{t|t}) - A_{m,t}(m^i_{t|t}, k^i_{t|t})\,\xi^i_{t|t}\Big),$$

$$\xi^i_{t+1|t} = A_\xi\,\tilde{\xi}^i_{t|t}, \quad P^i_{t+1|t} = Q_\xi + \tilde{P}^i_{t|t}, \quad Q_\xi = S_\xi\,S'_\xi.$$

The Kalman gain is

$$\tilde{K}^i_t = P^i_{t|t}A_{m,t}(m^i_{t|t}, k^i_{t|t})'\left(N^i_{t|t}\right)^{-1},$$

where

$$N^i_{t|t} = A_{m,t}(m^i_{t|t}, k^i_{t|t})P^i_{t|t}A_{m,t}(m^i_{t|t}, k^i_{t|t})'$$

By definition,

$$A_{m,t}(m^i_{t|t}, k^i_{t|t}) = \begin{pmatrix} A_{\bar{\pi}}(m^i_{t|t}, k^i_{t|t}) \\ A_T \\ I_3 \end{pmatrix},$$

where $A_{\bar{\pi}}(\cdot)$ is a 1×3 row that depends on the particle's current nonlinear state, and I_3 is the 3×3 identity. The predicted covariance associated with $\tilde{\xi}^i_{t|t}$ is given by

$$\tilde{P}^i_{t|t} = A_\xi P^i_{t|t}A'_\xi - L^i_{t|t}N^i_{t|t}L^i_{t|t}{}',$$

where $L^i_{t|t} = A_\xi\tilde{K}^i_{t|t}$. Although Carvalho et al. (2023) obtains fully analytical expressions of this form in a smaller state-space environment, here the extended dimension and richer nonlinearities make an element-by-element derivation unwieldy. We therefore rely on numerical matrix operations to invert $N^i_{t|t}$ and compute $\tilde{K}^i_t$ and $\tilde{P}^i_{t|t}$.

Step 7: Likelihood. Approximate the log-likelihood by

$$L(\cdot) \approx \sum_{t=1}^{T}\ln\left(\sum_{i=1}^{N} q^{(i)}_t\right).$$

Following Carvalho et al. (2023), we use $N = 2500$ particles and fix the random seeds for initial conditions, shock draws in the nonlinear prediction, and resampling.

C.5 Marginalized Smoother

We implement a joint backward-simulation smoother after the MPF (see Carvalho et al. (2023)). The objective is to draw $j = 1, \ldots, M$ trajectories of the model variables $\{\tilde{m}^j_{t|T}, \tilde{k}^j_{t|T}, \tilde{\xi}^j_{t|T}\}_{t=1}^T$. The forward filter allows drawing $\tilde{m}^j_{T|T}, \tilde{k}^j_{T|T}$ from the empirical distribution of $\{\tilde{m}^k_{t|t}, \tilde{k}^k_{t|t}\}_{k=1}^N$ where each particle has weight w^k_t. Conditional on $\tilde{m}^j_{T|T}, \tilde{k}^j_{T|T}$, we draw $\tilde{\xi}^j_{T|T}$ from the distribution $\mathcal{N}(\xi^j_{T|T}, P^j_{T|T})$.

For this algorithm, we write the system in a more compact formulation:

$$k_t = f_k(m_{t-1}, k_{t-1})$$

$$\begin{bmatrix} m_t \\ \xi_t \end{bmatrix} = h(m_{t-1}, k_{t-1}) + A(m_{t-1}, k_{t-1})\xi_{t-1} + \begin{bmatrix} 0_{5\times 3} \\ S_\xi \end{bmatrix} \epsilon_t,$$

where

$$h(m_{t-1}, k_{t-1}) \equiv \begin{bmatrix} h_{m,t}(m_{t-1}, k_{t-1}) \\ 0_{3\times 1} \end{bmatrix}, \quad A(m_{t-1}, k_{t-1}) \equiv \begin{bmatrix} A_{m,t}(m_{t-1}, k_{t-1}) \\ A_\xi \end{bmatrix}$$

Algorithm. For $t = T-1, \ldots, 1$
For each $j = 1, ..., M$
For each $i = 1, \ldots, N$
Compute

$$w^j_{t|t+1}(i) = \frac{w^i_t p\left(\tilde{m}^j_{t+1|t+1}, \tilde{k}^j_{t+1|t+1}, \tilde{\xi}^j_{t+1|t+1} | \tilde{m}^i_{t|t}, \tilde{k}^i_{t|t}, Y_t\right)}{\sum_{k=1}^N w^k_t p\left(\tilde{m}^j_{t+1|t+1}, \tilde{k}^j_{t+1|t+1}, \tilde{\xi}^j_{t+1|t+1} | \tilde{m}^k_{t|t}, \tilde{k}^k_{t|t}, Y_t\right)}$$

where the last line makes use of $w^i_t = 1/N$ because of resampling in the forward filter. We can express the previous probability distribution as

$$\begin{aligned} & p\left(m_{t+1|T}, k_{t+1|T}, \xi_{t+1|T} | m^i_{t|t}, k^i_{t|t}, Y_t\right) \\ = {} & p\left(m_{t+1|T}, \xi_{t+1|T} | m^i_{t|t}, k^i_{t|t}, Y_t\right) \times p(k_{t+1|T} | m^i_{t|t}, k^i_{t|t}, Y_t) \end{aligned}$$

which uses the fact that $k_{t+1|t} = f_k(m_{t|t}, k_{t|t})$. We then evaluate

$$p\left(\tilde{m}^j_{t+1|T}, \tilde{\xi}^j_{t+1|T} | m^i_{t|t}, k^i_{t|t}, Y_t\right) \times \mathbb{I}\left(\tilde{k}^j_{t+1} = f_k(m^i_{t|t}, k^i_{t|t})\right) = \begin{cases} p^{j,i}_{t|t+1}, & \text{if } \tilde{k}^j_{t+1|T} = f_k(m^i_{t|t}, k^i_{t|t}) \\ 0, & \text{otherwise} \end{cases}$$

where

$$
\begin{aligned}
p^{j,i}_{t|t+1} &\propto \exp\left\{-\frac{1}{2}\ln|\tilde{\Omega}^i_t| - \frac{1}{2}(\eta^{j,i}_{t+1})' \times (\tilde{\Omega}^i_t)^{-1} \times (\eta^{j,i}_{t+1})\right\} \\
\eta^{j,i}_{t+1} &= \begin{bmatrix} \tilde{m}^j_{t+1|t+1} \\ \tilde{\xi}^j_{t+1|t+1} \end{bmatrix} - \left[h(m^i_{t|t}, k^i_{t|t}) + A(m^i_{t|t}, k^i_{t|t})\xi^i_{t|t}\right] \\
\tilde{\Omega}^i_t &= Q + A(m^i_{t|t}, k^i_{t|t})P^i_{t|t}A(m^i_{t|t}, k^i_{t|t})' \\
Q &= \begin{bmatrix} 0 & 0 \\ 0 & S_\xi S'_\xi \end{bmatrix}
\end{aligned}
$$

The switching constraint can be written as

$$
\begin{aligned}
\mathbb{I}\left(\tilde{k}^j_{t+1} = f_k(m^i_{t|t}, k^i_{t|t})\right) = \mathbb{I}\left(\tilde{k}^j_{t+1} = \bar{g}^{-1}\right) \times \mathbb{I}\left(|A'_\theta m^i_{t|t}| > \bar{\theta}\sigma_f\right) \\
+ \left(1 - \mathbb{I}\left(\tilde{k}^j_{t+1} = \bar{g}^{-1}\right)\right) \times \mathbb{I}\left(|A'_\theta m^i_{t|t}| \le \bar{\theta}\sigma_f\right) \times \mathbb{I}\left(k^i_{t|t} = k^j_{t+1|t} - 1\right)
\end{aligned}
$$

