Price Gaps and Inflation Dynamics

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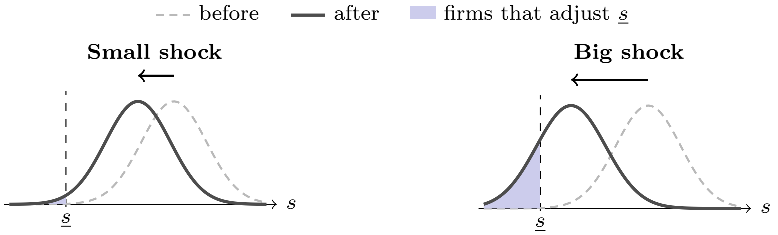
Motivation

- Renewed interest in **non-linear dynamics of price adjustment**
- In menu cost models, how many firms adjust to a shock is **endogenous**
- Literature: **bigger shocks** ⇒ disproportionately more firms adjust



normal distribution ⇒ **few** adjust

bigger shock ⇒ **many more** adjust

- Same shock ⇒ **adjusters** depend on distribution **upon impact**

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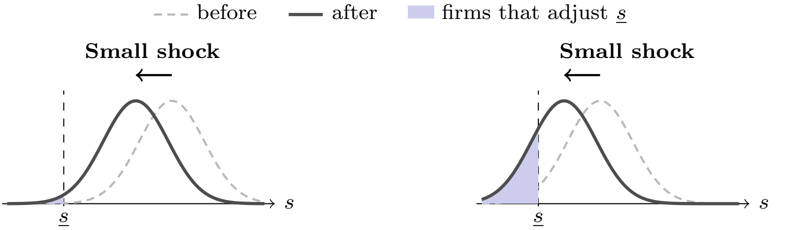

normal distribution ⇒ **few** adjust   **displaced distribution** ⇒ **many** adjust

- Same shock ⇒ **adjusters** depend on distribution **upon impact**

This paper: how the **price-gap distribution** shapes inflation

This Paper Literature

1. **Model: bring the gap distribution to center of analysis**
   - Random menu cost model (NS, 2010) $\rightarrow$ Ss pricing
   - Gap distribution G_t is the key state variable of the model
   - Shapes propagation of shocks and determines optimal policy
   - Also serves as leading indicator of inflation
2. **Method: recover price gaps empirically**
   - Cast random menu cost model in state-space form
   - Develop state space methods to estimate model
   - Our strategy: exploit the structure of Ss rules for filtering
3. **Application: UK CPI microdata (1996–2026)**
   - Estimate price gaps from millions of quote-lines
   - Gap distribution varies substantially over time
   - Monetary shock transmission can be twice as large
   - Gap moments improve inflation forecasts over random walk

State-space Methods for a Random Menu Cost Model

A Simple Random Menu Cost Model

Key assumptions Microfoundations

- Firm i sets its log price $p_{i,t}$ in discrete time
- Adjusting price entails a cost $c_{i,t} \in \{0, \bar{c}\}$; free with prob λ_t
- Its **reset price** $p^r_{i,t}$ (chosen upon adjustment) follows:

$$p^r_{i,t} = \mu_t + p^r_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_{\varepsilon,t})$$

- No aggregate uncertainty; unexpected shocks to $\lambda, \mu, \sigma_\epsilon$
- Firm problem written in terms of **price gap**: $s_{i,t} \equiv p_{i,t} - p^r_{i,t}$
- Optimal pricing policy is a standard ***Ss*** **rule** $(\underline{s}_t < 0 < \bar{s}_t)$:

$$s_{i,t} = \begin{cases} 0 & \text{with prob } \lambda_t \text{ or if } s_{i,t-1} - \mu_t - \varepsilon_{i,t} \notin [\underline{s}_t, \bar{s}_t] \\ s_{i,t-1} - \mu_t - \varepsilon_{i,t} & \text{otherwise} \end{cases}$$

- Key state for inflation dynamics: unobserved **price gap distribution**

$$G_t = G(\{s_{i,t}\}_i)$$

Price Setting in State-Space Representation

Observables:

- price $p_{i,t}$
- inaction $d_{i,t}$

Hidden states $\mathbf{x}_{i,t}$:

- reset price $p^r_{i,t}$
- free adjustment $\ell_{i,t}$

Parameters Θ_t:

- stochastic process $\mu_t, \sigma_{\epsilon,t}, \lambda_t$
- inaction thresholds $\underline{s}_t, \bar{s}_t$

1 Measurement equations

$$\text{(price)} \qquad p_{i,t} = p_{i,t-1} \cdot d_{i,t} + p^r_{i,t} \cdot (1 - d_{i,t}) \tag{1}$$

$$\text{(inaction)} \qquad d_{i,t} = \mathbb{1}\{p_{i,t-1} - p^r_{i,t} \in (\underline{s}_t, \bar{s}_t)\}(1 - \ell_{i,t}) + \mathbb{1}\{p_{i,t} = p^r_{i,t}\}\,\ell_{i,t} \tag{2}$$

2 Transitions for hidden states

$$\text{(reset price)} \qquad p^r_{i,t} = \mu_t + p^r_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_{\epsilon,t}) \tag{3}$$

$$\text{(free adj.)} \qquad \ell_{i,t} = \mathbb{1}\{v_{i,t} \leq \lambda_t\}, \quad v_{i,t} \sim \mathcal{U}(0,1) \tag{4}$$

3 Initial values for hidden states

Bayesian Estimation

We have a panel of data: assume common Θ and i.i.d. shocks and initial states.

Also, Θ is constant within an estimation window — but free to vary across.

Given $(p_{i,t}, d_{i,t})$, estimate Θ and hidden states $(p^r_{i,t}, \ell_{i,t})$ using a Gibbs sampler.

