The Future in Today's Prices: Evidence from Trade Policy Shocks

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Abstract

Do firms adjust prices to realized costs, expected costs, or both? We address this question using a new survey of U.S. small and medium-sized businesses that separately measures realized cost changes since the last price adjustment and expected cost changes over the subsequent year, including the share attributable to the new tariffs introduced in 2025. Cross-sectional variation in tariff exposure, combined with an orthogonalized expectations instrument, identifies the causal effects of realized and expected costs on price changes. Pass-through from realized trade-related costs is approximately 0.8, while expected future costs are partially incorporated at the time of adjustment. The relative importance of these channels varies systematically across firms: frequent price adjusters load primarily on current costs, whereas sticky-price firms place greater weight on expected costs; goods producers largely adjust contemporaneously to cost shifts, while services firms are more forward-looking; and higher tariff-related uncertainty shifts pricing toward expectations. While Calvo pricing can rationalize a role for nominal rigidity, the evidence aligns most closely with endogenous pricing frameworks in which frictions and uncertainty reshape the reset-price kernel across horizons.

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1 Introduction

A central feature of modern macroeconomic models is that firms set prices in a forward-looking manner. In New Keynesian and related frameworks, inflation dynamics depend not only on current marginal costs but also on firms' expectations about future costs and economic conditions. At the firm level, this behavior is characterized by a pricing rule in which the optimal reset price reflects a weighted average of expected marginal costs over the future duration of the price. In reduced form, a convenient benchmark that captures this forward-looking logic is represented by

$$\Delta P_i = \alpha + \beta\, \Delta C_i + \gamma\, \Delta C_i^e + \varepsilon_i, \tag{1}$$

where price changes respond to both realized cost changes since the last adjustment and expected future cost changes over the horizons during which the price is expected to remain in place, and possibly beyond.

This paper provides new micro-level evidence on how firms adjust prices in response to realized and expected cost changes. The evidence comes from a new quarterly survey of U.S. small and medium-sized businesses (SMBs), with approximately 500–600 firms per quarter from 2022:Q2 to 2025:Q4. The survey is designed to map directly into (1): it elicits (i) the firm's realized price change, (ii) the contemporaneous cost change since the previous price adjustment, and (iii) the firm's expected cost change over the subsequent year, measured at the time the price change is implemented – objects that are rarely observed jointly in standard firm-level datasets. Moreover, by focusing on SMBs – rather than large multiproduct firms – the empirical setting is closer to the single-product benchmark underlying much of the pricing literature.

Using these data, we estimate the causal effects of contemporaneous realized and expected future cost changes on firms' price adjustments by leveraging cross-firm variation in each component induced by differential exposure to trade-policy shocks. The baseline estimates indicate economically meaningful roles for both channels. The implied pass-through from realized trade-related cost changes to prices is approximately 0.8. In addition, expected future cost increases are partially incorporated at the time of price adjustment, with an estimated coefficient of about 0.4. Thus, firms' reset prices reflect both realized cost movements since the last adjustment and forward-looking considerations about anticipated cost changes.

Yet, results are quite nuanced: The importance of current and expected costs varies sharply across firms and environments. Frequent adjusters display largely contemporaneous pricing: nearly full pass-through of realized costs and little sensitivity to expected future costs. Infrequent adjusters, by contrast, place substantially more

weight on expected costs, with a muted response to realized cost changes. We also find systematic sectoral differences. Goods-producing firms exhibit near-complete contemporaneous pass-through and limited anticipatory pricing, whereas service-sector firms are significantly more forward-looking, loading on both realized and expected cost changes. Finally, uncertainty shifts pricing toward expectations. This is seen in two exercises. First, we split firms based on industry-level estimates of the prevalence of fixed-schedule (i.e., Taylor) pricing and find that forward-looking pricing behavior only exists in industries with relatively less fixed-schedule pricing. This is true for both firms that have long and short price durations and could reflect precautionary pricing behavior in firms that have greater uncertainty over the timing of future price adjustments. Second, using subjective uncertainty inferred from moments of firms' tariff-related cost expectations, we find that firms facing higher uncertainty respond more strongly to expected future costs, consistent with a tilt toward forward-looking pricing when the cost outlook is more uncertain.

Our identification strategy exploits unexpected trade policy changes as a source of cross-sectional variation. We use heterogeneity in firms' exposure to tariff changes announced in early 2025 to construct instruments for realized and expected cost changes. Trade policy generates plausibly exogenous variation in both realized costs and cost expectations, with exposure varying across firms by import intensity, sector, firm age, and supply-chain structure. By directly eliciting from firms the portion of their realized and expected cost changes attributable to trade policy, we obtain distinct instruments for contemporaneous and expected cost movements and isolate their independent effects on price changes.

We interpret this heterogeneity through a generalized-hazard framework of price setting. In these models, a firm's reset price is an intertemporal object: it reflects a weighted average of expected marginal costs over the periods in which the price is likely to remain in place. The weights are given by the reset-price kernel, pinned down by the survival profile of the price—equivalently, by the expected duration and the entire path of adjustment hazards. Importantly, both pricing frictions and uncertainty can shift these hazards: changes in the volatility of the firm's cost environment or in the perceived risk of price misalignment can alter the timing of adjustment and, in turn, reallocate kernel weight toward nearer or more distant horizons. As a result, uncertainty affects not only whether firms adjust, but also which horizons of costs are most salient at the time they reset prices.

This perspective rationalizes the empirical heterogeneity we document. Firms that adjust prices frequently place most weight on current costs, while firms with infrequent adjustment load more heavily on expected future costs, consistent with longer expected

price durations. Uncertainty can further tilt pricing toward expectations by shifting hazards and raising the cost of being mispriced going forward. While a Calvo model can capture the presence of pricing frictions, the patterns in the data align most closely with generalized-hazard and menu-cost frameworks—where frictions and uncertainty reshape the reset-price kernel—rather than with fixed-horizon Taylor pricing or Calvo models with an invariant hazard.

The remainder of the paper proceeds as follows. Section 2 describes the survey data and measurement of prices, costs, expectations, and trade exposure. Section 3 presents the empirical strategy and baseline results. Section 4 develops the generalized hazard framework and derives testable predictions linking pricing frictions, uncertainty, and the horizon profile of cost pass-through. Section 5 explores heterogeneity by adjustment frequency, sector, and uncertainty, and discusses aggregate implications. Section 6 concludes.

Related Literature

This paper contributes to three strands of literature. The first studies the role of expectations in inflation and price setting. A large macro tradition estimates forward-looking Phillips curves and the link between inflation and expected marginal costs using aggregate data Galí and Gertler (1999); Sbordone (2002) and evaluates identification and specification challenges in that approach (Mavroeidis et al., 2014; Barnichon and Mesters, 2020). More recently, a growing micro literature uses firm surveys to study how inflation and cost expectations map into firms' pricing and real decisions (Coibion et al., 2022; Boneva et al., 2022; Coibion et al., 2020; Andrade et al., 2022; Abberger et al., 2024). We contribute by combining direct firm-level measures of expected cost changes at the time of price adjustment with trade-policy-based identification, which allows us to separately quantify contemporaneous and anticipatory pass-through. Much of the existing survey evidence relates expected costs to expected prices over a common horizon. Our estimates instead isolate pre-emptive price adjustment to expected future costs and, in doing so, help discipline the pricing mechanisms embedded in forward-looking models.

A second strand of the literature studies the pass-through of cost shocks into prices, often exploiting large realized shocks or discrete policy events in micro price data. Prominent examples include exchange-rate movements and tax changes (Gopinath et al., 2010; Karadi and Reiff, 2019), as well as tariffs (Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021, 2025). We complement this work by using trade policy to identify not only pass-through from realized cost changes, but also anticipatory pass-through from expected future costs measured directly at the firm level, building

on recent work that exploits survey-based measures of cost expectations (Meier and Sheng, 2025; Ghassibe et al., 2025).[1]

Our analysis also speaks to an ongoing debate about the magnitude of pass-through to prices, specifically as faced by domestic consumers. Existing estimates vary widely. Using border prices, Amiti et al. (2019) find near-complete pass-through of tariffs into the prices paid by U.S. importers, while studies based on firm–product–level retail prices from large retailers find substantially lower pass-through (Cavallo et al., 2021, 2025). Our estimates lie between these benchmarks and are notably higher than those obtained from large-retailer data, despite also relying on firm-level information. There are several possible reasons for this difference. First, we use directly measured firm-level actual and expected cost increases rather than proxies based on statutory tariff rates or effective tariff rates derived from more aggregated data. As these rates likely overstate the true cost burden by not accounting for firm-specific exemptions or foreign supplier concessions, pass-through rates estimated using such measures would be a lower bound for true rates. Secondly, we focus on SMBs while larger firms may be more able to obtain such exemptions and concessions.[2] Lastly, SMBs are less likely to engage in multi-product pricing strategies, such as spreading price increases across products that are both affected and unaffected by a given cost shock, that would complicate the identification of pass-through using cross-product rather than cross-firm variation in prices and tariffs. Notably, retail pass-through can also be further shaped by distribution margins: as emphasized by Burstein et al. (2003), distribution costs are large and local-input intensive, creating a wedge between border costs and final consumer prices.

The third strand develops generalized-hazard and endogenous-adjustment models, including menu-cost frameworks, that discipline how price sensitivity is distributed across horizons (Alvarez et al., 2022; Werning, 2022). In these models, pricing frictions shape the reset-price kernel and thus the relative weight placed on current versus expected future marginal costs. Our contribution is to articulate the resulting predictions for cost pass-through and bring them to the data, exploiting heterogeneity in adjustment frequency, sector, and uncertainty to assess which pricing frameworks best organize the empirical patterns.

[1] While not their primary focus, the finding in Cavallo et al. (2025) that prices of affected goods rise within days of tariff announcements is consistent with anticipatory pass-through of the type we document.

[2] Indeed, the Appendix of Cavallo et al. (2021) discusses lower pass-through experienced at the border for larger importers.

2 Survey Data

We use a new quarterly survey of U.S. small and medium-sized businesses (SMBs) designed to measure firm outcomes and expectations at the decision-maker level. The survey is administered by Morning Consult (see also Hajdini et al., 2022, 2024). It was first fielded in 2022:Q2 as repeated cross-sections of roughly 500–600 firms and became a permanent quarterly survey in 2024:Q4. Respondents are SMB owners and other decision-makers recruited through vetted panel providers, with multiple checks to ensure data quality and to limit inattentive or automated responses.[3] Sampling is stratified by firm size, with equal quotas for sole proprietors, firms with 2–10 employees, 11–100 employees, and 101–500 employees. Our analysis primarily uses the 2025:Q3 wave (fielded between August 20, 2025 and August 29, 2025) with some supplemental information from the 2025:Q4 wave.