In order to draw the linear state for each trajectory $j = 1, \ldots, M$, we first draw the nonlinear state $\tilde{m}^j_{t|T}, \tilde{k}^j_{t|T}$ from the distribution of particles $\{m^k_{t|t}, k^k_{t|t}\}^N_{k=1}$ using the new set of weights $\{w^j_{t|t+1}(k)\}^N_{k=1}$. Conditional on the draw, sample from

$$
p\left(\xi_t | m^j_{1:t}, k^j_{1:t}, \xi_{t+1}, m_{t+1}, Y_t\right)
$$

We draw the linear state $\tilde{\xi}^j_{t|T}$ from the distribution

$$
\mathcal{N}\left(\xi^j_{t|t} + \Delta^j_t\left(\begin{bmatrix} \tilde{m}^j_{t+1|T} \\ \tilde{\xi}^j_{t+1|T} \end{bmatrix} - h\left(\tilde{m}^j_{t|T}, \tilde{k}^j_{t|T}\right) - A\left(\tilde{m}^j_{t|T}, \tilde{k}^j_{t,T}\right)\xi^j_{t|t}\right), \Lambda^j_{t|t}\right),
$$

where $\xi^j_{t|t}$ is the element in $\{m^k_{t|t}, k^k_{t|t}\}^N_{k=1}$ that corresponds to the same draw j from which the particles $\tilde{m}^j_{t|T}, \tilde{k}^j_{t|T}$ are obtained, and where

$$
\begin{aligned}
\Delta^j_t &= P^j_{t|t}A\left(\tilde{m}^j_{t|T}, \tilde{k}^j_{t|T}\right)'\left(Q + A\left(\tilde{m}^j_{t|T}, \tilde{k}^j_{t|T}\right)P^j_{t|t}A\left(\tilde{m}^j_{t|T}, \tilde{k}^j_{t|T}\right)'\right)^{-1} \\
\Lambda^j_{t|t} &= P^j_{t|t} - \Delta^j_t A\left(\tilde{\pi}^j_{t|T}, \tilde{k}^j_{t|T}\right)P^j_{t|t}
\end{aligned}
$$

C.6
The Marginalized Particle Filter

Standard particle filters perform poorly as the state dimension grows, especially in mixed linear-nonlinear DSGE systems. The marginalized particle filter (MPF, or Rao-Blackwellized PF) exploits the conditional linear-Gaussian structure: it tracks the nonlinear block with particles and updates the linear block analytically with a Kalman filter, reducing variance and computational cost (Schon; Gustafsson, 2005). We partition the state as

$$s_t = [x_t, m_t]', \tag{C-49}$$

where x_t denotes the state variable with conditionally linear dynamics and m_t denotes the nonlinear state variable.

The MPF algorithm. Our starting point is a state-space representation for a nonlinear DSGE model with measurement and transition laws

$$y_t = h_{0,t}(m_t) + H_t'(m_t)x_t + +u_t, \quad u_t \sim F_u(\cdot;\theta) \tag{C-50}$$

$$m_{t+1} = f_{m,t}(m_t) + A_{m,t}(m_t)x_t + G_{m,t}(m_t)\epsilon_{m,t}, \quad \epsilon_{m,t} \sim F_{m,\epsilon}(\cdot;\theta) \tag{C-51}$$

$$x_{t+1} = f_{x,t}(m_t) + A_{x,t}(m_t)x_{t-1} + G_{x,t}(m_t)\epsilon_{x,t}, \quad \epsilon_{x,t} \sim F_{x,\epsilon}(\cdot;\theta) \tag{C-52}$$

where the state noise is assumed white and Gaussian distributed with

$$\epsilon_t = \begin{bmatrix} \epsilon_{x,t} \\ \epsilon_{m,t} \end{bmatrix} \sim \mathcal{N}_t, \quad Q_t = \begin{bmatrix} Q_{x,t} & Q_{xm,t} \\ Q'_{xm,t} & Q_{m,t} \end{bmatrix}$$

We assume that $Q_{xm,t} = 0$, as it is standard in the DSGE literature. The measurement noise is assumed white and Gaussian distributed according to

$$u_t \sim \mathcal{N}(0, R_t)$$

Furthermore, $x_0 \sim \mathcal{N}(\bar{x}_0, \bar{P}_0)$. The density of m_0 can be arbitrary, but is assumed to be known. The filtering distribution $p(s_t|Y_{1:t})$ is split using Bayes' theorem

$$p(x_t, m_t|Y_{1:t}) = p(x_t|m_t, Y_{1:t})p(m_t|Y_{1:t}) \tag{C-53}$$

In this filtering algorithm, the first step is a measurement update using the information available in y_t. The second step is a measurement update using the information available in $\hat{m}_{t+1|t}$, and finally, there is a time update. Schon and Gustafsson (2005) show that the conditional probability density functions for x_t and x_{t+1} are given by

$$p(x_t|m_t, Y_{1:t}) = \mathcal{N}(\hat{x}_{t|t}, P_{t|t}) \tag{C-54}$$

$$p(x_{t+1}|m_{t+1}, Y_{1:t}) = \mathcal{N}(\hat{x}_{t+1|t}, P_{t+1|t}) \tag{C-55}$$

where

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t \left(y_t - h_{0,t} - H_t' \hat{x}_{t|t-1} \right)$$
$$K_t = P_{t|t-1} H_t \Omega_t^{-1}$$
$$P_{t|t} = P_{t|t-1} - K_t H_t' P_{t|t-1}$$
$$\Omega_t = H_t' P_{t|t-1} H_t + R_t$$

and

$$\hat{x}_{t+1|t} = f_{x,t} + A_{x,t} \hat{x}_{t|t} + L_t (z_t - A_{m,t} \hat{x}_{t|t})$$
$$P_{t+1|t} = A_{x,t} P_{t|t} A_{x,t}' + G_{x,t} Q_{x,t} G_{x,t}' - L_t N_t L_t'$$
$$N_t = A_{m,t} P_{t|t} A_{m,t}' + G_{m,t} Q_{m,t} G_{m,t}'$$
$$L_t = A_{x,t} P_{t|t} A_{m,t}' N_t^{-1}$$

where

$$z_t = m_{t+1|t} - f_{m,t}$$

In order to estimate $p(m_t|Y_{1:t})$, we use Bayes' theorem and the Markov property inherent in the state-space model:

$$p(m_t|Y_{1:t}) = \frac{p(y_t|m_t, Y_{1:t-1}) p(m_t|m_{t-1}, Y_{1:t-1})}{p(y_t|Y_{1:t-1})} p(m_{t-1}|Y_{1:t-1}), \tag{C-56}$$

where an approximation of $p(m_{t-1}|Y_{1:t-1})$ is provided by the previous approximation of the particle filter. The analytical expressions for $p(y_t|m_t, Y_{1,t-1})$ and $p(m_t|m_{t-1}, Y_{1:t-1})$ are given by

$$p(y_t|m_t, Y_{1:t-1}) = \mathcal{N}(h_{0,t} + H_t' \hat{x}_{t|t-1}, \Omega_t) \tag{C-57}$$

$$p(m_{t+1}|m_t, Y_{1:t}) = \mathcal{N}(f_{m,t} + A_{m,t} \hat{x}_{t|t}, N_t) \tag{C-58}$$

1. **Initialization.** Draw the iid initial particles from the distribution $m_0^j \sim p(m_0)$, specify $x_{0|0}^j$ and $P_{0|0}^j$.