- **Block 1:** Sample hidden states $(p^r_{i,t}, \ell_{i,t})$, conditional on parameters Θ
  - Forward filtering (uses data up to date t) Lemma
  - Backward sampling (uses all data, up to T) Lemma

$\star$ Leverage Ss policy to constrain the state space $\star$

Restricting the State Space

- No closed-form solution for recursions $\rightarrow$ numerical approximation
- Key insight: use the Ss rules to our advantage
- Measurement equation exactly bounds latent states
  - Small price change: reset price is observed, $\ell_{i,t} = 1$
  - Large price change: reset price is observed, $\ell_{i,t}$ unknown
  - No price change: bounds reset price to inaction region, $\ell_{i,t} = 0$
- We construct time-varying grids and weights for the latent states
- This speeds up filtering and backward sampling, ensuring accuracy.

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  ⋆ Leverage Ss policy to constrain the state space ⋆

- **Block 2:** Sample parameters Θ, conditional on hidden states $(p^r_{i,t}, \ell_{i,t})$
  - Use conjugate priors $\Longrightarrow$ stochastic process $\mu, \sigma_\epsilon, \lambda$ Details
  - Metropolis–Hastings step $\Longrightarrow$ inaction thresholds $\underline{s}, \bar{s}$

  ⋆ Leverage Ss policy to constrain the band search ⋆ Intuition

Alternate between blocks for each iteration $k = 2, \ldots, K$ after initialization.

Monte Carlo: recovers parameters and gaps with negligible bias Details

Application to UK Micro-Price Data

Data and Estimated Parameters

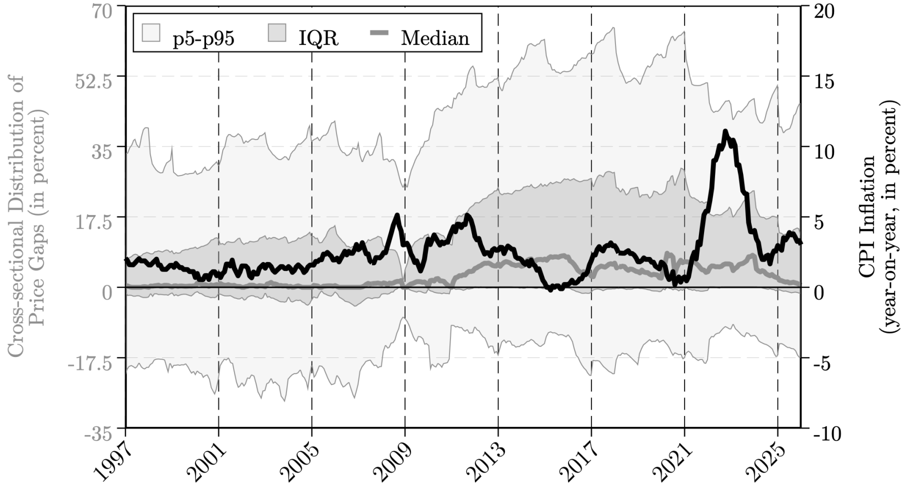
UK CPI microdata (ONS)

- Monthly shelf prices, 140+ locations, 1996m1–2026m1
- 35M+ quotes, 3.6M quote-lines, 1,337 items
- Clean: drop sales, substitutions, broken quote-lines
- Unit of observation i = quote-line; estimation runs at the item level
- Estimation windows aligned to calendar years
  - Extend until $\geq$10 up & 10 down price changes
  - 89% of the 15,664 item-windows span exactly 12 months
- Aggregate to item & CPI levels using official weights

Estimated parameters

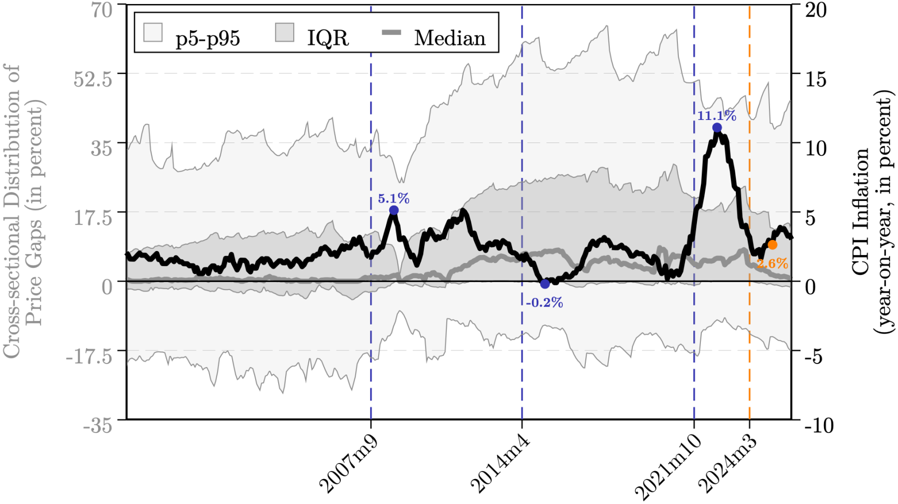
- Posterior means are reasonable and in line with the literature Details

Inflation and Price Gaps in the UK

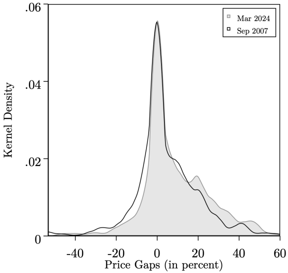


Zooming In on Inflation Extremes

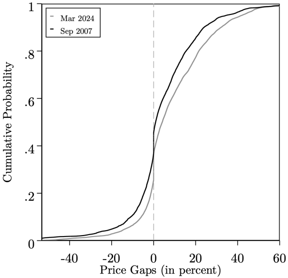
Inflation and Price Gaps in the UK



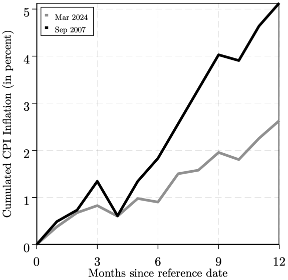
Case Study 1: September 2007 (Pre-2008 Peak)