We reweight observations to match the national SMB population using iterative proportional fitting (IPF), targeting region, industry, and firm size. In the weighted data, sectoral composition and firm characteristics are broadly consistent with external benchmarks: the most common sectors include retail trade, professional/scientific/technical services, construction, and health care and social assistance; firms are most likely to be located in the South Census region; and the median firm has been operating for more than seven years (Table A.1). The distribution of revenues is also comparable to Census aggregates, with a modest tilt toward lower revenue ranges consistent with an SMB-focused frame (Figure A.1). Demographic and role characteristics of respondents are reported in Table A.1; most respondents are C-level decision-makers, and the survey records race, gender, education, and political affiliation.

The central variables for this paper measure pricing and cost dynamics around firms' own price-setting decisions, with explicit separation of trade-policy components. Firms report the frequency of price changes and the time since the last adjustment. For the most recent price change, they report the size and direction of the price adjustment and the cumulative change in costs since the previous price change. Costs are reported both in total and for the portion attributable to trade policy, which permits a transparent decomposition of trade-related versus non-trade cost pressures. Appendix B contains the main questions.

The survey also elicits forward-looking beliefs at the time of price adjustment. Firms report expected cost changes over the subsequent 12 months, including average,

[3]For more information on Morning Consult's data-collection methodology, see "Morning Consult: Our Methodology," Morning Consult, `https://pro.morningconsult.com/our-methodology`. Accessed March 6, 2025.

downside, and upside scenarios, and separately report the trade-policy-driven component of those expected cost changes. Firms additionally report expected price changes over the same horizon. Finally, the survey measures exposure to trade policy directly: firms indicate which tariff or trade-policy categories affect their costs, how long they expect those effects to persist, and the average tariff rate paid on imported goods and services.

To ensure data quality, we exclude respondents who mechanically select "stay the same" across the full block of cost and price expectation questions spanning multiple horizons and categories (e.g., borrowing and credit costs). This exclusion targets inattentive response patterns rather than economically meaningful zero changes.

3 Empirical Strategy and Identification

Estimating forward-looking pass-through requires isolating variation in costs that shifts today's marginal cost separately from beliefs about future costs. In the cross section, those objects are typically entangled by persistence, common news, and suppliers' pricing. We show how one can exploit firm-level exposure to the 2025 trade-policy episode to generate independent shifters for each channel.

3.1 Trade policy instrument

We study whether firms adjust prices in response to both current cost changes and anticipated future cost changes. Let i index firms. Our pricing equation is

$$\Delta P_i \;=\; \alpha \;+\; \beta\,\Delta C_i \;+\; \gamma\,\Delta C_i^{e} \;+\; \varepsilon_i, \tag{2}$$

where ΔP_i is the percent change in the firm's price for its main product/service since the last adjustment, ΔC_i is the contemporaneous percent change in marginal cost since the last price adjustment, ΔC_i^e is the firm's expected percent change in marginal cost over the next 12 months, and ε_i captures all other determinants of ΔP_i. Because ΔC_i and ΔC_i^e can be jointly determined, $\mathbb{E}[\Delta C_i\,\varepsilon_i] \neq 0$ and/or $\mathbb{E}[\Delta C_i^e\,\varepsilon_i] \neq 0$, rendering OLS estimates of (β, γ) biased.

Intuitively, why may they be jointly determined? On the one hand, because some suppliers adjust prices today, and their pricing rule incorporates expectations of a news shock that is common to suppliers and firms, a firm's costs today may change because of such a common news shock. There could also be feedback due to news via wages (or other general equilibrium effects) but such a contemporaneous wage effect should be second-order due to wage rigidity. On the other hand, a current cost increase may

simply carry forward into expected cost increases due to persistent cost drivers.

3.2 Source of Exogenous Variation

To gain identification, we exploit heterogeneous exposure of firms to trade and the "Liberation Day" unexpected changes in trade policy. We use this exogenous variation as an instrument for current and expected cost changes, and make sure to orthogonalize any common movements between the two to separate current and expected cost channels.

The survey elicits two policy-linked measures of cost changes from each firm which form the basis for our identification:

$$Z_{1i} \equiv \Delta(C_i \mid \text{trade policy}), \tag{3}$$

$$\tilde{Z}_{2i} \equiv \Delta(C_i^e \mid \text{trade policy}). \tag{4}$$

Because for example persistence in input pricing may mechanically correlate $\tilde{Z}_{2i}$ with Z_{1i}, we orthogonalize:

$$Z_{2i} \;\equiv\; \tilde{Z}_{2i} \;-\; \Pi\, Z_{1i}, \qquad \text{where } \Pi \text{ is from the sample regression } \; \tilde{Z}_{2i} = \Pi Z_{1i} + \nu_i. \tag{5}$$

Thus Z_{2i} is the component of expected, trade-policy–related cost changes uncorrelated with (potentially policy-induced) current cost changes. Intuitively, orthogonalization creates a statistical split between current and expectations variation.

3.2.1 First stage and instrument relevance

We treat both ΔC_i and ΔC_i^e as endogenous and use the two instruments (Z_{1i}, Z_{2i}) in a 2SLS system (just- or over-identified depending on controls). Let X_i denote included controls (e.g., sector, price-stickiness group, time-since-last change, exposure indicators). The first stages are

$$\Delta C_i = \pi_{10} + \pi_{11}\, Z_{1i} + \pi_{12}\, Z_{2i} + \delta_1' X_i + u_{1i}, \tag{6}$$

$$\Delta C_i^e = \pi_{20} + \pi_{21}\, Z_{1i} + \pi_{22}\, Z_{2i} + \delta_2' X_i + u_{2i}. \tag{7}$$

Relevance (rank condition). The 2×2 matrix $\Pi_{\text{FS}} = \begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{bmatrix}$ must have full column rank:

$$\operatorname{rank}\big(\operatorname{Cov}\big([Z_{1i}, Z_{2i}], [\Delta C_i, \Delta C_i^e]\big)\big) = 2. \tag{8}$$

Empirically, we report first-stage F-statistics and Sanderson–Windmeijer conditional F-statistics.

3.2.2 Exclusion restrictions and identifying assumptions

Our identifying content is the set of conditional moment restrictions

$$\mathbb{E}\big[\,(Z_{1i}, Z_{2i})'\,\big(\Delta P_i - \alpha - \beta\,\Delta C_i - \gamma\,\Delta C_i^e - \theta' X_i\big)\,\big|\,X_i\big] = 0, \tag{9}$$

implied by:

Assumption A (Exogeneity / Exclusion). Conditional on X_i,

$$\mathbb{E}[Z_{1i}\,\varepsilon_i \mid X_i] = 0, \qquad \mathbb{E}[Z_{2i}\,\varepsilon_i \mid X_i] = 0, \tag{10}$$

and (Z_{1i}, Z_{2i}) affect ΔP_i only through ΔC_i and ΔC_i^e.

Our main identifying assumption in terms of **current costs** is that trade-policy measures – to first order – differentially shift firms' input costs according to their trade exposure, thereby exogenously moving *current* production costs for reasons unrelated to firm-specific shocks. This is the core exclusion story for Z_{1i}. We acknowledge a secondary effect: current input quotes may also reflect suppliers' reactions to *future* trade policy (pre-pricing or persistence). This does not undermine identification because the underlying trade-policy shock is exogenous; thus, the induced movements in current costs remain as-if exogenous to firm-specific pricing shocks, and the expectations channel is handled separately below. In terms of **expected future costs**, our survey simply elicits the part of expected cost changes due to changes in trade policy on beliefs ($\tilde{Z}_{2i}$). This variation is assumed to be exogenous and to affect prices only through ΔC_i^e, not directly and through current input costs. To reinforce our identification assumptions, we orthogonalize the expectations instrument to the current-cost instrument so that the expectations variation is independent of contemporaneous policy-induced cost movements.

Assumption B (No cross-channel contamination after residualization).

$$\mathrm{Cov}(Z_{1i}, \Delta C_i^e \mid X_i) = 0, \qquad \mathrm{Cov}(Z_{2i}, \Delta C_i \mid X_i) = 0. \tag{11}$$

The orthogonalization in (5) and controls X_i (e.g., indicators for being policy-affected, sector exposure, and expected policy duration) are designed to satisfy (11).

3.2.3 Estimation

Stacking (2) over firms and writing $W_i = [\,\Delta C_i \;\; \Delta C_i^e \;\; X_i\,]$ and $Z_i = [\,Z_{1i} \;\; Z_{2i} \;\; X_i\,]$, our 2SLS estimator solves

$$\widehat{\theta}_{\text{2SLS}} \;=\; \arg\min_{\theta} \left(\sum_i Z_i'(\Delta P_i - W_i\theta)\right)' \left(\sum_i Z_i Z_i'\right)^{-1} \left(\sum_i Z_i'(\Delta P_i - W_i\theta)\right), \quad (12)$$

with $\theta = (\alpha, \beta, \gamma, \theta_X)'$. We report heteroskedasticity-robust (or jackknife) standard errors and, when over-identified, the Hansen J-test to assess (9).

3.2.4 Extension: Strategic complementarities

Firms may adjust prices not only because their own costs change, but also because competitors adjust their prices. Competitors change prices when their current costs shift and when their beliefs about future costs shift. To capture this, define peer averages for firm i as $W\Delta C_i = \sum_{j\neq i} w_{ij}\Delta C_j$ for peers' current costs and $W\Delta C_i^e = \sum_{j\neq i} w_{ij}\Delta C_j^e$ for peers' expected costs (beliefs). In the baseline, $w_{ij} = 1/N_i$ where N_i is the number of firms in the full sample (leave-one-out for i); as a robustness specification, $w_{ij} = 1/N_i$ where N_i is the number of firms in i's sector (leave-one-out).

Notably, there is a problem with using such peer averages. They are endogenous because peer averages co-move with i's pricing error due to common shocks (economy-wide trade policy), simultaneity (my price depends on theirs and theirs on mine), and omitted factors (local demand, contract cycles). Uninstrumented peer means therefore bias estimates—this is the Manski "reflection problem." A solution lies in proper instrumentation and carefully taking into account a *shared aggregate trade-policy component* that mechanically loads both own and peer instruments.