2. For $t = 1, \ldots, T$:

   (a) For each particle $j = 1, \ldots, M$, Evaluate the importance weights

   $$q_t^j = p\left(y_t | m_{t|t-1}^j, Y_{1:t-1} \right),$$

   where the likelihood is given by Equation C-57. Therefore,

$$q_t^j = w_{t-1}^j |\Omega_t|^{-1/2} \exp\left\{-\frac{1}{2}\left(y_t - h_{0,t} - H_t'\hat{x}_{t|t-1}\right)' \Omega_t^{-1}\left(y_t - h_{0,t} - H_t'\hat{x}_{t|t-1}\right)\right\}, \tag{C-59}$$

where w_{t-1}^j denotes the particle weight from the previous period.

(b) **Resampling:** One could use the systematic resampling scheme such as $p(m_{t|t}^j = m_{t|t-1}^i) = \tilde{q}_t^i$, where $\tilde{q}_t^j = q_t^j / \sum_{i=1}^M q_t^i$. In the systematic resampling scheme, provided that the number of effective particles (effective sample size), computed as

$$\text{ESS}_t = \frac{1}{\sum_{j=1}^M (w_t^j)^2},$$

falls below some threshold (e.g. $\text{ESS}_t < 0.75M$) we resample and generate a distribution of particles $\{m_{t|t}^j\}_{j=1}^M$ with corresponding weights $w_t^j = 1/N$ for all $j = 1, \ldots, M$. In case of not resampling the weights are $w_t^j = \tilde{q}_t^j$.

(c) **Kalman filter measurement update:** For all particles $j = 1, \ldots, M$, evaluate

$$\begin{aligned}
\hat{x}_{t|t} &= \hat{x}_{t|t-1} + K_t\left(y_t - h_{0,t} - H_t'\hat{x}_{t|t-1}\right)\\
K_t &= P_{t|t-1}H_t\Omega_t^{-1}\\
P_{t|t} &= P_{t|t-1} - K_tH_t'P_{t|t-1}
\end{aligned}$$

(d) **Particle filter time update (prediction):** For all particles $j = 1, \ldots, M$, predict new particles using

$$m_{t+1|t}^j \sim \mathcal{N}(f_{m,t} + A_{m,t}\hat{x}_{t|t}^j, N_t)$$

(e) **Kalman filter time update (prediction):** For all particles $j = 1, \ldots, M$, predict the linear state using

$$\begin{aligned}
\hat{x}_{t+1|t}^j &= f_{x,t} + A_{x,t}\hat{x}_{t|t}^j + L_t(z_t^j - A_{m,t}\hat{x}_{t|t}^j)\\
P_{t+1|t} &= A_{x,t}P_{t|t}A_{x,t}' + G_{x,t}\bar{Q}_{x,t}G_{x,t}' - L_tN_tL_t'\\
L_t &= A_{x,t}P_{t|t}A_{m,t}'N_t^{-1}
\end{aligned}$$

C.7 Tables

Table C.1: PCE series classified by price-change frequency (flexible: quarterly-frequency >0.5).

Flexible prices	**Rigid prices**
Accommodations	Audio-video
Air transportation	Commercial and vocational schools
Alcoholic beverages purchased for off-premises consumption	Dental services
Children's and infants' clothing	Educational books
Electricity	Financial services
Food and nonalcoholic beverages purchased for off-premises consumption	Food furnished to employees (including military)
Food produced and consumed on farms	Gambling
Fuel oil and other fuels	Glassware
Furniture and furnishings	Higher education
Ground transportation	Hospitals
Household appliances	Household maintenance
Household supplies	Internet access
Jewelry and watches	Life insurance
Men's and boys' clothing	Luggage and similar personal items

Continued on next page

Flexible prices	Rigid prices
Motor vehicle fuels	Magazines
Motor vehicle parts and accessories	Membership clubs
Natural gas	Motor vehicle maintenance and repair
Net purchases of used motor vehicles	Musical instruments
New motor vehicles	Net health insurance
Other clothing materials and footwear	Net household insurance
Telecommunication services	Nursing homes
Tobacco	Paramedical services
Water transportation	Personal care and clothing services
Women's and girls' clothing	Personal care products
	Pharmaceutical and other medical products
	Physician services
	Postal and delivery services
	Professional and other services
	Recreational books

Continued on next page

Flexible prices	**Rigid prices**
	Recreational items
	Social services and religious activities
	Sporting equipment
	Sports and recreational vehicles
	Telephone and related communication equipment
	Therapeutic appliances and equipment
	Video
	Water supply and sanitation

Table C.2: Calibration summary (rounded values).

Symbol	**Parameter name**	**Value**
Preferences		
β	Discount factor	0.99
φ	Frisch inverse (labor curvature)	2.0
η	Across-sector CES elasticity	1.0
Sectoral statistics		
n_1, n_2	True CPI weights (flexible, rigid)	0.38,0.62
$\tilde{n}_1, \tilde{n}_2$	Perceived (salience) weights	0.68,0.32
θ_1, θ_2	Calvo stickiness	0.33,0.74
Monetary policy		
τ_1, τ_2	Reaction to sectoral inflation	$1.5, 2.5$
λ_x	Reaction to output	0.10
Shock processes		
$\rho_1, \rho_2, \rho_\varphi$	AR(1) persistence (sector 1, sector 2, policy)	0.93,0.64,0.71
$\sigma_{a1}, \sigma_{a2}, \sigma_\varphi$	Innovation SDs	0.0138,0.0019,0.0045
Learning		
$\bar{\theta}$	Switching threshold	0.04
$\bar{g}$	Constant gain	0.25

Table C.3: Calibrated policy-function loadings (Baseline; $\tilde{n}_1 = 0.38$).

	T_{t-1}	$a_{1,t}$	$a_{2,t}$	φ_t	$\bar{\pi}_t$
$\pi_{1,t}$	−0.547	−0.590	0.239	−0.884	—
$\pi_{2,t}$	0.109	0.052	−0.219	−0.548	—
c_t	0.125	0.505	0.366	−0.317	—
$\tilde{\pi}_t$	−0.140	−0.192	−0.045	−0.675	—
T_t	0.344	−0.642	0.458	−0.337	—

Table C.4: Calibrated policy-function loadings (Baseline-DW; $\tilde{n}_1 = 0.68$).

	T_{t-1}	$a_{1,t}$	$a_{2,t}$	φ_t	$\bar{\pi}_t$
$\pi_{1,t}$	-0.540	-0.611	0.253	-0.895	—
$\pi_{2,t}$	0.112	0.031	-0.210	-0.556	—
c_t	0.025	0.699	0.231	-0.217	—
$\tilde{\pi}_t$	-0.331	-0.406	0.105	-0.786	—
T_t	0.348	-0.642	0.463	-0.340	—

Table C.5: Calibrated policy-function loadings (Anchoring; $\tilde{n}_1 = 0.38$).

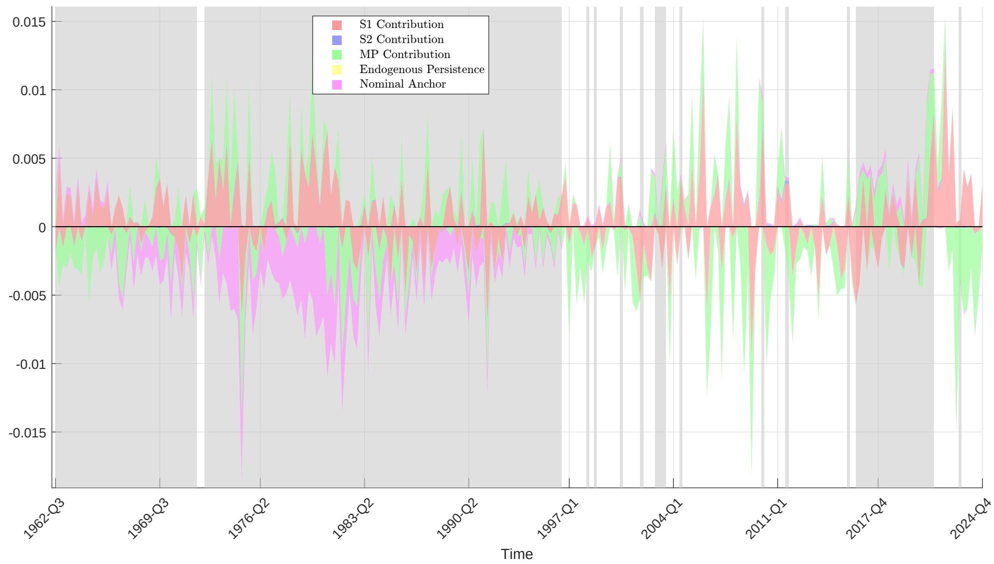
	T_{t-1}	$a_{1,t}$	$a_{2,t}$	φ_t	$\bar{\pi}_t$
$\pi_{1,t}$	-0.547	-0.590	0.239	-0.884	0.520
$\pi_{2,t}$	0.109	0.052	-0.219	-0.548	0.374
c_t	0.125	0.505	0.366	-0.317	0.035
$\tilde{\pi}_t$	-0.140	-0.192	-0.045	-0.675	0.430
T_t	0.344	-0.642	0.458	-0.337	0.146