(a) Density



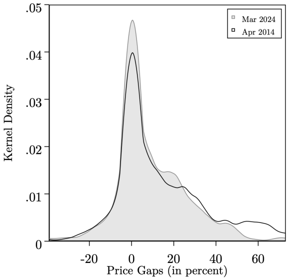
(b) CDF



(c) Cumulative inflation

One-sided: mass below reset ⇒ pending increases ⇒ inflation peaks at 5.1%

Case Study 2: April 2014 (Pre-2015 Deflation)



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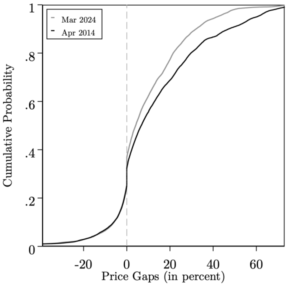
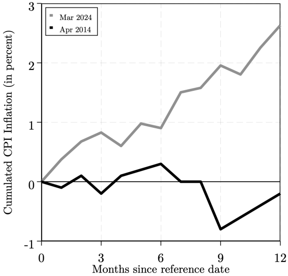


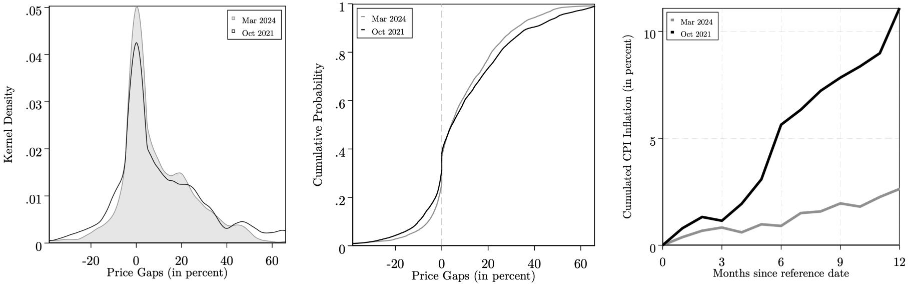
(b) CDF



(c) Cumulative inflation

One-sided: overhang of pending cuts $\Rightarrow$ inflation bottoms at -0.2%

Case Study 3: October 2021 (Pre-2022 Surge)



(a) Density (b) CDF (c) Cumulative inflation

Two-sided: fat in both tails ⇒ Ukraine war resolves it upward, 11.1% peak

Price Gaps and Shock Propagation

State-dependent Local Projections

Monetary shocks

For each COICOP class c, horizon h:

$$\begin{aligned}\log P_{c,t+h} = \alpha_h \Delta i_t &+ \beta_h^{+} \Delta i_t^{+} \mathrm{m}_{c,t-1} + \beta_h^{-} \Delta i_t^{-} \mathrm{m}_{c,t-1} \\ &+ \gamma_h \Delta i_t \,\mathrm{sd}_{c,t-1} + \zeta_h^{+} \Delta i_t^{+} \mathrm{sk}_{c,t-1} + \zeta_h^{-} \Delta i_t^{-} \mathrm{sk}_{c,t-1} \\ &+ \eta_h \Delta i_t \,\mathrm{k}_{c,t-1} + \mathbf{w}_{c,t}' \boldsymbol{\Gamma}_h + e_{c,t+h}\end{aligned}$$

- $\log P_{t+h}^c$ is the log of the published price index for COICOP class c
- Δi_t: change in 1-year gilt yield; $\Delta i_t^{\pm} \equiv \max / \min\{\Delta i_t, 0\}$
- $\mathrm{m}, \mathrm{sd}, \mathrm{sk}, \mathrm{k}$: standardized moments of the class-c gap distribution at $t-1$
- Mean & skewness (odd moments) enter **sign-dependently**
- $\mathbf{w}_{c,t}$: class FE + 12 lags of Δi_t, $\log P^c$, moments & macro
- Δi_t and interactions are instrumented using $\mathbf{z}_t$ and $\mathbf{z}_t \times$ moments
- $\mathbf{z}_t$: target, path, and QE shocks from Braun et al. (2025)

$\Rightarrow$ Additional exercise using **oil-price shocks** (Känzig, 2021)

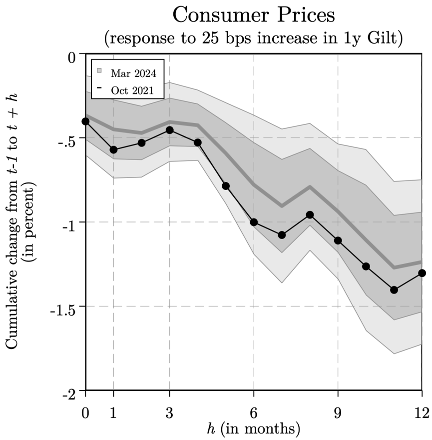
Testing for State Dependency

	$h = 0$	$h = 1$	$h = 3$	$h = 6$	$h = 9$	$h = 12$
Δi_t	-0.309**	-0.356**	-0.325**	-0.621**	-0.724**	-0.966**
	(0.106)	(0.162)	(0.103)	(0.153)	(0.172)	(0.206)
$\Delta i_t^+ \times \mathrm{m}_{c,t-1}$	-0.270**	-0.248**	-0.083	-0.438*	-0.574**	-0.695**
	(0.147)	(0.139)	(0.342)	(0.322)	(0.280)	(0.347)
$\Delta i_t^- \times \mathrm{m}_{c,t-1}$	-0.034	0.015	0.145*	0.399**	0.445**	0.424**
	(0.068)	(0.086)	(0.124)	(0.150)	(0.182)	(0.219)
$\Delta i_t \times \mathrm{sd}_{c,t-1}$	-0.109**	-0.127**	-0.029	-0.224**	-0.291**	-0.170*
	(0.059)	(0.064)	(0.185)	(0.119)	(0.123)	(0.142)
$\Delta i_t^+ \times \mathrm{sk}_{c,t-1}$	0.187**	0.120	0.084	0.169	0.546*	0.458*
	(0.112)	(0.178)	(0.220)	(0.240)	(0.342)	(0.337)
$\Delta i_t^- \times \mathrm{sk}_{c,t-1}$	-0.022	-0.047*	-0.053	-0.096*	-0.047	-0.076
	(0.030)	(0.045)	(0.063)	(0.074)	(0.084)	(0.089)
$\Delta i_t \times \mathrm{k}_{c,t-1}$	-0.079**	0.036	0.083*	0.056	0.018	-0.062
	(0.033)	(0.045)	(0.081)	(0.084)	(0.075)	(0.089)
F interactions	1.995**	1.976**	0.477	1.382*	1.820*	1.656*