Specifically, the approach is to residualize each instrument by its group mean and gain identification from cross-sectional exposure differences. Concretely, define a grouping $g(i)$ (e.g., sector, or the full sample as one group). Let $\bar{Z}_{1,g}$ be the mean of Z_1 within group g and define $\tilde{Z}_{1i} = Z_{1i} - \bar{Z}_{1,g(i)}$. Use $\tilde{Z}_{1i}$ in place of Z_{1i}. For expectations, we analogously first form the raw expectations instrument $\tilde{Z}_{2i}^{raw}$ from the survey, residualize it by group to obtain $\breve{Z}_{2i} = \tilde{Z}_{2i}^{raw} - \overline{\tilde{Z}}_{2\,g(i)}$, and then orthogonalize to the residualized current-cost instrument: $Z_{2i} = \breve{Z}_{2i} - \Pi\,\tilde{Z}_{1i}$. This two-step procedure removes the aggregate policy component and then separates current from expectations variation. We apply the same residualization to peer instruments. That is, we define $\widetilde{WZ}_{1i} = \sum_{j\neq i} w_{ij}\tilde{Z}_{1j}$ and $\widetilde{WZ}_{2i} = \sum_{j\neq i} w_{ij}Z_{2j}$ using the same w_{ij} as for $W\Delta C_i$ and

$W\Delta C_i^e$.

The previous price setting equation now becomes

$$\Delta P_i = \alpha + \beta\,\Delta C_i + \gamma\,\Delta C_i^e + \beta^P\,W\Delta C_i + \gamma^P\,W\Delta C_i^e + \theta' X_i + \varepsilon_i, \tag{13}$$

with endogenous regressors $\{\Delta C_i, \Delta C_i^e, W\Delta C_i, W\Delta C_i^e\}$ and instrument set $\{\tilde{Z}_{1i}, Z_{2i}, \widetilde{WZ}_{1i}, \widetilde{WZ}_{2i}\}$, plus controls X_i and group fixed effects. The exclusion restriction is then transparent in a cross-section: after removing group means, $\tilde{Z}_{1i}$ shifts ΔC_i but has no remaining direct path to other firms' prices; Z_{2i} shifts ΔC_i^e and is orthogonal to $\tilde{Z}_{1i}$; $\widetilde{WZ}_{1i}$ and $\widetilde{WZ}_{2i}$ shift the peer cost channels $W\Delta C_i$ and $W\Delta C_i^e$, respectively. Identification comes from *within-group cross-sectional exposure differences*, not from aggregate policy movements.

We then estimate our price setting equation by 2SLS with the endogenous set and residualized instruments described above, include group (e.g., sector) fixed effects, use leave-one-out weights in the peer constructions, and cluster at the group level. Coefficients β and γ recover own pass-through—current and forward-looking—while β^P and γ^P recover strategic complementarities, i.e., responses to others' current costs and to others' beliefs. Because the instruments are purged of the aggregate component and expectations shifters are orthogonalized to current-cost shifters, the decomposition remains clean in a single-cross-section setting.

4 Results

This section presents our main empirical results. First, using firm-level exposure to the 2025 trade-policy episode as an instrument, we find economically large pass-through from both realized cost changes and expected cost changes: in the full sample, we obtain a coefficient of $\widehat{\beta} \approx 0.80$ for the pass-through of realized cost changes to prices and a coefficient of $\widehat{\gamma} \approx 0.39$ for the pass-through of expected cost changes to prices. Second, the relative importance of the two channels is highly heterogeneous: frequent adjusters respond almost entirely to contemporaneous costs, whereas infrequent adjusters load much more on expected costs. Third, splitting by residual tariff-related uncertainty reveals an additional reallocation across horizons, with high-uncertainty firms pricing expected cost changes much more strongly than low-uncertainty firms.

Table 1: Price Changes and (Expected) Cost Changes

	(1) OLS	(2) IV	(3) IV First Stages	(4) IV First Stages
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.598***	0.798***		
	(0.051)	(0.125)		
ΔC_i^e	0.253***	0.387**		
	(0.077)	(0.158)		
Z_{1i}			0.629***	0.246***
			(0.101)	(0.057)
Z_{2i}			-0.135	0.610***
			(0.103)	(0.077)
Constant	4.158***	2.923***	2.257***	4.814***
	(0.599)	(1.065)	(0.703)	(0.407)
N	537	526	526	526
R^2	0.365	0.347	0.202	0.264
SW F-stats			44.80	75.21

Note: Columns (1) and (2) contain OLS and IV regressions of price changes on actual contemporaneous cost changes and expected future cost changes as in equation (2). The instruments used are Z_{1i} defined in equation (3) and Z_{2i} defined in equation (5). Columns (3) and (4) are the first stage regressions from the IV, corresponding to equations (6) and (7). Both OLS and IV estimates are obtained using jackknife procedures that excludes observations that are overly influential to our main coefficients of interest. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.1 Estimating Causal Effects

Our benchmark estimation of equation (2), presented in Table 1, reveals that actual price changes have an OLS coefficient on contemporaneous cost changes of about 0.6 and on expected cost changes over the next year of 0.25. When we instrument with variables constructed from (expected) cost changes due to tariffs, the coefficient on contemporaneous cost changes grows to 0.8 and the coefficient on expected cost changes to 0.39. Both instruments are strong, with Sanderson-Windmeijer F-stats for multiple endogenous regressors that well exceed the rule-of-thumb threshold of 10.

Note from Table 2 that if univariate OLS regressions of price changes on either actual or expected cost changes tend to yield estimates that are more tilted toward expected future cost changes—a smaller coefficient on current cost changes and larger coefficient on expected cost changes. Using our instruments brings univariate IV estimates closer to the jointly estimated coefficients in Table 1.

As another way to identify anticipatory pricing purely in expectation of increases in costs, we implement our same identification strategy but at a time before actual costs could have been affected by any new tariff policies. To this end, we limit attention to price changes that occurred between November 2024 and January 2025 (inclusive).

Table 2: Univariate Regressions of Price Changes on (Expected) Cost Changes

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		IV		IV First Stages	
	ΔP_i	ΔP_i	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.679***		0.874***			
	(0.075)		(0.104)			
ΔC_i^e		0.558***		0.411***		
		(0.081)		(0.157)		
Z_{1i}					0.649***	
					(0.090)	
Z_{2i}						0.673***
						(0.106)
Constant	5.432***	5.247***	4.442***	5.377***	2.512***	6.035***
	(0.635)	(0.748)	(0.923)	(1.278)	(0.715)	(0.442)
N	538	539	543	527	543	527
R^2	0.189	0.103	0.216	0.056	0.206	0.174
SW F-stats					51.66	40.50

Note: Columns (1) and (2) ((3) and (4)) contain OLS (IV) univariate regressions of price changes on either actual contemporaneous cost changes or expected future cost changes. The instruments used are Z_{1i} defined in equation (3) and Z_{2i} defined in equation (5). Columns (5) and (6) are the first stage regressions from the IV. Both OLS and IV estimates are obtained using jackknife procedures that excludes observations that are overly influential to our main coefficients of interest. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We can then estimate equation (2) using these responses with the same identification strategy, again constructing instruments from actual and expected tariff-related cost changes reported for those months.[4] Table A.3 in the Appendix presents the results showing that, while there were similar reduced-form relationships between price changes and (expected) cost changes in the November 2024 through January 2025 period, these prices were not reacting specifically to changes in cost expectations caused by expected tariffs at least when we look at the overall behavior of all SMBs.

Table A.3 in the Appendix shows that, if we limit attention to only firms with more than 10 employees (including the owner), then we do detect a purely pre-emptive effect of tariff-caused expected cost changes on prices in the November 2024 through January 2025 time frame.[5] This suggests that there may be fixed costs associated with making

[4]For this analysis, we use responses to the question on specifically January 2025 price changes, and associated retrospective actual contemporaneous and expected cost changes as of January and for price changes in November and December 2024, we use the responses related to the most recent price change for those respondents who indicated that this price change occurred eight or nine months ago (relative to the August 2025 survey).

[5]Similar results obtain for firms with $500,000 or greater revenues in the preceding fiscal year, though we prefer the employment measure of firm size as there may be greater volatility in revenues from year-to-year.

anticipatory price changes in advance of expected cost changes.

Average price duration and pass-through. We next also assess whether firms with stickier prices set prices with more emphasis on expected future cost movements than contemporaneous ones. Figure A.3 in the Appendix displays the distribution of average price durations across firms in our sample. The duration of prices at the median firms is 6 months. We do so by limiting to firms that report typically changing prices every seven or more months, about half of the firms. Panel A) of Table 3 reports these results. Indeed, the reduced-form relationships indicate that prices for these firms move more with expected future cost movements and less with contemporaneous cost changes. In the IV estimation, only expected future cost movements have a statistically significant effect on prices.

On the flip side, Panel B) of Table 3 reports the results of our estimation but now including only SMBs who indicate a price duration of six or fewer months. In both the reduced-form and IV regressions, we now see that only contemporaneous costs matter and, in both cases, have a one-to-one relationship with prices.

Differences in pass-through across sectors. Looking separately within only goods- or services-producing firms, Table 4 shows that goods producers fully passed through contemporaneous cost changes while not responding to expected future changes. On the other hand, services firms are more forward-looking in their pricing. Note that this result is not simply an artifact of differential price stickiness between the two sectors. In our sample, the mean price duration is the same among services and goods firms while the median price duration is 3 months longer for services firms. However, even estimating only within the set of firms with stickier prices (defined in Table 3 as those who change prices every seven or more months), services firms are still more forward-looking than goods firms.

Type of price setting and pass-through. We can also examine whether firms that typically adjust prices on a fixed schedule (i.e., Taylor) pricing respond differently to current and expected future cost changes. To do so, we split our sample using industry-level estimates of the prevalence of fixed-schedule pricing.[6] No firms in the "Agriculture, Forestry, Fishing, and Hunting" and "Utilities" industries adjust prices on a fixed schedule while nearly all firms in "Administrative and Support and Waste Management and Remediation Services" do. The median firm is from an industry in which roughly one-third of firms state that they change prices on a fixed schedule.

[6]These industry level estimates are based on responses from a 2025:Q4 survey wave in which we directly ask firms whether they typically adjust prices on a fixed schedule or irregularly.