Table C.6: Calibrated policy-function loadings (Anchoring-DW; $\tilde{n}_1 = 0.68$).

	T_{t-1}	$a_{1,t}$	$a_{2,t}$	φ_t	$\bar{\pi}_t$
$\pi_{1,t}$	-0.540	-0.611	0.253	-0.895	0.276
$\pi_{2,t}$	0.112	0.031	-0.210	-0.556	0.199
c_t	0.025	0.699	0.231	-0.217	-0.161
$\tilde{\pi}_t$	-0.331	-0.406	0.105	-0.786	0.252
T_t	0.348	-0.642	0.463	-0.340	0.077

C.8
Figures

Figure C.3: Forecast error decomposition by state: shocks, terms of trade, and anchor.



Notes: Stacked area plot of smoothed forecast error contributions by state: sectoral productivity shocks, monetary-policy shock, terms-of-trade component, and the long-run inflation target. Gray shading marks unanchored regimes (constant-gain learning). See Appendix C.1.5 for the algebra and loadings. Here we set $\tau_1 = 2.5$ and $\tau_2 = 1.5$, making policy more responsive to flexible prices.

C.8.1
PCE Data

Figure C.4: Flexible vs. Rigid Price PCE Series

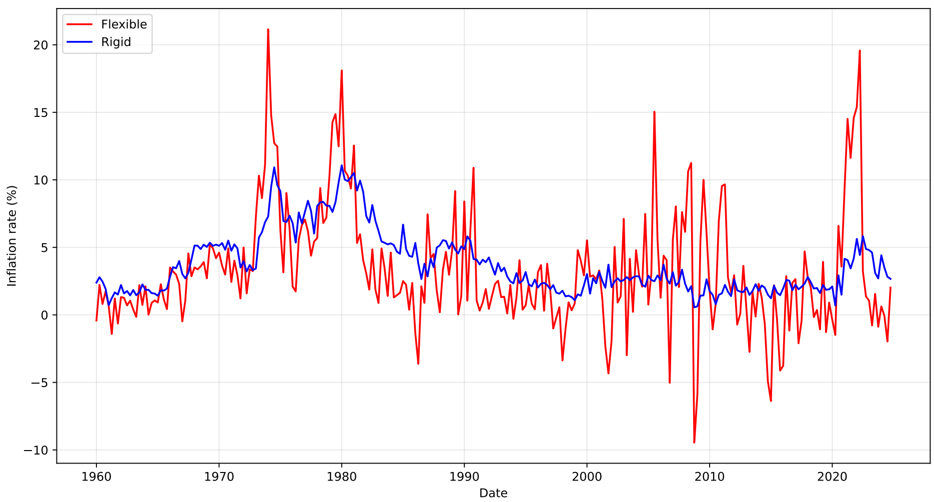


Figure C.5: Contributions to Flexible Price Inflation

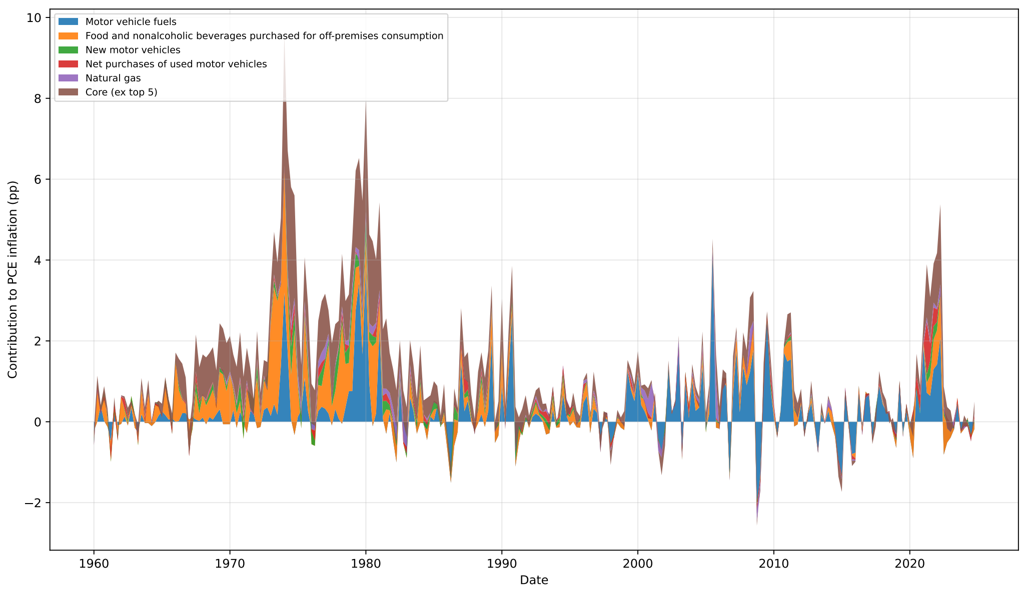
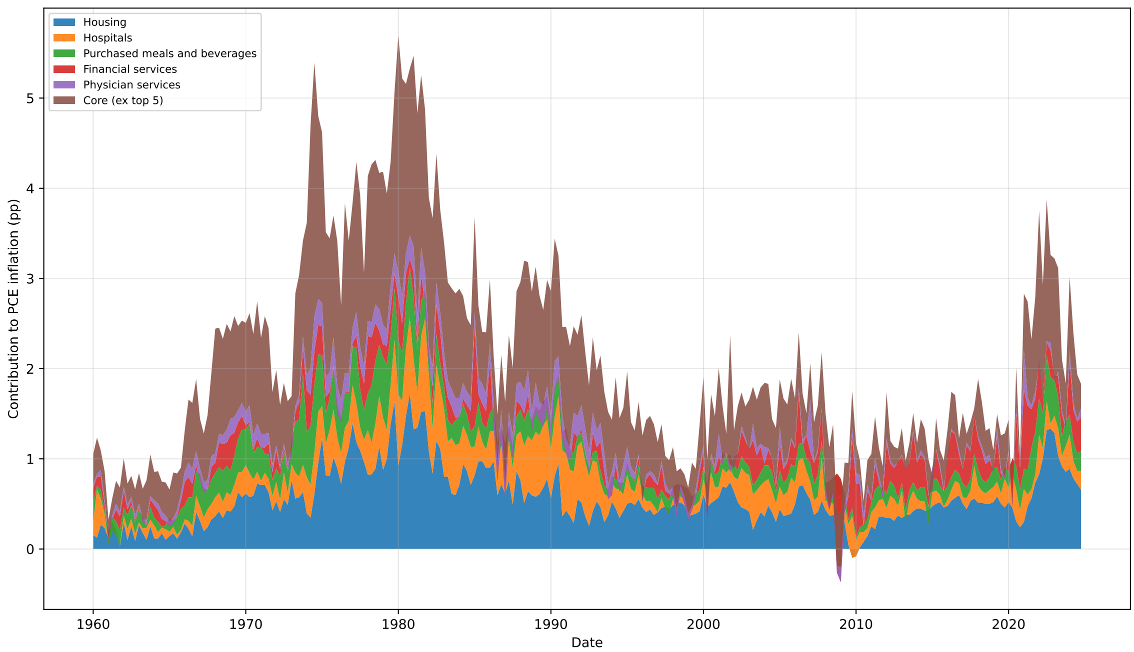


Figure C.6: Contributions to Rigid Price Inflation



C.8.2 Additional impulse responses

This section presents impulse-response functions (IRFs) from our calibrated model. The figures display the dynamics of inflation, perceived inflation, forecast errors, the long-run anchor, and sectoral inflation under different shocks. Each figure reports results for three cases: no learning, initially anchored beliefs, and initially unanchored beliefs.