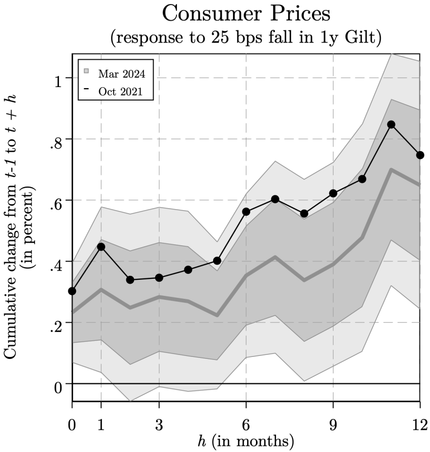
Notes: Coefficients from panel state-dependent LP-IV specification with standard errors clustered by COICOP class in parentheses. LP coefficients are scaled to a 25 bps change in the 1y Gilt rate. Δi_t and its interactions are instrumented with target, path, and QE monetary policy surprises from Braun et al. (2025) and their interactions with lagged moments. The F interactions row reports the F-statistic for the null that all interaction coefficients are jointly zero. * (**) denotes rejection at the 32% (10%) significance level.

IRFs to Monetary Shocks

The State of the Economy When the Shock Hits (Oct 2021 *vs* benchmark)



(a) 25 bp tightening

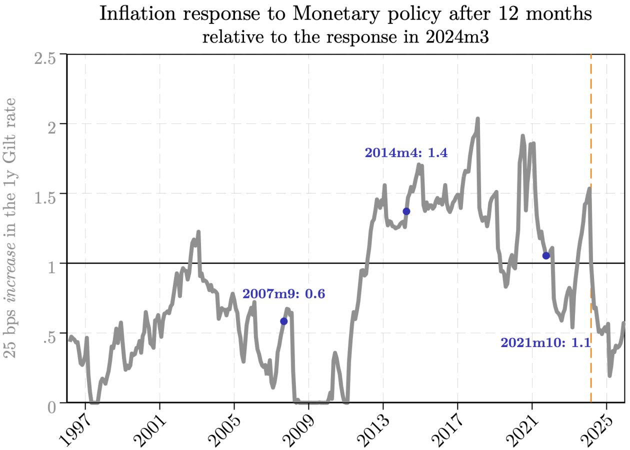


(b) 25 bp easing

- Difference from benchmark is **statistically significant** Difference IRFs
- Difference is also **economically meaningful**: 25–50% stronger

Monetary Policy Pass-through over Time

Hiking Rates



- Pass-through ranges from **twice the benchmark** down to **zero**
- The same holds for a monetary **easing** Cutting rates

The Predictive Content of Price Gaps

The Predictive Content of Price Gaps

1. Does the distribution predict inflation? Granger causality

Panel VAR, 12 lags: gap moments $\overset{\Longrightarrow}{\not\Leftarrow}$ inflation **one-directional**

2. How much do we gain? Details

Estimated on 1996m2–2016m1, **out-of-sample** evaluation 2016m2–2026m1

Benchmark: random walk $\widehat{\pi}^{y}_{t+h} = \pi^{y}_{t}$ (Atkeson and Ohanian, 2001)

RMSPE ratio: Price Gaps *vs.* Atkeson-Ohanian

Horizon	OOS Forecast Evaluation Sample		
	Full sample	Low inflation	High inflation
12	0.98	0.66*	1.00
15	0.86	0.53**	0.88
18	0.78*	0.50**	0.80*
21	0.74**	0.51**	0.76**
24	0.72**	0.56**	0.74**

Conclusion

Today

- Price gap distribution G_t is the key state of menu cost models
- We develop **state-space methods** to recover price gaps from prices
- UK micro-data (1997–2026): economy spends long spells far from ergodic
- **We show and quantify empirically how G_t shapes:**
  - **Propagation**: same shock, very different effects depending on G_t
  - **Prediction**: gap moments forecast inflation in and out of sample

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Looking ahead

- Designing **optimal policy** around the gap distribution G_t
- **Method generalizes**: beyond pricing and to richer menu cost models

Appendix

Relation to the Literature Back

- **Price setting under menu costs**
  - Golosov and Lucas (2007); Nakamura and Steinsson (2010); Auclert et al. (2024)
  - *Non-linear dynamics:* Golosov and Lucas (2007), Blanco et al. (2024a,b), Karadi et al. (2025), Gagliardone et al. (2025)

  ⇒ Gap distribution as alternative source of non-linearity

- **Estimation in nonlinear state-space models**
  - Kitagawa (1987); Särkkä (2013); Herbst and Schorfheide (2015)

  ⇒ Grid-based filtering and smoothing for Ss pricing models

- **Understanding inflation**
  - *State-dependent shocks:* Shapiro (2024), Bernanke and Blanchard (2025)
  - *Forecasting:* Faust and Wright (2013); Stock and Watson (1999, 2009); Edge and Gürkaynak (2010)