Table 3: Price Changes and (Expected) Cost Changes, by Average Price Duration

Panel A) Price duration of 7 Months or more

	(1) OLS	(2) IV	(3) IV First Stages	(4)
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.389***	0.213		
	(0.129)	(0.279)		
ΔC_i^e	0.649***	0.599**		
	(0.129)	(0.241)		
Z_{1i}			0.646***	0.256***
			(0.145)	(0.079)
Z_{2i}			-0.120	0.633***
			(0.204)	(0.110)
Constant	3.327***	4.646***	2.876**	5.419***
	(0.689)	(1.659)	(1.246)	(0.595)
N	257	254	254	254
R^2	0.374	0.384	0.121	0.196
SW F-stats			31.32	37.53

Panel B) Price duration of 6 Months or less

	(1) OLS	(2) IV	(3) IV First Stages	(4)
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.886***	1.140***		
	(0.096)	(0.242)		
ΔC_i^e	-0.045	0.274		
	(0.133)	(0.207)		
Z_{1i}			0.515***	0.315***
			(0.092)	(0.093)
Z_{2i}			-0.006	0.671***
			(0.067)	(0.118)
Constant	4.526***	2.209	1.669***	4.131***
	(1.042)	(1.495)	(0.437)	(0.530)
N	279	272	272	272
R^2	0.314	0.255	0.305	0.397
SW F-stats			29.98	30.69

Note: Columns (1) and (2) contain OLS and IV regressions of price changes on actual contemporaneous cost changes and expected future cost changes as in equation (2). The instruments used are Z_{1i} defined in equation (3) and Z_{2i} defined in equation (5). Columns (3) and (4) are the first stage regressions from the IV, corresponding to equations (6) and (7). The two panels are estimated on subsamples defined by firms' reported frequency of price changes. Both OLS and IV estimates are obtained using jackknife procedures that excludes observations that are overly influential to our main coefficients of interest. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Price Changes and (Expected) Cost Changes, by Sector

Panel A) Goods-producing firms

	(1) OLS	(2) IV	(3) IV First Stages	(4) IV First Stages
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	1.039***	1.076***		
	(0.129)	(0.192)		
ΔC_i^e	-0.496***	0.137		
	(0.180)	(0.245)		
Z_{1i}			0.741***	0.253***
			(0.146)	(0.077)
Z_{2i}			0.043	0.889***
			(0.174)	(0.096)
Constant	5.700***	2.615**	0.885	3.911***
	(0.946)	(1.150)	(0.637)	(0.446)
N	186	177	177	177
R^2	0.350	0.540	0.587	0.569
SW F-stats			10.98	48.36

Panel B) Services-producing firms

	(1) OLS	(2) IV	(3) IV First Stages	(4) IV First Stages
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.447***	0.694***		
	(0.096)	(0.166)		
ΔC_i^e	0.467***	0.469***		
	(0.101)	(0.166)		
Z_{1i}			0.570***	0.227***
			(0.117)	(0.070)
Z_{2i}			-0.134	0.637***
			(0.144)	(0.085)
Constant	3.656***	3.077***	2.865***	4.974***
	(0.740)	(1.097)	(0.953)	(0.498)
N	346	340	340	340
R^2	0.337	0.376	0.102	0.216
SW F-stats			36.73	67.82

Note: Columns (1) and (2) contain OLS and IV regressions of price changes on actual contemporaneous cost changes and expected future cost changes as in equation (2). The instruments used are Z_{1i} defined in equation (3) and Z_{2i} defined in equation (5). Columns (3) and (4) are the first stage regressions from the IV, corresponding to equations (6) and (7). The two panels are estimated on subsamples of only goods- or services-producing firms. Both OLS and IV estimates are obtained using jackknife procedures that excludes observations that are overly influential to our main coefficients of interest. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows that firms from industries with low prevalence of Taylor-type pricing (i.e., those in which relatively more firms adjust prices irregularly) are the ones who respond more to expected future costs while firms in industries in which fixed-schedule adjustment is more prevalent tend to only react to contemporaneous price changes. Importantly, the result is not simply reflecting differences due to variation in price durations as firms in industries where fixed-schedule pricing is more prevalent are not forward-looking regardless of whether they have low or high price durations. Instead, the increased forward-looking pricing behavior of firms in industries with less fixed-schedule pricing may reflect some precautionary pricing behavior in the face of greater uncertainty over when they will be able to next change prices—behavior that is not apparent in typical linearized exogenous-hazard models.

Uncertainty and the horizon of pass-through. In Table 6 we split firms by residual tariff-related uncertainty (below vs. above the median), where uncertainty is measured as the dispersion of tariff-attributed cost expectations after netting out realized tariff costs and the mean expected tariff cost change. The estimates show a sharp reallocation across channels: low-uncertainty firms (Panel A) exhibit close to one-for-one pass-through of contemporaneous costs and essentially no response to expected costs, whereas high-uncertainty firms (Panel B) load strongly on expected cost changes and much less on contemporaneous costs. This pattern is consistent with state-dependent pricing models in which uncertainty reshapes the effective reset-price kernel across horizons (and/or raises the shadow cost of price misalignment), and it is harder to reconcile with exogenous-hazard models in which uncertainty does not reallocate the timing weights.

Table 5: Price Changes and (Expected) Cost Changes, by Price Setting Type

Panel A) Firms in industries in which adjusting prices on a fixed schedule is less prevalent

	(1) OLS	(2) IV	(3) IV First Stages	(4)
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.513***	0.594		
	(0.164)	(0.412)		
ΔC_i^e	0.318**	0.711**		
	(0.148)	(0.304)		
Z_{1i}			0.379**	0.245**
			(0.161)	(0.122)
Z_{2i}			-0.154	0.592***
			(0.160)	(0.140)
Constant	5.085***	0.865	3.434**	5.499***
	(1.026)	(3.454)	(1.366)	(0.817)
N	214	209	209	209
R^2	0.243	-0.046	0.042	0.159
SW F-stats			9.37	20.17

Panel B) Firms in industries in which adjusting prices on a fixed schedule is more prevalent

	(1) OLS	(2) IV	(3) IV First Stages	(4)
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.639***	0.847***		
	(0.091)	(0.144)		
ΔC_i^e	0.277**	0.322		
	(0.113)	(0.267)		
Z_{1i}			0.621***	0.236***
			(0.109)	(0.074)
Z_{2i}			0.084	0.635***
			(0.103)	(0.088)
Constant	3.365***	3.593***	1.650***	4.396***
	(0.604)	(1.040)	(0.463)	(0.458)
N	322	311	311	311
R^2	0.379	0.304	0.371	0.278
SW F-stats			37.09	51.21

Note: Columns (1) and (2) contain OLS and IV regressions of price changes on actual contemporaneous cost changes and expected future cost changes as in equation (2). The instruments used are Z_{1i} defined in equation (3) and Z_{2i} defined in equation (5). Columns (3) and (4) are the first stage regressions from the IV, corresponding to equations (6) and (7). The two panels are estimated on subsamples split by the industry-level prevalence of fixed-schedule price adjustment. The "less prevalent" sample consists of firms in industries in which fewer than one-third of respondents indicated that they adjust prices on a fixed schedule and the "more prevalent sample" are the remaining firms. Both OLS and IV estimates are obtained using jackknife procedures that excludes observations that are overly influential to our main coefficients of interest. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Price Changes and (Expected) Cost Changes, by Residual Tariff Uncertainty

Panel A) Low Residual Tariff Uncertainty

	(1) OLS	(2) IV	(3) IV First Stages	(4) IV First Stages
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.879***	1.164***		
	(0.101)	(0.204)		
ΔC_i^e	0.010	-0.158		
	(0.122)	(0.210)		
Z_{1i}			0.684***	0.401***
			(0.079)	(0.057)
Z_{2i}			0.162	0.768***
(residualized)			(0.119)	(0.109)
Constant	3.455***	2.893***	1.218**	3.340***
	(0.681)	(0.835)	(0.581)	(0.342)
N	186	174	174	174
R^2	0.591	0.374	0.559	0.660
SW F-stats			20.68	50.69

Panel B) High Residual Tariff Uncertainty

	(1) OLS	(2) IV	(3) IV First Stages	(4) IV First Stages
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.433**	-0.150		
	(0.195)	(0.844)		
ΔC_i^e	0.394***	0.917**		
	(0.142)	(0.402)		
Z_{1i}			0.368**	0.033
			(0.179)	(0.124)
Z_{2i}			0.084	0.532**
(residualized)			(0.172)	(0.258)
Constant	4.034***	2.383	2.066***	6.877***
	(0.925)	(2.689)	(0.708)	(0.945)
N	153	146	146	146
R^2	0.203	0.121	0.119	0.162
SW F-stats			4.39	8.73

Note: Low-uncertainty (high-uncertainty) firms in Panel A (Panel B) are below (above) the median of residual tariff-related uncertainty (dispersion of tariff-attributed cost expectations, residualized with respect to realized tariff costs and the mean expected tariff cost change). Columns (1)–(2) report OLS and 2SLS estimates of (2). Columns (3)–(4) report first stages for ΔC_i and ΔC_i^e. Instruments are Z_{1i} (tariff-attributed realized cost change) and Z_{2i} (tariff-attributed expected cost change orthogonalized to Z_{1i}). Jackknife procedure as in the baseline; robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Pricing Models

To interpret the empirical evidence, the section below introduces a simple theoretical framework that clarifies how firms map current and expected cost changes into price adjustments. The model is designed to isolate the role of pricing frictions and expectations in shaping pass-through across horizons, rather than to provide a fully specified quantitative environment. Its purpose is to organize the results, highlight the key economic mechanisms, and discipline the comparison between alternative pricing frameworks used in the literature.

5.1 Setup and assumptions

We consider a standard price-setting environment in which firms face idiosyncratic restrictions on their ability to reset prices. Time is discrete, $t = 0, 1, 2, \ldots$, and a firm that resets its price in period t chooses a (log) reset price $\hat{p}_t^*$. Between resets, the price remains fixed.

We assume that the firm's frictionless target price, net of markups, equals its real marginal cost,

$$\hat{p}_t^\dagger = \hat{mc}_t.$$

The firm faces a quadratic cost of deviating from this target and discounts future profits at rate $\beta \in (0, 1)$.

Let $\tau \in \{1, 2, \ldots\}$ denote the (random) time until the next reset. The distribution of τ is summarized by its *survival function*

$$S_j \equiv \Pr_t(\tau > j), \qquad j = 0, 1, 2, \ldots,$$

which captures the probability that a price chosen in t remains effective j periods ahead. The sequence $\{S_j\}$ is itself implied by a possibly state-dependent or age-dependent hazard rate of adjustment, but we keep the analysis general and treat it as given for now. Next, we derive the mapping between the hazard process—or equivalently, the survival profile S_j—and the sensitivity of today's optimal reset price to expected marginal costs at different horizons. We do so in the context of a simple linear–quadratic (LQ) problem that encompasses Calvo, Taylor, and menu-cost models as special cases.

5.2 The LQ pricing problem and the general weight formula

Conditional on being able to reset in period t, the firm minimizes the expected discounted squared deviations between its chosen price and its desired target during the random lifetime of the price:

$$\hat{p}_t^* = \arg\min_p \mathbb{E}_t \left[\sum_{k=0}^{\tau-1} \beta^k \left(p - \hat{p}_{t+k}^\dagger \right)^2 \right].$$

The first-order condition yields a discounted average of expected target prices over the price's random duration:

$$\hat{p}_t^* = \frac{\mathbb{E}_t \left[\sum_{k=0}^{\tau-1} \beta^k \, \hat{p}_{t+k}^\dagger \right]}{\mathbb{E}_t \left[\sum_{k=0}^{\tau-1} \beta^k \right]} = \frac{\sum_{k\geq 0} \beta^k S_k \, \mathbb{E}_t \hat{p}_{t+k}^\dagger}{\sum_{k\geq 0} \beta^k S_k}. \tag{14}$$

Since $\hat{p}_{t+k}^\dagger = \hat{mc}_{t+k}$, this relationship immediately implies a linear mapping between expected marginal costs at each horizon and the reset price.