Three features govern dynamics in our two-sector model: (i) segmented labor and heterogeneous stickiness, which generate a relative-price state, (ii) salience-distorted perceptions of aggregate inflation, and (iii) a switching-gain learning rule that turns forecast errors into updates of the long-run mean. Together, these forces can stabilize or destabilize the system depending on the shock, its sectoral footprint, and the belief regime.

Two mechanisms dampen dynamics. First, high stickiness in sector 2 (θ_2 large) limits the pass-through of $\bar{\pi}_t$ into $\pi_{2,t}$ ($\gamma_{\pi,2} < \gamma_{\pi,1}$), weakening the feedback. Second, large initial gains when beliefs start unanchored can stabilize after an initial jump: a big update at $t = 1$ shrinks f_t, pushing θ_t back below threshold and returning the system to decreasing gain. In this case, $g_t f_{t-1}$ adjusts the anchor in a way that lowers future forecast errors, especially when shocks are transitory and the forecast model for real variables is correct.

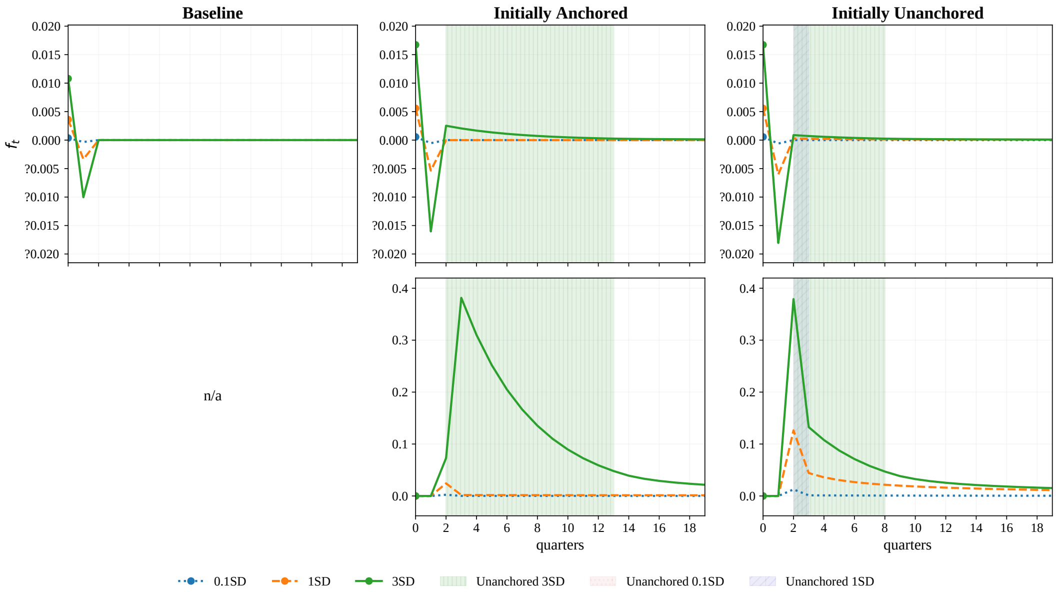
Three alignments magnify dynamics. First, salience amplification ($\tilde{n}_1 > n_1$) raises f_t for shocks tilted toward the flexible block, increasing the chance of switching. Second, asymmetric pass-through ($\gamma_{\pi,1} > \gamma_{\pi,2}$) means a higher anchor inflates sector 1 more strongly, raising T_t and widening the gap between perceived and actual inflation. Third, policy-perception mismatch arises because the Taylor rule reacts to true CPI weights n_k while learning uses $\tilde{n}_k$. When perceptions overweight sector 1, policy under-reacts at the salient margin, allowing T_t and $\tilde{\pi}_t$ to feed persistence into forecast errors.

Sector-1 productivity shocks (a_1). With $(n_1, n_2) = (0.38, 0.62)$ and $(\tilde{n}_1, \tilde{n}_2) = (0.68, 0.32)$, any tilt toward sector 1 appears larger in perceived inflation. Because agents form aggregate inflation expectations using $\tilde{\pi}_t$, salience raises the likelihood of unanchoring for the same disturbance. The resulting revision in $\bar{\pi}_t$ shifts the intercept of sectoral NKPCs and interacts with α_5, which governs T_t, to determine the persistence of the response.[3]

A negative sector-1 productivity shock raises $\pi_{1,t}$ and lowers $\pi_{2,t}$ on impact through marginal costs. Because households overweight the flexible block ($\tilde{n}_1 > n_1$), perceived inflation $\tilde{\pi}_t$ moves more than the CPI. Since the switching test depends on $\tilde{\pi}_t$, shocks tilted toward sector 1 generate larger forecast errors and are more likely to trigger unanchoring. Once unanchored, the constant gain amplifies the pass-through of $\bar{\pi}_t$ into sectoral inflation, further tilting relative prices toward sector 1 and propagating imbalances through the terms-of-trade state T_{t-1}.

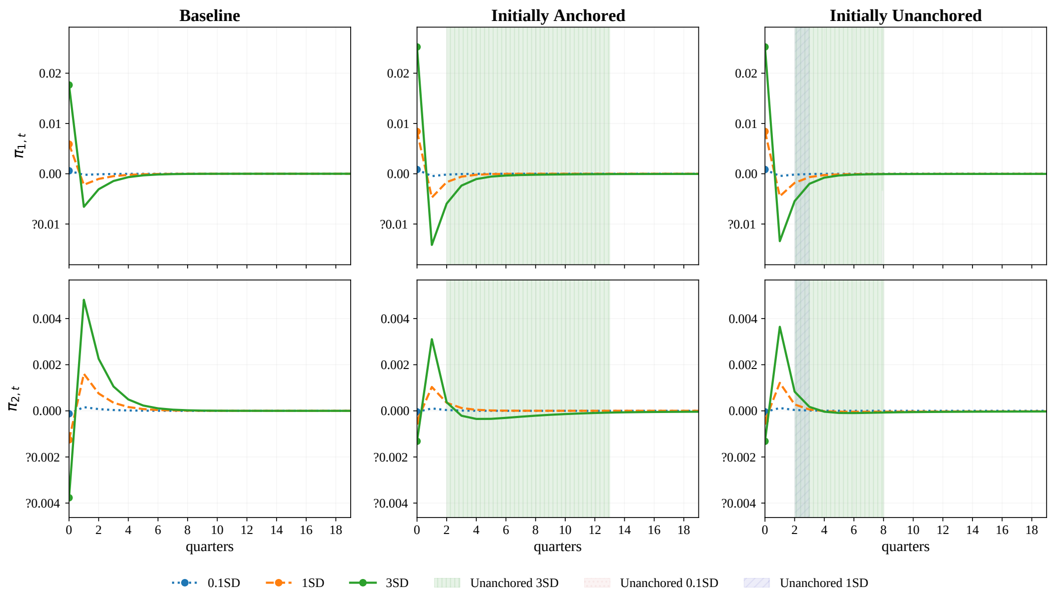
[3]The gap $\tilde{\pi}_t - \pi_t = (\tilde{n}_1 - n_1)(\pi_{1,t} - \pi_{2,t}) = (\tilde{n}_1 - n_1)\Delta T_t$ scales with ΔT_t.