  ⇒ Micro-level price gaps improve macro understanding

Microfoundations

Households Back

- Representative household maximizes:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log C_t - N_t\right] \quad \text{where} \quad C_t = \left(\int_0^1 c_t(i)^{\frac{\epsilon-1}{\epsilon}} di\right)^{\frac{\epsilon}{\epsilon-1}}$$

$$\text{s.t.} \quad P_t C_t = M_t \quad \text{(cash-in-advance)}$$

where M_t is nominal spending, controlled by policy

- Optimality conditions:

$$W_t = M_t \qquad \text{(Labor supply: } W_t = P_t C_t = M_t\text{)}$$

$$c_t(i) = \left(\frac{P_t(i)}{P_t}\right)^{-\epsilon} C_t \qquad \text{(Demand for variety } i\text{)}$$

Microfoundations

Firms Back

- Firm i produces using labor: $y_t(i) = A_t(i) \cdot N_t(i)$
- Idiosyncratic productivity follows a random walk:

$$\log A_t(i) = \log A_{t-1}(i) + a_{i,t}, \quad a_{i,t} \sim \mathcal{N}(0, \sigma_a^2)$$

- Nominal marginal cost (with cost-push shock ϕ_t):

$$MC_t(i) = (1 - \phi_t)\frac{W_t}{A_t(i)} = (1 - \phi_t)\frac{M_t}{A_t(i)}$$

- Static profit-maximizing price:

$$P_t^*(i) = \underbrace{\tfrac{\epsilon}{\epsilon - 1}}_{\text{markup}}(1 - \phi_t)\frac{M_t}{A_t(i)}$$

Microfoundations

Desired price dynamics Back

Desired price dynamics

The log desired price evolves as:

$$p_t^*(i) = \nu_t + p_{t-1}^*(i) + \varepsilon_{i,t}, \qquad \varepsilon_{i,t} \equiv -a_{i,t}$$

where the desired-price drift is:

$$\nu_t \equiv \underbrace{\Delta \log(1-\phi_t)}_{\text{cost-push shock}} + \underbrace{\Delta \log M_t}_{\text{nominal spending growth}}$$

- **Normal times:** $\phi_t = \bar{\phi}$, policy sets $\Delta \log M_t = \bar{\nu} \Rightarrow$ constant drift
- **Cost-push shock:** ϕ_t moves, policy chooses response via M_t

Microfoundations

Aggregation and evolution of H_t Back

- Let H_t (density h_t) be the distribution of desired-price gaps $x_{i,t} \equiv p_{i,t} - p^*_{i,t}$
- It evolves according to:

$$H_t = \mathcal{T}(H_{t-1}; \nu_t, \sigma_\varepsilon, \underline{x}_t, \bar{x}_t, x^*_t)$$

- CES price index implies:

$$1 = \int B_t(i)\, e^{(1-\epsilon)x_{i,t}}\, di, \qquad B_t(i) \equiv \big(P^*_t(i)/P_t\big)^{1-\epsilon}$$

- Inflation identity:

$$\pi_t = \nu_t + \underbrace{\int (x_{i,t} - x_{i,t-1})\, di}_{\text{change in average gap}}$$

Recentering to the reset price gives the main-text identity $\pi_t = \mu_t + \Delta E[s_t]$.

Microfoundations

From desired price to reset price Back

- Under positive drift, the Ss policy resets the desired-price gap to a small point x_t^* (≈ 0.014), not to 0
- Define the **reset price** $p_{i,t}^r \equiv p_{i,t}^* + x_t^*$ and **reset-price gap**

$$s_{i,t} \equiv p_{i,t} - p_{i,t}^r = x_{i,t} - x_t^*$$

- Reset-price drift: $\mu_t \equiv \nu_t + \Delta x_t^* \approx \nu_t$
- Ss now resets s to 0; inaction region recenters:

$$\underline{s}_t \equiv \underline{x}_t - x_t^* < 0 < \bar{x}_t - x_t^* \equiv \bar{s}_t$$

- Distribution: $g_t(s) = h_t(s + x_t^*) \;\Rightarrow$
  $E[s_t] = E[x_t] - x_t^*, \;\; \mathrm{Var}(s_t) = \mathrm{Var}(x_t)$

The main text works directly with $(p^r,\, s,\, \mu_t,\, G_t)$; the desired-price objects $(p^*,\, x,\, \nu_t,\, H_t)$ stay behind the scenes.

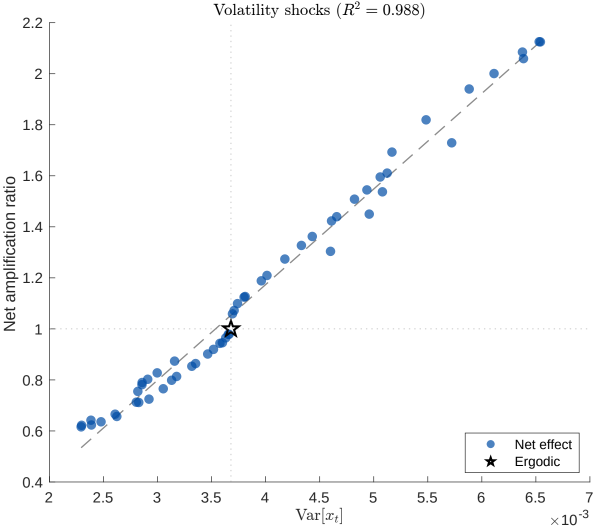
Calibration Back

Parameter	Description	Value	Source	Data	Model
Set externally					
β	Discount factor (monthly)	0.997	4% annual real rate		
μ	Steady-state drift (monthly)	0.00165	2% annual inflation		
Calibrated internally					
σ_ε	Idiosyncratic shock s.d.	0.073	Freq. of price change	12.6%	12.6%
λ	Free adjustment probability	0.120	Mean $\|\Delta p\|$	15.3%	15.3%
ξ	Menu cost	0.547	Kurtosis of Δp	3.8	3.8
Implied Ss rule					
$\underline{s}$	Lower threshold	-0.488			
$\bar{s}$	Upper threshold	0.480			

Notes: Target moments are from UK CPI micro data as reported by Blanco (2021). The parameters σ_ε, λ, and ξ are jointly calibrated to match the three target moments. The Ss rule parameters are obtained from the optimal policy solution given the structural parameters. Thresholds are expressed in terms of the reset price gap.