Proposition 1 (General weight formula)**.** *For any (possibly state-dependent) reset process summarized by $\{S_j\}_{j\geq 0}$, the sensitivity of the optimal reset price to expected marginal costs at horizon j is given by*

$$\frac{\partial \hat{p}_t^*}{\partial \, \mathbb{E}_t \hat{mc}_{t+j}} \;=\; w_j \;\equiv\; \frac{\beta^j \, S_j}{\sum_{k\geq 0} \beta^k S_k}, \qquad j = 0, 1, 2, \ldots \tag{15}$$

That is, the weight assigned to expected marginal costs j periods ahead equals their discounted survival probability, normalized by the expected discounted lifetime of the price.

Equation (15) highlights the central intuition: a price set in period t will still be relevant in future periods only if it survives until then, so future marginal costs are weighted by the joint effect of discounting and survival. Specifically, the numerator in the expression represents the present value of the firm's desired price path, weighted by both discounting and the probability that today's price remains in effect at each future date. The discount factor β^k captures the standard intertemporal weighting of future periods, while the survival probability S_k enforces relevance—future desired prices only matter if the firm's current price is still active then. In this way, the numerator aggregates the expected target (or marginal cost) path over the expected lifetime of the price, but filters it by both time preference and the likelihood that the price survives.

The denominator has a normalizing role. It is the present value of one unit of payoff

received in every period that the current price survives, which can be interpreted as the expected discounted duration of the price. Dividing the numerator by this term rescales the weighted sum of future targets into an average per surviving period. As a result, if desired prices were constant over time, the firm would optimally set its reset price equal to that constant target. The denominator therefore ensures that the resulting weights form a proper probability distribution over horizons, with the w_j summing to one.

5.3 Specific hazard structures

We next illustrate how the general expression (15) specializes to familiar models and to richer menu-cost environments.

Proposition 2 (Calvo pricing)**.** *If the probability of not resetting in any given period is constant and equal to $\theta \in (0,1)$, then $S_j = \theta^j$. Substituting into (15) gives*

$$w_j = (1-\beta\theta)(\beta\theta)^j.$$

Under this memoryless process, the weight declines geometrically with horizon j. The degree of price rigidity, governed by θ, determines how strongly the firm internalizes expected future marginal costs.

Proposition 3 (Taylor contracts)**.** *If prices are fixed for exactly N periods, then $S_j = 1$ for $0 \le j \le N-1$ and $S_j = 0$ thereafter. The weights are then*

$$w_j = \frac{(1-\beta)\,\beta^j}{1-\beta^N}, \quad 0 \le j \le N-1, \qquad w_j = 0 \text{ for } j \ge N.$$

Each horizon up to $N-1$ enters with a constant geometric decay due only to discounting. In the limiting cases, $N = 1$ corresponds to perfectly flexible prices, while $N \to \infty$ approximates full rigidity.

Proposition 4 (Calvo comparative statics in θ)**.** *Under Calvo pricing the weight at horizon j is $w_j = (1-\beta\theta)(\beta\theta)^j$ with $0 < \beta < 1$ and $0 \le \theta < 1$. Its derivative with respect to θ equals*

$$\frac{\partial w_j}{\partial \theta} = \beta(\beta\theta)^{j-1}\big[j - (j+1)\beta\theta\big], \qquad j \ge 1,$$

and $\partial w_0/\partial\theta = -\beta < 0$.

Cutoffs in θ for a given horizon j. *For any fixed $j \geq 1$, the sign of $\partial w_j/\partial\theta$ flips at*

$$\theta_j^\star \;=\; \frac{j}{(j+1)\,\beta}.$$

Specifically, $\partial w_j/\partial\theta > 0$ if $\theta < \theta_j^\star$, equals zero at $\theta = \theta_j^\star$, and is negative if $\theta > \theta_j^\star$.

Cutoffs in j for a given θ. *Equivalently, fixing θ (and β), there is a horizon cutoff*

$$j^\star(\beta\theta) = \left\lfloor \frac{\beta\theta}{1-\beta\theta} \right\rfloor$$

such that $\partial w_j/\partial\theta < 0$ for $j \leq j^\star$ and $\partial w_j/\partial\theta > 0$ for $j \geq j^\star + 1$.

The two cases above apply to different questions: the first considers a particular horizon, and asks for the passthrough elasticity with respect to price stickiness at that horizon; the second considers a particular price stickiness (for example, a set of firms subject to the same price stickiness) and compares derivatives as a function of horizon (along which these firms may be heterogeneous).

What happens intuitively? In the first case, increasing θ makes prices more persistent, which has two opposing effects on the weight placed on horizon j. On the one hand, greater stickiness lengthens the expected lifetime of the price, shifting overall weight toward later horizons. On the other hand, it mechanically downweights all horizons through the normalization term, since the price is expected to last longer overall. For short horizons j, the normalization effect dominates and the weight falls with θ; for sufficiently distant horizons, the longer survival probability dominates and the weight rises. The cutoff $\theta_j^\star$ is exactly where these two forces balance, causing the derivative to flip sign.

In the second case, the same two forces operate, but the question is reversed. Fixing θ pins down the overall degree of price persistence, and an infinitesimal increase in stickiness reallocates weight *across* horizons rather than at a single horizon. Because higher θ raises the probability that a price survives into the future, the weight profile becomes more *back-loaded*: distant horizons benefit disproportionately from the increase in survival. At the same time, the normalization required to keep the weights summing to one reduces mass at short horizons, making the kernel less *front-loaded*. As a result, $\partial w_j/\partial\theta < 0$ for early horizons, while sufficiently distant horizons gain weight. The cutoff $j^\star(\beta\theta)$ marks the horizon at which the survival amplification from greater persistence exactly offsets the normalization effect, so that the derivative switches sign.

Taken together, the two cutoffs provide complementary views of the same reallocation mechanism. Holding j fixed and varying θ asks whether a given horizon lies

in the front or the back of the kernel at that level of stickiness, while holding θ fixed and varying j maps out which horizons lose or gain weight as the kernel tilts from front-loaded toward back-loaded.

Proposition 5 (Taylor comparative statics in N)**.** *Under Taylor pricing, the sensitivity weights $w_j(N)$ satisfy*

$$\frac{\partial w_j(N)}{\partial N} = -\frac{(1-\beta)\,\beta^j\,\beta^N \ln(\beta)}{(1-\beta^N)^2} < 0, \qquad \textit{for all } 0 \le j < N-1 \textit{ and } 0 < \beta < 1.$$

Here, for any fixed j that remains within the support, $w_j(N)$ decreases strictly with N. The weights assigned to horizons already inside the support shrink as N rises, while newly added horizons $j \in \{N, \ldots, N'-1\}$ acquire positive mass. Consequently, total probability mass shifts monotonically to longer horizons: the mean horizon increases with N, and the distribution $\{w_j(N)\}$ moves rightward in first-order stochastic dominance.

The comparative static reflects the deterministic nature of Taylor contracts. When the contract length N increases, survival is certain up to $N-1$ and zero thereafter; no intermediate hazard governs the likelihood of adjustment. As N grows, the denominator $1-\beta^N$ rises, uniformly reducing all existing weights within the support. At the same time, the extension of the support introduces new positive weights at higher horizons. The result is a simple rightward expansion of the distribution—longer expected price duration and higher average horizon—without the sign flip characteristic of Calvo's probabilistic survival. In the limits, $w_0(1) = 1$ in the fully flexible case and $w_j(N) \to (1-\beta)\beta^j$ as $N \to \infty$, which coincides with the Calvo limit as $\theta \to 1$.

Now, consider a menu-cost environment with Poisson opportunities at rate ν, i.i.d. random menu costs $K \sim F$, quadratic flow loss cx^2 in the price gap x, and a Gaussian AR(1) target

$$x_{k+1} = \rho x_k + \varepsilon_{k+1}, \qquad \varepsilon_k \sim \mathcal{N}(0, \sigma^2), \qquad x_0 = 0.$$

Let the state-dependent adjustment hazard be $\lambda(x) = \nu F(a(x))$, where $a(x)$ is the value gain from resetting. To gain tractability in what follows, we approximate survival by replacing the path-dependent adjustment hazard with its horizon-by-horizon expectation. This is natural because the LQ reset-price problem is itself formulated in expectations, and the weights w_j summarize sensitivities of an expected discounted objective. The resulting first-order, mean-field approximation preserves the leading-order dependence of adjustment risk on the state and on uncertainty, while abstracting from higher-order heterogeneity across realization paths. The implied survival profile inherits the correct scaling with the horizon implied by the underlying state dynamics,

which is the object of interest for the kernel. Two benchmark limits obtain:

Proposition 6 (Menu-cost kernels)**.** (i) Stationary target ($|\rho| < 1$): endogenous geometric kernel. *The implied weights are geometric, with an endogenously determined decay parameter:*

$$w_j = (1 - \beta e^{-h_\infty})\,(\beta e^{-h_\infty})^j.$$

(ii) Random-walk target ($\rho = 1$): stretched-exponential kernel. *The resulting weights are non-Calvo and decay more steeply than exponential:*

$$w_j = \frac{\beta^j\, e^{-A\, j^{3/2}}}{\sum_{k\geq 0} \beta^k\, e^{-A\, k^{3/2}}}.$$

In both cases, $w_j = \beta^j S_j / \sum_{k\geq 0} \beta^k S_k$ *follows directly from the general LQ pricing kernel, with the survival profile* S_j *endogenously shaped by* $(c, \nu, F, \sigma, \rho)$*.*

Proof. For small and medium price gaps, the Hamilton–Jacobi–Bellman equation implies a locally linear gain function, so that the adjustment hazard takes the form

$$\lambda(x) \approx \lambda_1 |x|,$$

where the coefficient $\lambda_1 > 0$ depends only on the primitives (c, ν, F). Taking expectations under the Gaussian AR(1) law of motion determines the expected hazard path. □

When the target is stationary ($|\rho| < 1$), the expected absolute deviation of the target evolves as

$$\mathbb{E}|x_k| = \sqrt{\tfrac{2}{\pi}}\, \frac{\sigma\, \sqrt{1 - \rho^{2k}}}{\sqrt{1 - \rho^2}},$$

which converges to a constant $\sqrt{2/\pi}\,\sigma/\sqrt{1-\rho^2}$ as k increases. The average hazard therefore stabilizes at

$$h_\infty = \lambda_1 \sqrt{\tfrac{2}{\pi}}\, \frac{\sigma}{\sqrt{1 - \rho^2}},$$

yielding geometric survival $S_j \simeq e^{-j h_\infty}$ and the associated geometric kernel in part (i).