Figure C.7: Forecast errors f_t and switching statistic θ_t for sector-1 shocks (a_1).



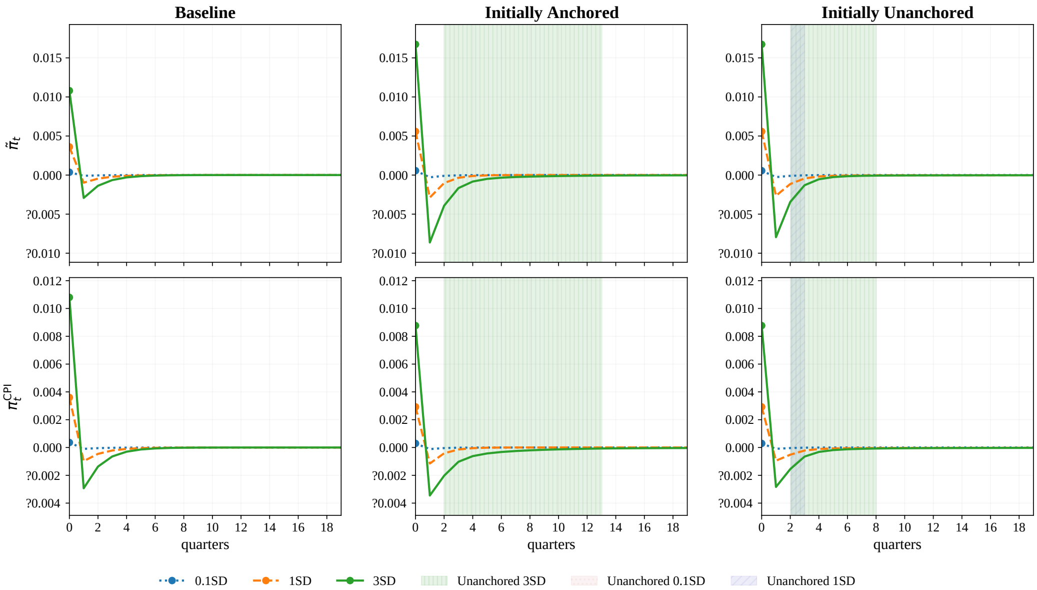
Notes: Columns: Baseline (no θ_t panel), Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Top: forecast errors f_t. Bottom: switching statistic θ_t. Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

Figure C.8: Sectoral inflation $\pi_{1,t}$ and $\pi_{2,t}$ after sector-1 shocks (a_1).



Notes: Columns: Baseline, Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Rows: $\pi_{1,t}$ and $\pi_{2,t}$. Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

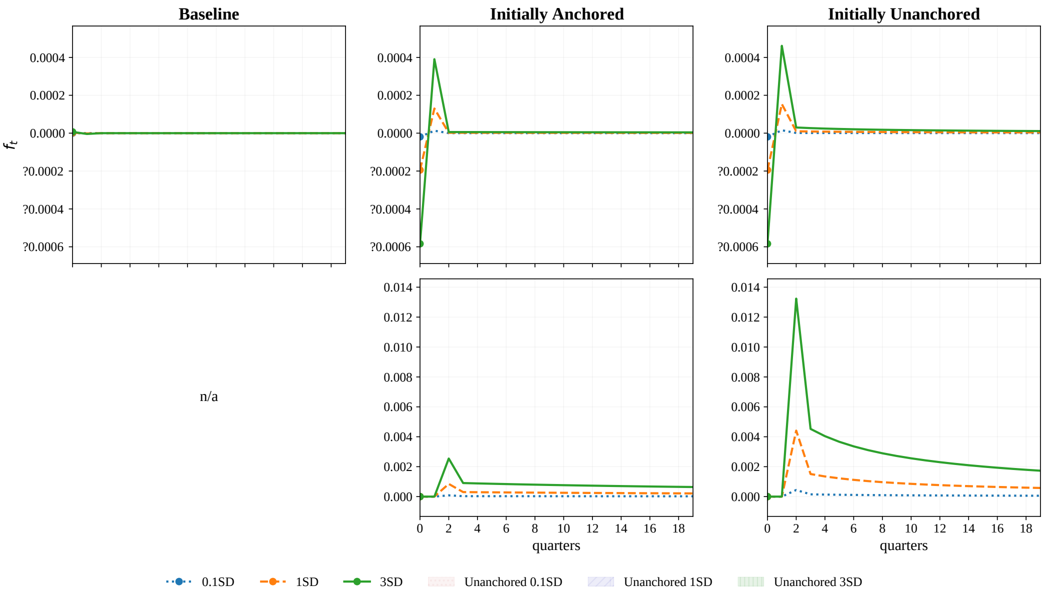
Figure C.9: Perceived inflation $\tilde{\pi}_t$ versus CPI inflation π_t after sector-1 shocks (a_1).



Notes: Columns: Baseline, Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Top: $\tilde{\pi}_t$. Bottom: π_t. Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

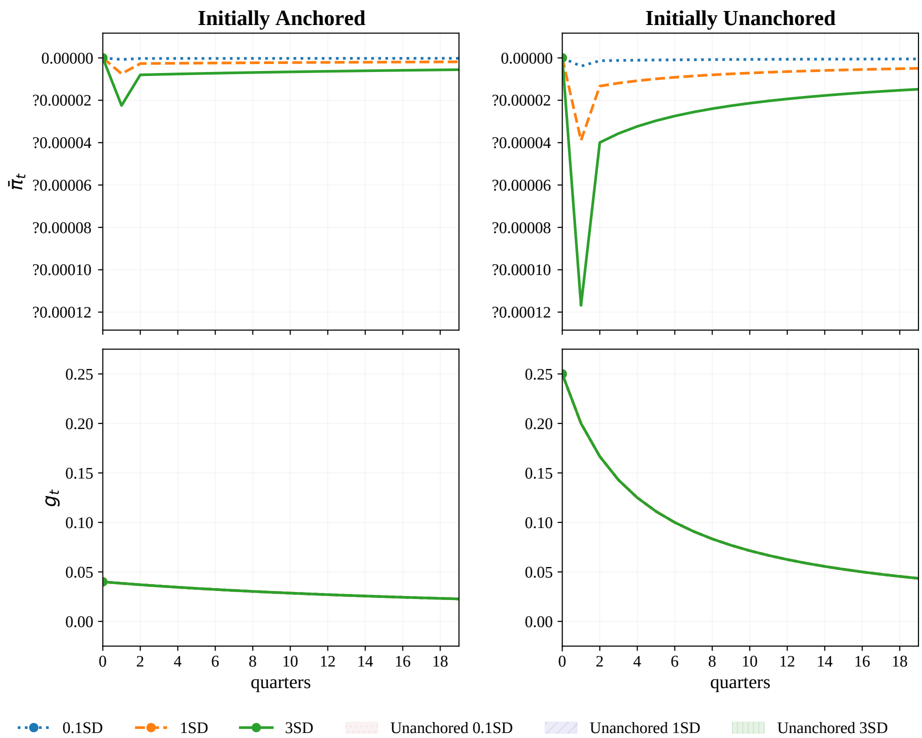
Sector-2 productivity shocks (a_2). A disturbance in the sticky block raises $\pi_{2,t}$ on impact and moves $\pi_{1,t}$ in the opposite direction through the terms-of-trade linkage. Because perceived inflation overweights the flexible sector, $\tilde{\pi}_t$ reacts less to a_2 than to a_1 for the same standardized size. Forecast errors are smaller and rarely cross the threshold. Learning mostly operates in decreasing-gain mode, so revisions in $\bar{\pi}_t$ are small and gradual, adding little persistence beyond the T_{t-1} channel.