Amplification under Volatility Shocks

Back



Recovering States from Micro Price Data

Forward filtering backward sampling

Back

Lemma 1: Forward filtering

Given our state-space representation:

$$f(\mathbf{x}_{1:n,t} \,|\, p_{1:n,1:t}; \boldsymbol{\theta}) = \prod_{i=1}^{n} f(\mathbf{x}_{i,t} \,|\, p_{i,1:t}; \boldsymbol{\theta}) \tag{5}$$

$$f(\mathbf{x}_{1:n,t} \,|\, p_{1:n,1:t-1}; \boldsymbol{\theta}) = \prod_{i=1}^{n} f(\mathbf{x}_{i,t} \,|\, p_{i,1:t-1}; \boldsymbol{\theta}) \tag{6}$$

where the individual densities evolve according to:

$$f(\mathbf{x}_{i,t} \,|\, p_{i,1:t-1}; \boldsymbol{\theta}) = \int f(\mathbf{x}_{i,t} \,|\, \mathbf{x}_{i,t-1}; \boldsymbol{\theta})\, f(\mathbf{x}_{i,t-1} \,|\, p_{i,1:t-1}; \boldsymbol{\theta})\, d\mathbf{x}_{i,t-1} \tag{7}$$

$$f(\mathbf{x}_{i,t} \,|\, p_{i,1:t}; \boldsymbol{\theta}) \propto f(p_{i,t} \,|\, \mathbf{x}_{i,t}, p_{i,t-1}; \boldsymbol{\theta})\, f(\mathbf{x}_{i,t} \,|\, p_{i,1:t-1}; \boldsymbol{\theta}) \tag{8}$$

Recovering States from Micro Price Data

Forward filtering backward sampling Back

Lemma 2: Backward sampling

Given our state-space representation:

$$f(\mathbf{x}_{1:n,1:T} \,|\, p_{1:n,1:T}; \boldsymbol{\theta}) = \prod_{i=1}^{n} f(\mathbf{x}_{i,1:T} \,|\, p_{i,1:T}; \boldsymbol{\theta}) \tag{9}$$

$$f(\mathbf{x}_{i,1:T} \,|\, p_{i,1:T}; \boldsymbol{\theta}) = f(\mathbf{x}_{i,T} \,|\, p_{i,1:T}; \boldsymbol{\theta}) \prod_{t=1}^{T-1} f(\mathbf{x}_{i,t} \,|\, \mathbf{x}_{i,t+1}, p_{i,1:t}; \boldsymbol{\theta}) \tag{10}$$

$$f(\mathbf{x}_{i,t} \,|\, \mathbf{x}_{i,t+1}, p_{i,1:t}; \boldsymbol{\theta}) \propto f(\mathbf{x}_{i,t+1} \,|\, \mathbf{x}_{i,t}; \boldsymbol{\theta})\, f(\mathbf{x}_{i,t} \,|\, p_{i,1:t}; \boldsymbol{\theta}) \tag{11}$$

This allows the latent state trajectory to be sampled backwards from time T to 1, one firm at a time.

Full Bayesian Estimation

Priors with closed-form updates

Back

- When possible, use conjugate priors to allow closed-form updates:

$$\mu \sim \mathcal{N}\left(\mu_0, \Sigma_{\mu,0}\right) \tag{12}$$

$$\gamma \equiv \frac{1}{\sigma_\varepsilon^2} \sim Gamma\left(\frac{\nu_0}{2}, \frac{\nu_0}{2}\sigma_0^2\right) \tag{13}$$

$$\lambda \sim Beta\left(a_0, b_0\right) \tag{14}$$

- These prior choices are guided by economic theory
- Conditional posteriors can be derived analytically

Full Bayesian Estimation

A Gibb sampler - details

For each iteration $k = 2, \dots, K$:

1. **Draw trend inflation:** $\mu^{(k)} \sim p(\mu \mid \mathbf{\Theta}^{(-\mu)}, X^{(k-1)}, Z)$
2. **Draw shock volatility:** $\sigma_\varepsilon^{(k)} \sim p(\sigma_\varepsilon \mid \mathbf{\Theta}^{(-\sigma)}, X^{(k-1)}, Z)$
3. **Draw free adjustment probability:** $\lambda^{(k)} \sim p(\lambda \mid \mathbf{\Theta}^{(-\lambda)}, X^{(k-1)}, Z)$
4. **Draw inaction bounds:**
   - Lower: $\underline{s}^{(k)} \sim p(\underline{s} \mid \mathbf{\Theta}^{(-\underline{s})}, X^{(k-1)}, Z)$
   - Upper: $\bar{s}^{(k)} \sim p(\bar{s} \mid \mathbf{\Theta}^{(-\bar{s})}, X^{(k-1)}, Z)$
5. **Draw latent states:** $X^{(k)} \sim p(X \mid \mathbf{\Theta}^{(k)}, Z)$
   via FFBS (Forward Filtering Backward Sampling)

$\mathbf{\Theta}^{(-x)}$ indicates conditioning on all parameters except x

Full Bayesian Estimation

Metropolis-Hastings for $(\underline{s}, \bar{s})$ Back

- Key property of our model: the measurement equation has **no noise**.
- Conditional on states and parameters, likelihood is either 0 or 1.
- We propose values from bounded supports that yield likelihood = 1.
- This implies the likelihood ratio cancels in MH acceptance ratio.
- To construct proposal supports:
  - **Fact 1:** All price gaps must lie in the inaction region, thus:

$$\bar{J}_{\underline{s}} = \min\left\{0,\, p_{i,t} - p^r_{i,t}\right\}, \quad \underline{J}_{\bar{s}} = \max\left\{0,\, p_{i,t} - p^r_{i,t}\right\}$$

  - **Fact 2:** Non-free price changes come from outside inaction region
    - Provides additional restrictions to refine proposal bounds.