When the target instead follows a random walk ($\rho = 1$), its expected deviation grows as

$$\mathbb{E}|x_k| = \sqrt{\tfrac{2}{\pi}}\, \sigma \sqrt{k}.$$

The cumulative hazard thus rises with the sum $\sum_{\ell \leq j} \sqrt{\ell}$, which scales as $j^{3/2}$. This

gives a survival function of the stretched-exponential form

$$S_j \simeq e^{-Aj^{3/2}}, \qquad A = \tfrac{2}{3}\lambda_1\sigma\sqrt{\tfrac{2}{\pi}}.$$

Substituting these survival expressions into the general kernel

$$w_j = \frac{\beta^j S_j}{\sum_{k\geq 0}\beta^k S_k}$$

produces the two weighting formulas reported in the proposition. □

Now consider the same menu-cost environment as above, but let K denote a scale parameter of the menu-cost distribution (for instance, the upper bound $\bar{K}$ under a uniform distribution or the mean $1/\eta$ under an exponential one). An increase in K raises adjustment costs and thereby reduces the state hazard $\lambda(x)$, lengthening price durations. Two analytically tractable limits characterize how this change in K maps into the reset-price kernel.

Proposition 7 (Effect of menu costs on sensitivity)**.** *In the stationary AR(1) case ($|\rho| < 1$), the weights remain geometric but become more back-loaded as K increases. In the random-walk case ($\rho = 1$), the weights retain their stretched-exponential form but decay more slowly, with mass shifting toward longer horizons. In both cases, higher K raises the mean horizon of the reset-price kernel and reallocates sensitivity from near to distant periods. Moreover, higher menu costs K always lower the contemporaneous weight.*

Proof sketch. For small and medium gaps, the Hamilton–Jacobi–Bellman equation again implies a local linearization of the gain function, $a(x) \approx \lambda_1(K)|x|$, where $\lambda_1(K) > 0$ is decreasing in K and depends on the primitives (c, ν, F). The implied survival profile is determined by expectations of the price gap under the Gaussian AR(1) law of motion.

(i) Stationary target ($|\rho| < 1$). The expected absolute gap converges to a constant, producing an effective constant hazard

$$h_\infty(K) = \lambda_1(K)\sqrt{\tfrac{2}{\pi}}\,\frac{\sigma}{\sqrt{1-\rho^2}}, \qquad h'_\infty(K) < 0.$$

Defining the endogenous stickiness parameter $\tilde{\theta}(K) = e^{-h_\infty(K)}$, the kernel is

$$w_j(K) = (1-\beta\tilde{\theta})\,(\beta\tilde{\theta})^j.$$

Since $\tilde{\theta}'(K) > 0$, the derivative $\partial w_j/\partial K$ follows the Calvo pattern: near-term weights fall, long-horizon weights rise, and the mean horizon

$$\mathbb{E}[j] = \frac{\beta\tilde{\theta}}{1-\beta\tilde{\theta}}$$

increases monotonically in K.

(ii) Random-walk target ($\rho = 1$). Here the expected gap grows with $\sqrt{k}$, generating a stretched-exponential survival

$$S_j \simeq e^{-A(K)j^{3/2}}, \qquad A(K) = \tfrac{2}{3}\lambda_1(K)\sigma\sqrt{\tfrac{2}{\pi}}, \qquad A'(K) < 0,$$

and the corresponding kernel

$$w_j(K) = \frac{\beta^j e^{-A(K)j^{3/2}}}{\sum_{k\geq 0}\beta^k e^{-A(K)k^{3/2}}}.$$

As K increases, $A(K)$ declines, survival decays more slowly, and the distribution of weights shifts to longer horizons. Pointwise, $\partial w_j/\partial K < 0$ for short horizons and $\partial w_j/\partial K > 0$ for large ones, implying a rightward shift of the kernel and an increase in the mean horizon.

Finally, in both cases (i) and (ii), higher menu costs always lower the contemporaneous weight. This follows from the identity

$$w_0(K) = \Big(\sum_{k\geq 0}\beta^k S_k(K)\Big)^{-1},$$

which holds for any survival profile. Since an increase in K reduces adjustment hazards and (weakly) raises survival probabilities $S_k(K)$ at all horizons, the discounted expected duration $\sum_{k\geq 0}\beta^k S_k(K)$ increases, implying

$$\frac{\partial w_0(K)}{\partial K} < 0.$$

□

Intuitively, an increase in menu costs makes price adjustment less attractive for any given deviation, lowering the state hazard and lengthening survival. In the stationary case ($|\rho| < 1$), this acts much like a Calvo model with an endogenous stickiness parameter $\tilde{\theta}(K) = e^{-h_\infty(K)}$ that rises with K. The resulting kernel remains geometric, so higher K simply stretches the time profile of responsiveness without changing its

shape. In contrast, when the target follows a random walk ($\rho = 1$), the expected deviation grows over time and the cumulative hazard rises with $j^{3/2}$. Here a larger K reduces the decay parameter $A(K)$, generating a stretched-exponential survival that decays more slowly than any geometric process. The kernel therefore shifts mass toward distant horizons more sharply and exhibits a heavier tail. In sum, both cases imply back-loading of price sensitivities as menu costs rise, but the stationary case preserves a geometric form while the random-walk case produces a more gradual, fat-tailed attenuation of weights.

5.4 Discussion

The results above make transparent how the structure of adjustment frictions maps into the temporal profile of price responsiveness. Under Calvo or Taylor assumptions, the cross-sectional profile of weights (w_j) declines geometrically or truncates sharply with horizon, reflecting the exponential or deterministic survival structure implied by those mechanisms. As price rigidity increases, the overall distribution of weights shifts to longer horizons—early-period sensitivities fall while those at intermediate horizons (such as a few quarters ahead) can rise, consistent with empirical calibration. Menu-cost environments instead produce richer, endogenously shaped survival patterns. When the price gap evolves approximately as a random walk, survival follows a stretched-exponential form, leading to heavier weighting of near-term marginal costs and faster attenuation of distant ones. Conversely, when the process for desired prices is stationary, the model collapses back to a geometric form, but with an effective hazard rate (h_∞) that is itself a function of underlying primitives ($(c, \nu, F, \sigma, \rho)$).

Overall, the generalized formulation $w_j = \beta^j S_j / \sum_k \beta^k S_k$ provides a unified representation for a wide class of price-setting environments, offering a convenient kernel for linking marginal cost dynamics to reset-price behavior in both micro and aggregate models.

5.5 Uncertainty and the reset-price kernel

How does increased uncertainty in desired prices (or marginal costs) affect the reset-price weights? This subsection first lays out the effects depending on a simple distinction between exogenous and endogenous kernels that characterize Calvo or Taylor models of pricing, and menu cost models. For exogenous kernels, the central prediction is an invariance result. For endogenous kernels, increased uncertainty raises adjustment hazards for a given, small price gap and therefore front-loads the reset-price

kernel.[7]

Second, increased volatility may induce further, nuanced changes in price adjustment behavior, for example through capacity constraints, inventory exposure, or precautionary supply-chain management. In such cases, uncertainty may increase the elasticity of the desired price with respect to marginal cost and potentially undo the front-loading effect, leading to an increase in pass-through.

Proposition 8 (Exogenous kernels: Calvo/Taylor invariance to uncertainty)**.** *Let uncertainty in desired prices (or marginal costs) rise in the sense of a mean-preserving spread of the innovation process, while holding* (β, θ) *or* (β, N) *fixed. Then the reset-price kernel*

$$w_j \equiv \frac{\beta^j S_j}{\sum_{k\geq 0} \beta^k S_k}$$

is unchanged for all j*. Equivalently, for any two uncertainty levels* σ *and* σ'*,* $w_j(\sigma) = w_j(\sigma')$ *for all* j*.*

Proof sketch. The kernel depends on σ only through the survival profile $S = \{S_j\}_{j\geq 0}$. Under Calvo ($S_j = \theta^j$) and Taylor ($S_j = \mathbf{1}\{j \leq N-1\}$), S is parameterized solely by (θ) or (N) and does not depend on σ. Hence both numerator and denominator of w_j are invariant to σ, implying $w_j(\sigma) = w_j(\sigma')$. □

In Calvo and Taylor environments, adjustment probabilities are exogenously fixed and independent of the volatility of shocks. As a result, higher uncertainty affects firms' pricing decisions only through expectations of future marginal costs, not through the duration structure itself. The survival profile—and thus the relative weights assigned to different horizons—remains unchanged. Put differently, uncertainty modifies the level and dispersion of desired prices but does not alter how far into the future firms look when setting their reset prices. This neutrality reflects the purely time-dependent nature of the hazard in Calvo and Taylor models, which decouples the adjustment process from the stochastic environment.

Proposition 9 (Endogenous kernels: uncertainty front-loads menu-cost weights)**.** *In the above menu-cost environment, where the survival profile* $S_j(\sigma)$ *is endogenous and depends on the volatility of the target process, and where adjustment hazards are governed by small and medium price gaps, let the target follow a Gaussian AR(1) with persistence* $|\rho| \leq 1$ *and innovation variance* σ^2*. Then:*

[7]This front-loading result is derived analytically under a local approximation in which hazard variation is governed by the dispersion of price gaps rather than also by movements in adjustment thresholds. In general menu-cost models, higher uncertainty also increases the option value of waiting and can widen inaction bands, so the net effect on hazards is ambiguous. The local formulation isolates the gap-dispersion channel that dominates for small and medium price gaps and yields a tractable, unambiguous prediction.

(i) Stationary target ($|\rho| < 1$). *The effective constant hazard is*

$$h_\infty(\sigma) = \lambda_1 \sqrt{\tfrac{2}{\pi}} \, \frac{\sigma}{\sqrt{1-\rho^2}},$$

so that $S_j(\sigma) \simeq e^{-j h_\infty(\sigma)}$ *and*

$$w_j(\sigma) = (1 - \beta e^{-h_\infty(\sigma)})(\beta e^{-h_\infty(\sigma)})^j.$$

Because $h'_\infty(\sigma) > 0$*, higher uncertainty raises near-term sensitivities* ($w_0 \uparrow$) *and lowers sufficiently distant ones* ($w_j \downarrow$ *for large* j)*; the mean horizon decreases.*

(ii) Random-walk target ($\rho = 1$). *Survival takes the stretched-exponential form*

$$S_j(\sigma) \simeq e^{-A(\sigma) j^{3/2}}, \qquad A(\sigma) = \tfrac{2}{3} \lambda_1 \sigma \sqrt{\tfrac{2}{\pi}},$$

implying

$$w_j(\sigma) = \frac{\beta^j e^{-A(\sigma) j^{3/2}}}{\sum_{k \geq 0} \beta^k e^{-A(\sigma) k^{3/2}}}.$$

An increase in σ *raises* $A(\sigma)$*, accelerates the decay of survival, and shifts mass toward near horizons, reducing the mean adjustment horizon.*

Intuitively, in models with state-dependent hazards, greater volatility widens the dispersion of price gaps, increasing the probability that firms with small and medium gaps hit their adjustment thresholds. The expected hazard rises, survival shortens, and the reset-price kernel becomes more front-loaded. In stationary environments this appears as a higher effective constant hazard $h_\infty(\sigma)$; in random-walk settings it shows up as a larger decay parameter $A(\sigma)$. In both cases, uncertainty reallocates sensitivity from distant to near horizons.