Figure C.10: Forecast errors f_t and switching statistic θ_t for sector-2 shocks (a_2).



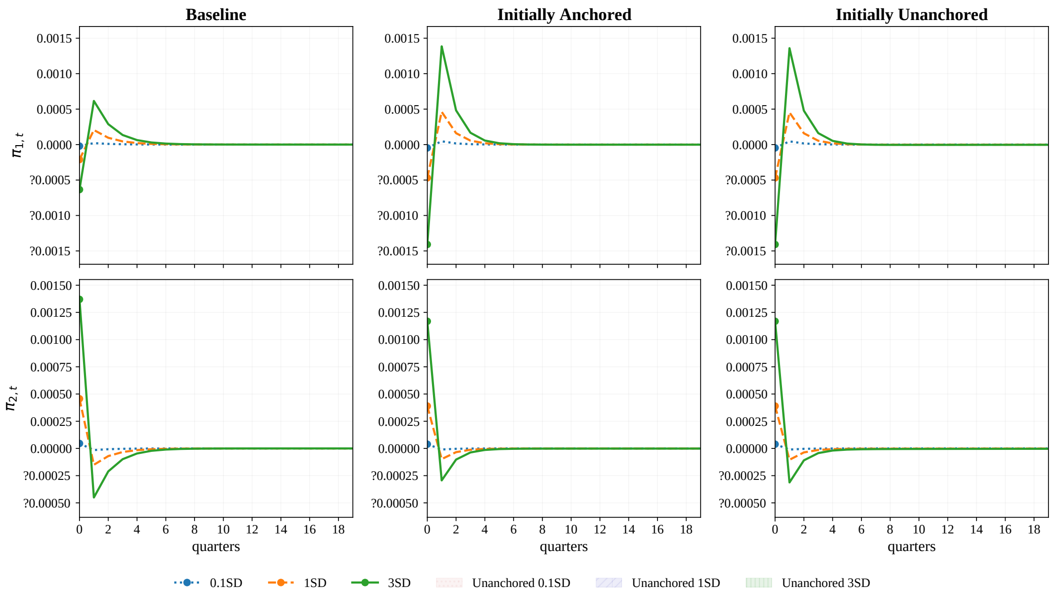
Notes: Columns: Baseline (no θ_t panel), Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Top: forecast errors f_t. Bottom: switching statistic θ_t. Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

Figure C.11: Long-run anchor $\bar{\pi}_t$ and gain g_t for sector-2 shocks (a_2).



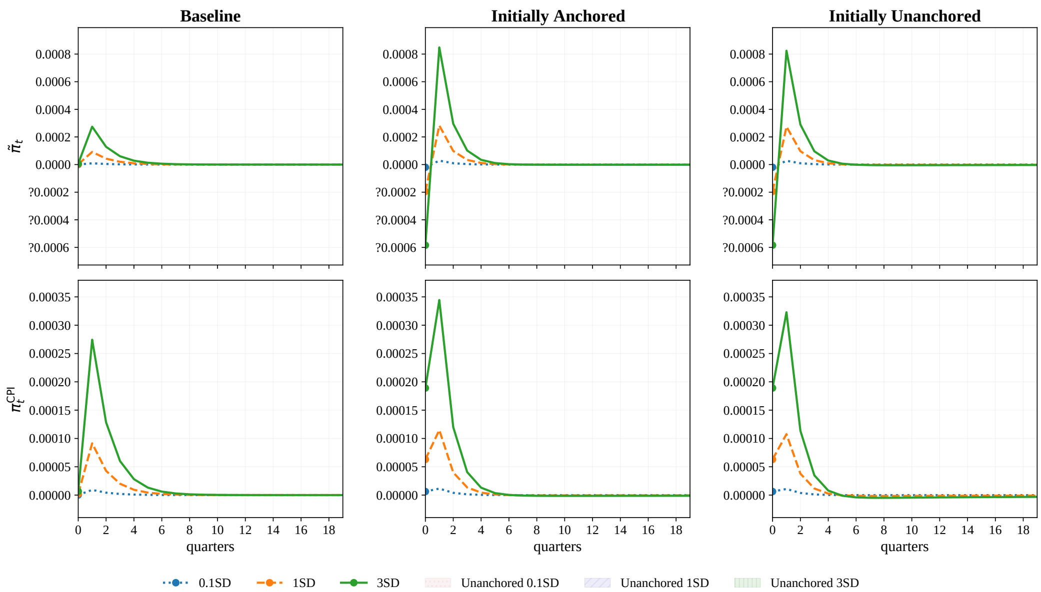
Notes: Columns: Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Rows: $\bar{\pi}_t$ (top), g_t (bottom). Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

Figure C.12: Sectoral inflation responses to sector-2 shocks (a_2).



Notes: Columns: Baseline, Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Rows: $\pi_{1,t}$ (top), $\pi_{2,t}$ (bottom). Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

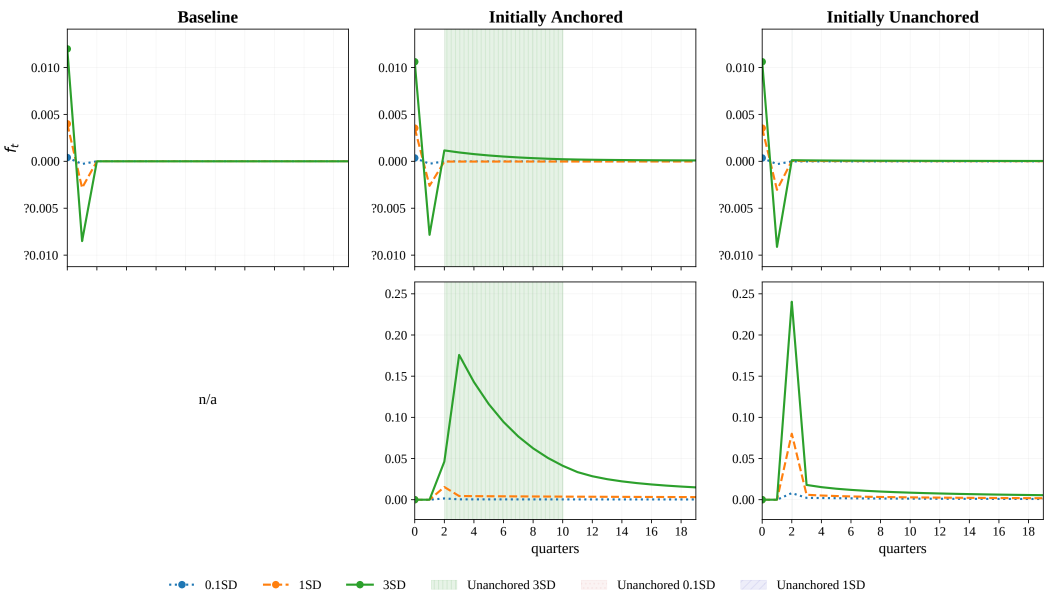
Figure C.13: Perceived versus CPI inflation for sector-2 shocks (a_2).