Monte Carlo Experiment

Finite-sample recovery

Back

	True	Bias		SD	
		Small	Large	Small	Large
(a) Parameters					
$\underline{s}$	-20.18	0.00	0.00	0.08	0.04
$\bar{s}$	18.90	0.00	0.00	0.10	0.06
μ	0.28	-0.00	-0.00	0.10	0.06
σ_e	3.85	0.04	0.02	0.14	0.09
λ	6.53	-0.04	-0.03	0.43	0.30
(b) Price Gaps					
Ind	-1.02	0.00	0.00	5.82	5.46
Mean	-1.02	0.00	0.00	0.41	0.36
Std	8.25	-0.11	-0.04	0.25	0.24
Skew	-0.03	-0.01	-0.00	0.09	0.09
Kurt	2.66	0.08	0.05	0.13	0.14

Notes: Monte Carlo averages over 1000 replications. True values for Panel (a) are DGP parameters in percentage points. True values for Panel (b) are signed moments averaged over time within each replication and then across replications. Panel (a) reports posterior bias (posterior mean minus true value) and posterior standard deviation for each structural parameter. Panel (b) reports the same statistics for the individual price gap (Ind) and the cross-sectional mean, standard deviation, skewness, and kurtosis of price gaps. All parameter values and price gaps are in percentage points; skewness and kurtosis are scale-free. Small and Large refer to samples with $N = 300$ and $T = 12$ and $T = 24$, respectively.

Estimated Parameters

Back

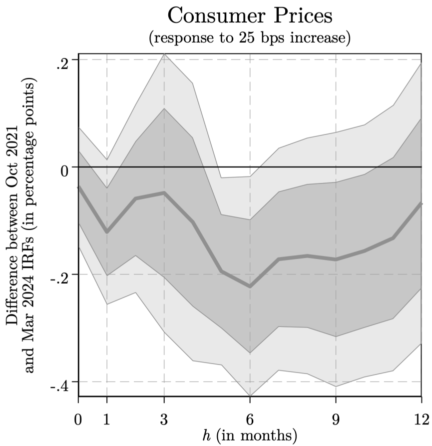
Summary statistics for estimated parameters

	$\hat{\underline{s}}$	$\hat{\bar{s}}$	$\hat{\mu}$	$\hat{\sigma}_{\varepsilon}$	$\hat{\lambda}$	Calv.
Mean	-33.04	49.47	0.11	8.90	7.04	66.53
Median	-22.06	40.42	0.15	8.03	5.14	70.00
Std Dev	33.30	34.11	1.08	4.97	6.39	26.79
IQR	37.94	44.35	0.99	6.08	5.59	47.14
Minimum	-198.95	1.01	-19.13	0.00	0.21	0.00
Maximum	-1.00	198.87	8.53	46.39	71.30	100.00

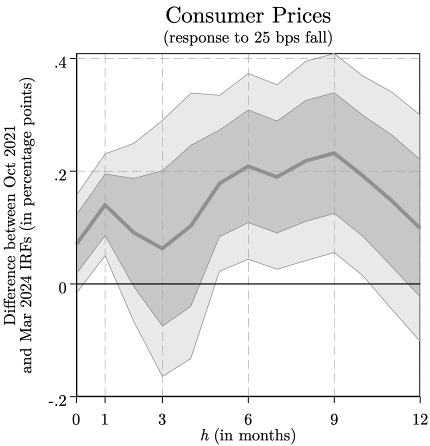
Notes: Summary statistics computed across 15,664 item-window pairs. All statistics are in percent, rounded to two decimals. Calvoness is the share of non-zero price changes inside the inaction region.

IRFs to Monetary Shocks

Difference from benchmark: Oct 2021 – Mar 2024 Back



(a) 25 bp tightening — difference

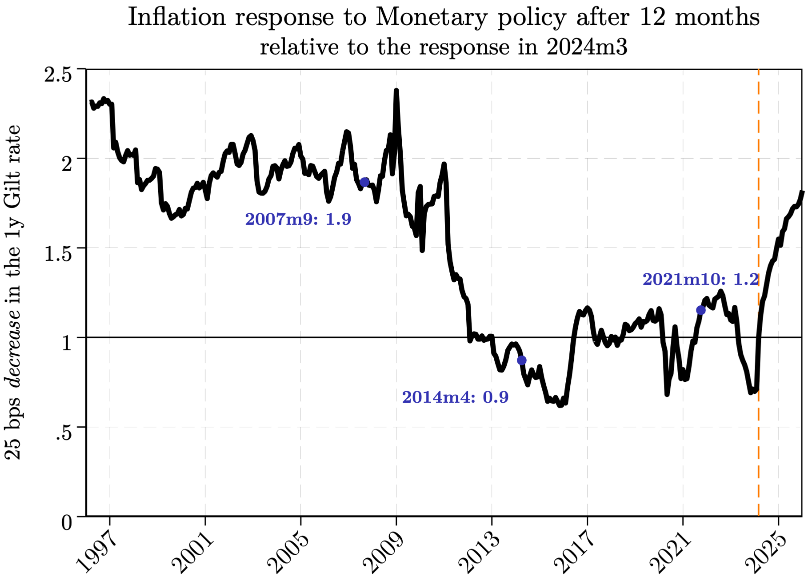


(b) 25 bp easing — difference

Notes: Difference in the cumulative CPI response to a 25 bp tightening (a) and easing (b), October 2021 minus the March 2024 benchmark, from the state-dependent LP-IV. Dark/light bands: 68% and 90% CI; significant where the band excludes zero.