A more complex role of uncertainty

We now allow uncertainty to influence not only the timing of price adjustment but also the firm's effective cost of deviating from its desired price. When volatility in marginal costs rises—for instance, due to uncertainty about trade policy, exposure to inventory risk, or capacity constraints—firms may place a higher value on avoiding future misalignment. A parsimonious way to capture this precautionary motive is to let uncertainty scale up the desired price in the quadratic loss. Because uncertainty has not effect in the case of exogenous kernels, we focus on the case of endogenous

kernels.[8]

Formally, a firm under these assumptions now solves the following problem

$$\hat{p}_t^*(\sigma) = \arg\min_p \mathbb{E}_t \left[\sum_{k=0}^{\tau-1} \beta^k \big(p - a(\sigma)\, \hat{mc}_{t+k}\big)^2 \right],$$

where $a(\sigma) > 0$ is continuously differentiable and increasing in σ. The adjustment mechanism, and hence the survival profile $S_j(\sigma)$, is unchanged, so that

$$\hat{p}_t^*(\sigma) = a(\sigma) \sum_{j\geq 0} w_j(\sigma)\, \mathbb{E}_t \hat{mc}_{t+j}, \qquad w_j(\sigma) = \frac{\beta^j S_j(\sigma)}{\sum_{k\geq 0} \beta^k S_k(\sigma)}.$$

Thus the sensitivity to a marginal-cost shock at horizon j is

$$\psi_j(\sigma) = a(\sigma)\, w_j(\sigma).$$

Proposition 10 (Pass-Through When Uncertainty Affects Marginal Costs))**.** *Let $a(\sigma) > 0$ be continuously differentiable with $a'(\sigma) > 0$, and let $\sum_{j\geq 0} w_j(\sigma) = 1$. Then pass-through at horizon j increases with uncertainty if and only if*

$$\frac{a'(\sigma)}{a(\sigma)} \;>\; -\frac{w_j'(\sigma)}{w_j(\sigma)}.$$

Proof. Since $\psi_j(\sigma) = a(\sigma) w_j(\sigma)$,

$$\frac{\partial \psi_j(\sigma)}{\partial \sigma} = a'(\sigma) w_j(\sigma) + a(\sigma) w_j'(\sigma).$$

Pass-through at horizon j increases with uncertainty when this derivative is positive. Dividing by $a(\sigma) w_j(\sigma) > 0$ yields the condition

$$\frac{a'(\sigma)}{a(\sigma)} > -\frac{w_j'(\sigma)}{w_j(\sigma)}.$$

□

As the proposition shows, uncertainty affects pass-through through two channels.

Amplification: $a(\sigma)$ scales up the shadow cost of being misaligned with future

[8] Under exogenous kernels (Calvo or Taylor), the reset-price kernel is invariant to uncertainty. Hence, letting uncertainty scale the shadow cost of misalignment affects pass-through only through amplification, with no horizon reallocation; with endogenous kernels, by contrast, uncertainty also shifts the horizon weights, which can offset amplification.

marginal costs. The elasticity $a'(\sigma)/a(\sigma)$ measures how strongly this precautionary motive rises with uncertainty.

Kernel front-loading: In state-dependent environments such as menu costs, higher volatility widens the distribution of price gaps, raises the adjustment hazard. For small and medium gaps—where the adjustment hazard is locally increasing in the gap—this raises the expected adjustment hazard and shortens the expected lifetime of the current price. As a consequence, more weight is placed on the immediate horizon, so that $w_0'(\sigma) > 0$: the reset-price kernel becomes *front-loaded*. Because the weights must sum to one, this increase in w_0 necessarily comes at the expense of nearby horizons. Thus, *for many small* $j > 0$ we have $w_j'(\sigma) < 0$. Only at sufficiently distant horizons does the steepening of the tail overturn this pattern, yielding $w_j'(\sigma) > 0$ for large enough j. In short, locally around the inaction region, uncertainty compresses the kernel toward the present, raising w_0, lowering most early-horizon weights, and thinning the long tail.

Given these two forces, pass-through rises when the strength of amplification exceeds the rate at which the kernel shifts mass away from that horizon. For small horizons, the kernel effect may dominate, reducing $\psi_j(\sigma)$. For sufficiently distant horizons, the kernel effect reverses, $w_j'(\sigma) > 0$, and pass-through necessarily increases.
Exogenous kernels (Calvo/Taylor). Note that under Calvo or Taylor pricing the reset-price kernel is invariant to uncertainty, so Proposition 10 collapses to a pure amplification result: uncertainty raises pass-through at all horizons whenever it increases the shadow cost of price misalignment.

6 Conclusion

This paper provides new evidence on how firms incorporate current and expected costs into price setting, and how pricing frictions shape the relative importance of these channels. Using firm-level data that directly measure realized and expected cost changes—and their trade-policy components—we show that prices respond both to contemporaneous costs and to anticipated future costs, but in systematically different ways across firms. Frequent adjusters (and goods producers) exhibit largely contemporaneous pass-through, while sticky-price firms (and service producers) load more heavily on expectations, with uncertainty tilting pricing further toward forward-looking considerations.

These patterns are difficult to reconcile with fixed-horizon pricing models, but arise naturally in generalized-hazard and menu-cost frameworks where adjustment timing and the reset-price kernel are endogenous. From a policy perspective, the results point

to a role for dispersion management: what matters for inflation is not only the average expected path of costs, but also how unevenly shocks are perceived and transmitted across firms. Policies and communication that reduce disagreement and uncertainty about the cost outlook—or that limit the cross-sectional dispersion in exposure—can dampen price pressure by compressing the upper tail of firms that preemptively price in large future increases, especially among infrequent adjusters.

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A Tables and Figures

Table A.1: Owner Characteristics

	%		%
Race		**Urban vs. Rural**	
White	79.0	Urban	30.1
Black	15.0	Suburban	50.6
Other	6.1	Rural	19.3
Ethnicity		**Census Region**	
Non-Hispanic	90.8	Northeast	19.4
Hispanic	9.2	Midwest	18.5
		South	35.8
Gender		West	26.2
Male	58.1		
Female	41.9	**Role**	
		C-Level	72.7
Education		Vice President	1.5
less than college	47.2	Director	8.8
bachelor's degree	33.6	Manager	17.0
postgraduate degree	19.2		
Political Ideology			
Liberal	25.6		
Moderate	39.1		
Conservative	35.3	N=599	

Notes: Weighted percentages of respondents in different demographic groups and categories. *Sources:* Authors' calculations using data from Morning Consult.

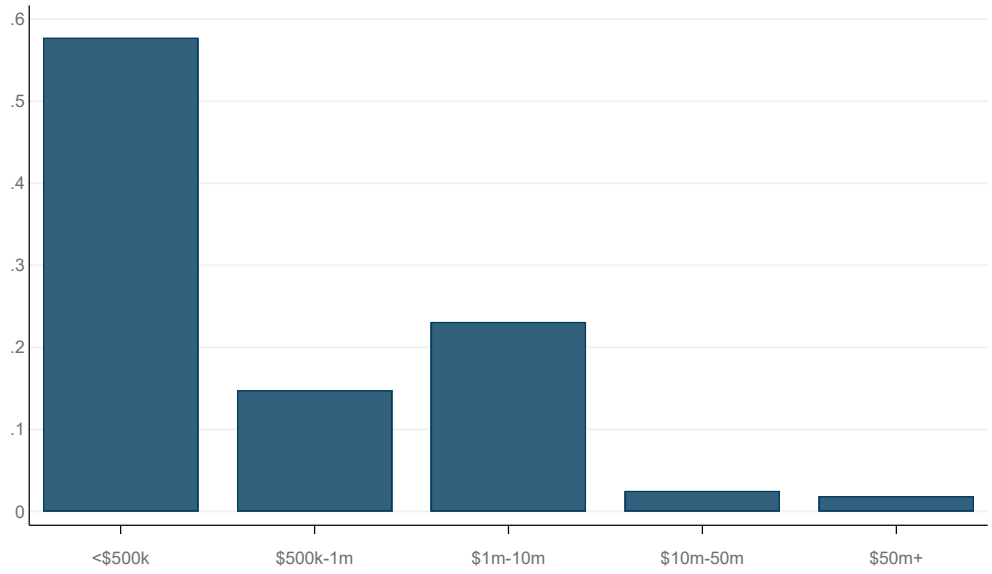
Table A.2: Industry

	Weight	Target
Group 1	**32.0**	**32.2**
Professional, Scientific, and Technical Services	16.2	14.4
Finance and Insurance	5.7	4.0
Real Estate and Rental and Leasing	5.1	5.9
Management of Companies and Enterprises	2.8	0.2
Information	2.2	1.5
Administrative and Support and Waste Management and Remediation Services	0.0	6.2
Group 2	**26.0**	**24.6**
Health Care and Social Assistance	8.3	11.2
Education Services	6.6	1.7
Arts, Entertainment, and Recreation	5.6	2.3
Accommodation and Food Services	5.5	9.3
Group 3	**20.3**	**18.8**
Retail Trade	16.3	10.5
Wholesale Trade	3.9	4.4
Transportation and Warehousing	0.1	3.8
Group 4	**17.7**	**17.4**
Construction	10.8	12.8
Manufacturing	4.0	4.0
Agriculture, Forestry, Fishing and Hunting	2.2	0.3
Utilities	0.7	0.1
Mining, Quarrying, and Oil and Gas Extraction	0.0	0.2
Group 5	**4.1**	**7.0**
Other Services (except Public Administration)	4.1	7.0