Notes: Columns: Baseline, Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Top: perceived inflation $\tilde{\pi}_t$. Bottom: CPI inflation π_t. Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

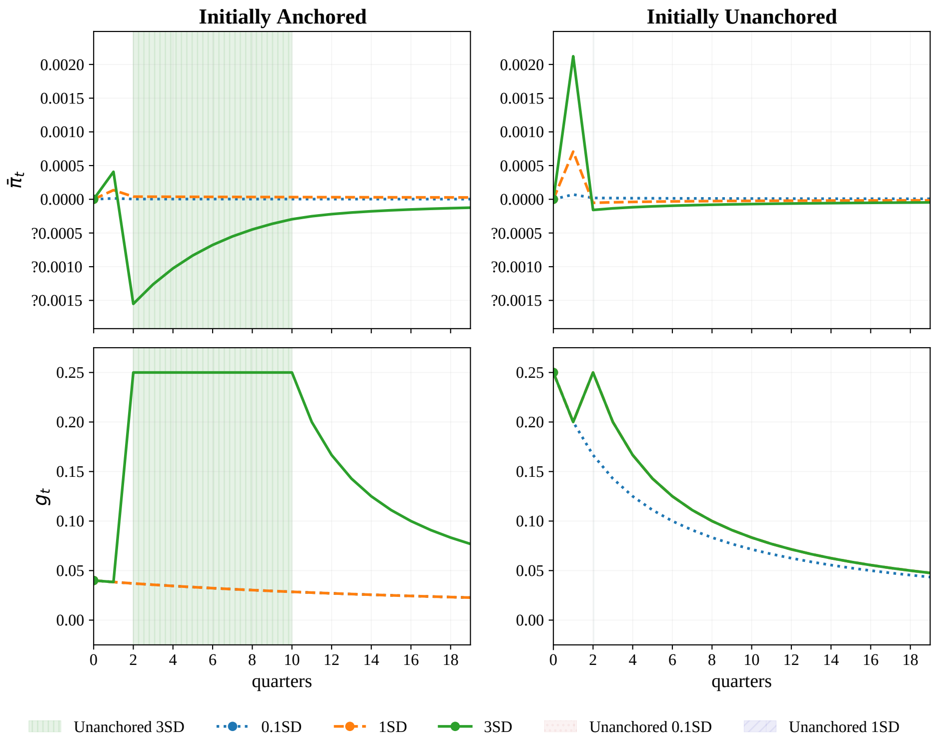
Monetary shocks (φ). A policy shock raises demand and inflation in both sectors on impact. Because the flexible block responds faster, perceived inflation overshoots relative to CPI, inflating f_t and θ_t for large shocks. When the distance test flips the gain, revisions in $\bar{\pi}_t$ pass through more strongly to the flexible block ($\gamma_{\pi,1} > \gamma_{\pi,2}$), nudging the terms of trade and slowing convergence. If beliefs start unanchored, the large initial revision lowers subsequent forecast errors and shortens the unanchored spell. This follows directly from the gain-weighted update in Appendix C.1.5. The persistence of unanchoring therefore depends on how quickly the self-referential feedback decays.

Figure C.14: Forecast errors f_t and switching statistic θ_t after monetary shocks (φ).



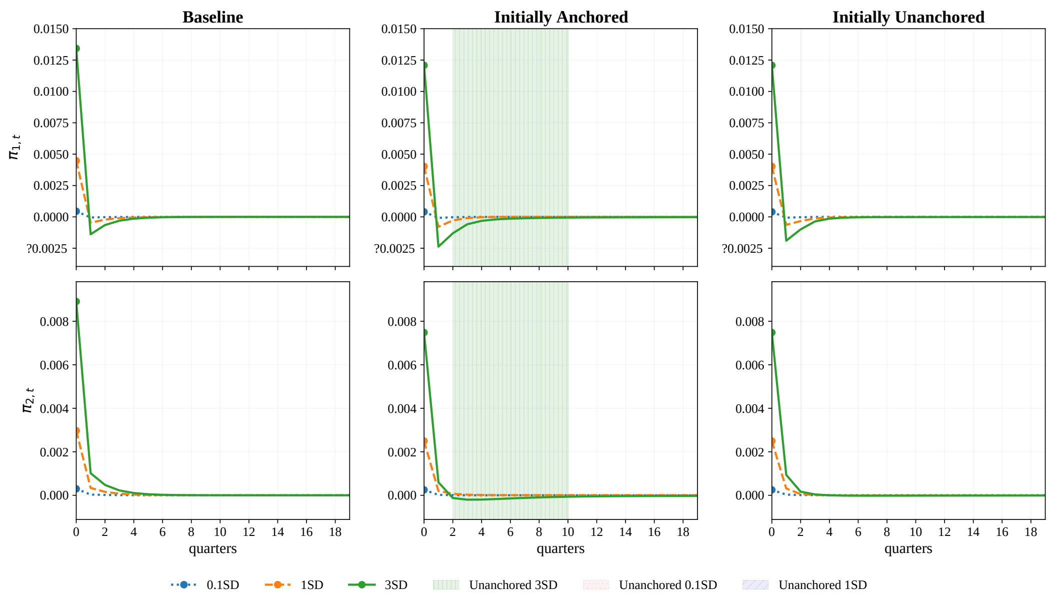
Notes: Three columns: Baseline (no learning; bottom panel omitted), Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Rows plot f_t and θ_t (normalized distance). Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shading marks constant-gain periods.

Figure C.15: Long-run anchor $\bar{\pi}_t$ and gain g_t for monetary shocks (φ).



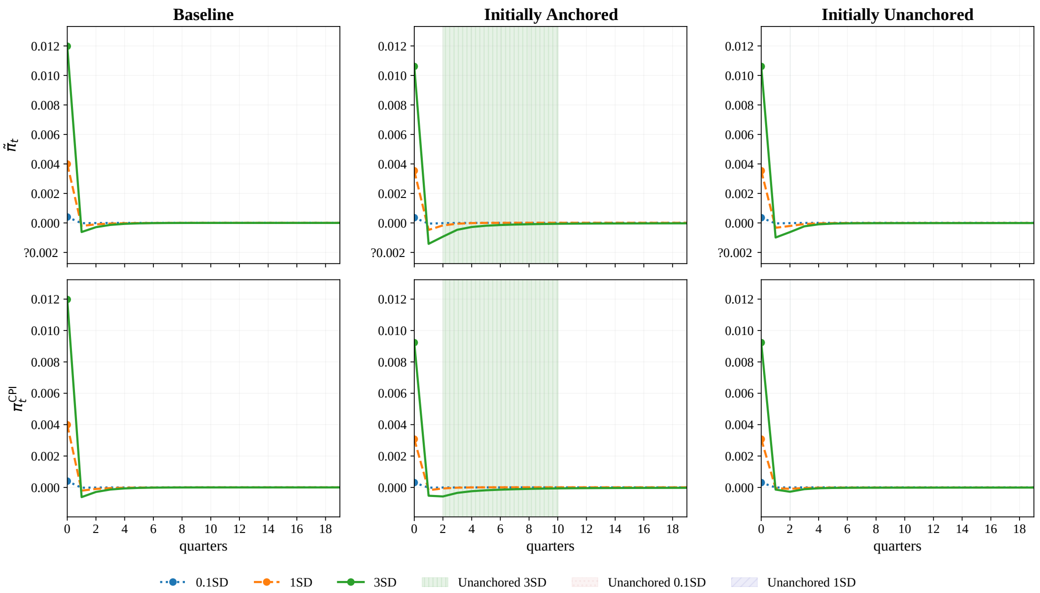
Notes: Columns: Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Rows: $\bar{\pi}_t$ (top), g_t (bottom). Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

Figure C.16: Sectoral inflation responses to monetary shocks (φ).



Notes: Columns: Baseline, Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Rows: $\pi_{1,t}$ (top), $\pi_{2,t}$ (bottom). Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.

Figure C.17: Perceived versus CPI inflation for monetary shocks (φ).



Notes: Columns: Baseline, Initially Anchored ($k_0 = 25$), Initially Unanchored ($k_0 = 1/\bar{g}$). Top: perceived inflation $\tilde{\pi}_t$. Bottom: CPI inflation π_t. Line styles: $0.1\sigma, 1\sigma, 3\sigma$. Shaded regions mark constant-gain periods.