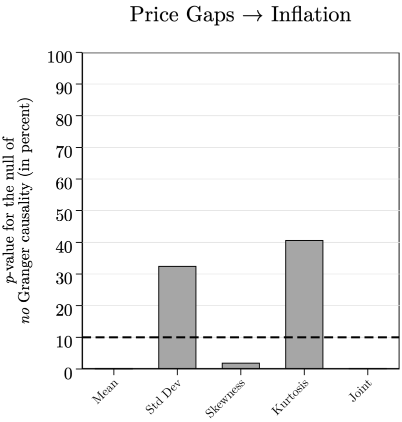
Monetary Policy Pass-through over Time

Cutting Rates Back

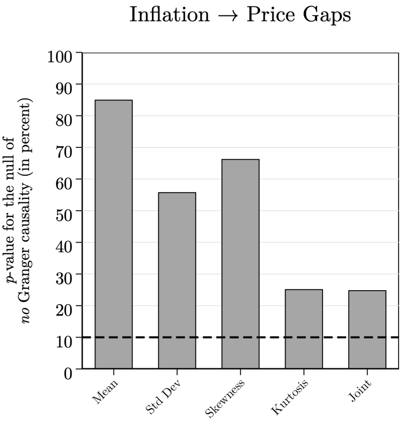


In-sample: Testing for Granger Causality

Back



(a) Gap moments ⇒ inflation



(b) Inflation ⇒ gap moments

One-directional: gap moments Granger-cause inflation, not the reverse

Out-of-sample: Forecasting Setup Back

- Year-on-year inflation **forecasts** based on,

$$\pi^y_{t+h} = \alpha + \mathbf{m}_t^{f\prime}\boldsymbol{\beta} + e_t$$

- $\mathbf{m}_t^f$: **real-time** estimates of standardized price gap moments
- Coefficients estimated on **estimation sample**: 1996m2 - 2016m1
- Forecasts evaluated **out-of-sample**: 2016m2 - 2026m1
- Compare with a **random walk** process: $\widehat{\pi}^y_{t+h} = \pi^y_t$
  - Used as a benchmark since Atkeson and Ohanian (2001)

References

References

Atkeson, Andrew and Lee E. Ohanian, "Are Phillips Curves Useful for Forecasting Inflation?," *Federal Reserve Bank of Minneapolis Quarterly Review*, 2001, *25* (1), 2–11.

Auclert, Adrien, Rodolfo Rigato, Matthew Rognlie, and Ludwig Straub, "New Pricing Models, Same Old Phillips Curves?," *The Quarterly Journal of Economics*, 2024, *139* (1), 121–186.

Bernanke, Ben S. and Olivier J. Blanchard, "What Caused the US Pandemic-Era Inflation?," *American Economic Journal: Macroeconomics*, 2025, *17* (3), 1–35.

Blanco, Andrés, Corina Boar, Callum Jones, and Virgiliu Midrigan, "Nonlinear Dynamics in Menu Cost Economies? Evidence from U.S. Data," 2024. NBER Working Paper 32748.

—, —, —, and —, "Nonlinear Inflation Dynamics in Menu Cost Economies," 2024. NBER Working Paper 32094.

Blanco, Andrés, "Optimal Inflation Target in an Economy with Menu Costs and a Zero Lower Bound," *American Economic Journal: Macroeconomics*, 2021, *13* (3), 108–141.

Braun, Robin, Silvia Miranda-Agrippino, and Tuli Saha, "Measuring Monetary Policy in the UK: The UK Monetary Policy Event-Study Database," *Journal of Monetary Economics*, 2025, *149*, 103645.

Edge, Rochelle and Refet S. Gürkaynak, "How Useful Are Estimated DSGE Model Forecasts for Central Bankers," *Brookings Papers on Economic Activity*, 2010, *2010* (2), 209–244.

Faust, Jon and Jonathan H. Wright, "Forecasting Inflation," in Graham Elliot and Allan Timmermann, eds., *Handbook of Economic Forecasting*, Vol. 2A, Elsevier, 2013, chapter 1, pp. 2–56.

Gagliardone, Luca, Mark Gertler, Simone Lenzu, and Joris Tielens, "Micro and Macro Cost-Price Dynamics in Normal Times and During Inflation Surges," 2025. NBER Working Paper 33478.

Golosov, Mikhail and Robert E. Lucas, "Menu Costs and Phillips Curves," *Journal of Political Economy*, April 2007, *115* (2), 171–199.

Herbst, Edward P. and Frank Schorfheide, *Bayesian Estimation of DSGE Models*, first ed., Princeton University Press, 2015.

Känzig, Diego R., "The Macroeconomic Effects of Oil Supply News: Evidence from OPEC Announcements," *American Economic Review*, 2021, *111* (4), 1092–1125.

References

Karadi, Peter, Anton Nakov, Galo Nuño, Ernesto Pastén, and Dominik Thaler, "Strike While the Iron is Hot: Optimal Monetary Policy with a Nonlinear Phillips Curve," 2025. ECB Working Paper 3068.

Kitagawa, Genshiro, "Non-Gaussian State-Space Modeling of Nonstationary Time Series," *Journal of the American Statistical Association*, December 1987, *82* (400), 1032–1041.

Nakamura, Emi and Jón Steinsson, "Monetary Non-Neutrality in a Mutisector Menu Cost Model," *The Quarterly Journal of Economics*, August 2010, *125* (3), 961–1013.

Särkkä, Simo, *Bayesian Filtering and Smoothing* Institute of Mathematical Statistics Textbooks, first ed., Cambridge University Press, 2013.

Shapiro, Adam Hale, "Decomposing Supply- and Demand-Driven Inflation," *Journal of Money, Credit and Banking*, 2024.

Stock, James H and Mark W Watson, "Forecasting inflation," *Journal of monetary economics*, 1999, *44* (2), 293–335.

Stock, James H. and Mark W. Watson, "Phillips Curve Inflation Forecasts," in Jeffrey Fuhrer, Yolanda Kodrzycki, Jane Little, and Giovanni Olivei, eds., *Understanding Inflation and the Implications for Monetary Policy*, Cambridge, MA: MIT Press, 2009, pp. 101–186.