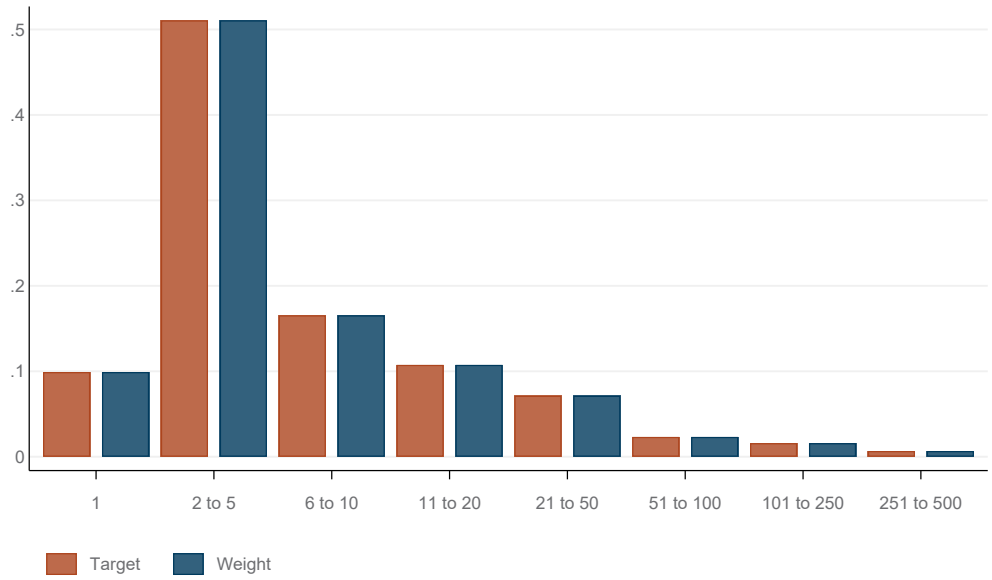
Notes: The table shows the distribution of firms in our sample across sectors. *Sources:* Authors' calculations using data from Morning Consult.

Figure A.1: Firm Characteristics I

(a) Revenues



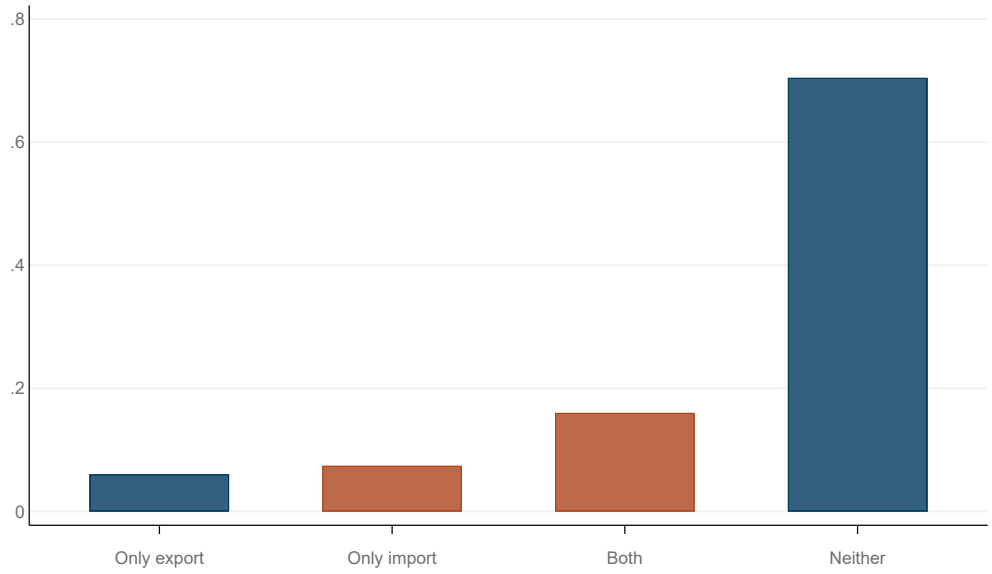
(b) Employees



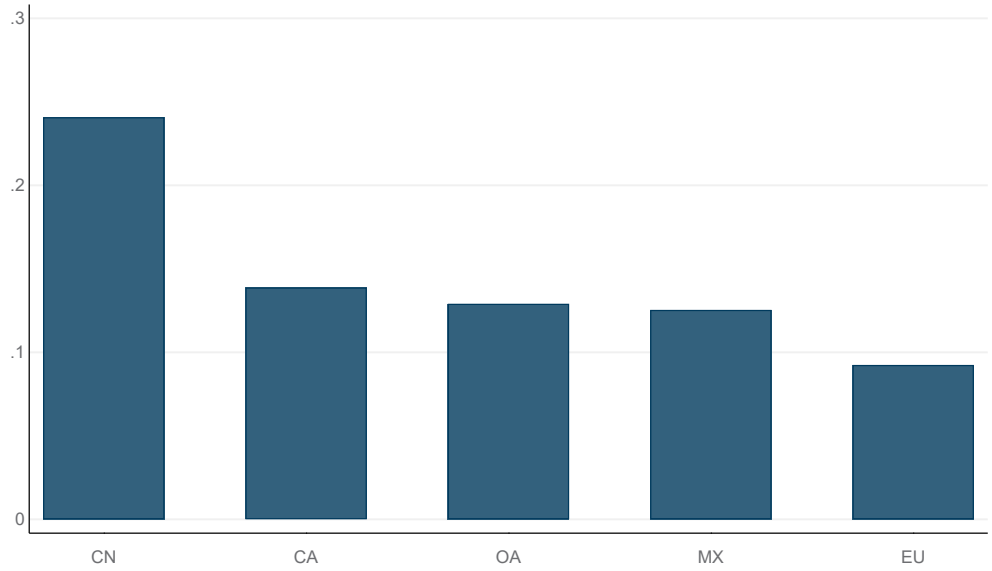
Notes: The figure displays the distribution of annual revenue (panel a) and the number of employees (panel b) across firms in the sample.

Figure A.2: Firm Characteristics I

(a) Trade status



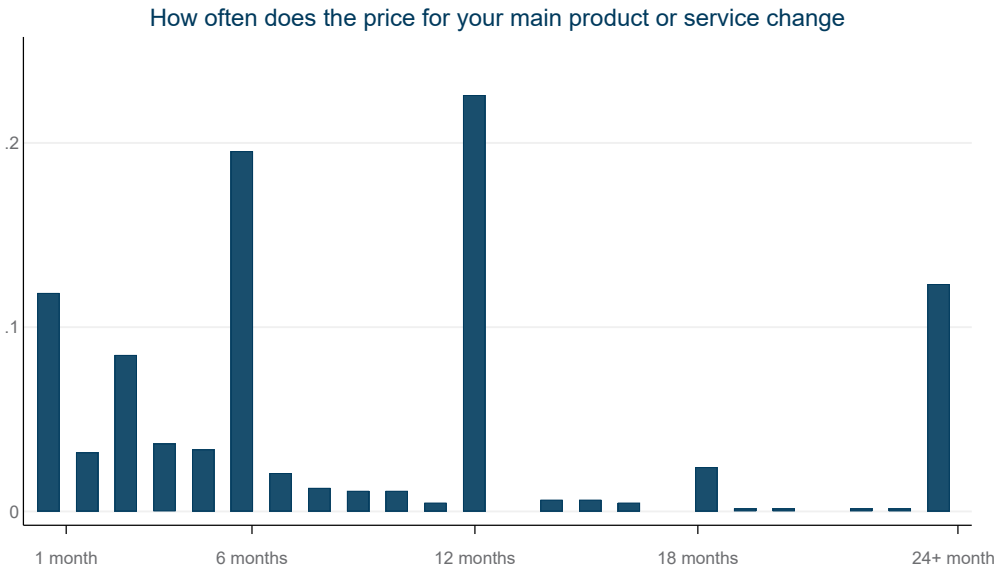
(b) Tariff Impact



Notes: The figure displays the distribution of trade status (panel a) and impact of tariffs (panel b) across firms in the sample.

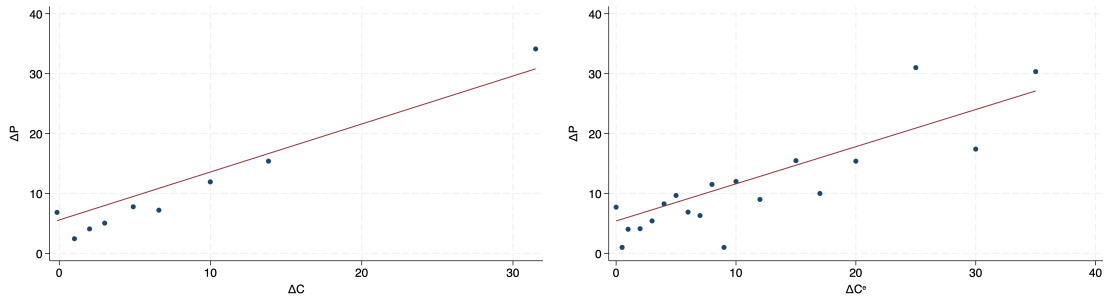
Figure A.3: Firm Characteristics III

(a) Price duration



Notes: The figure displays the distribution of average price durations across firms in the sample.

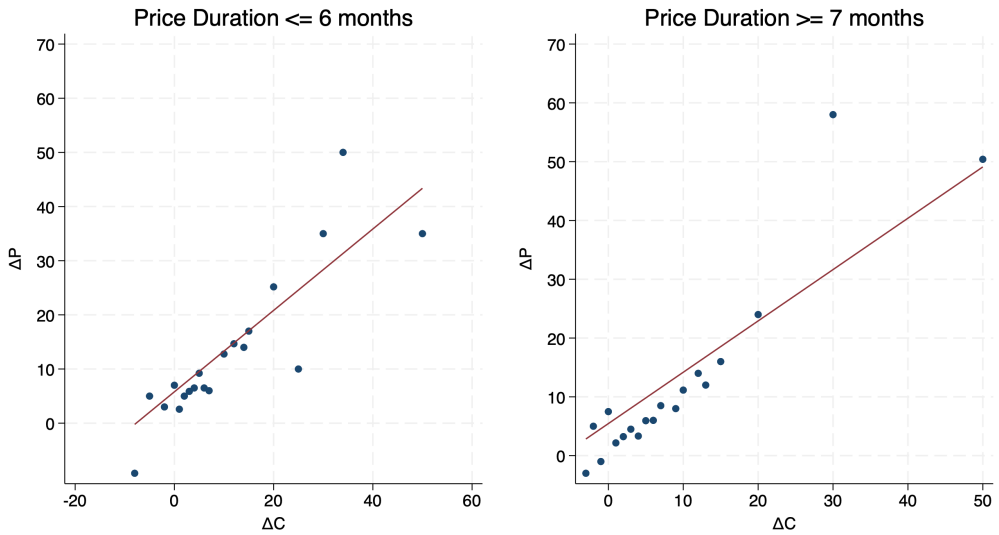
Figure A.4: Relationship between Actual Price Change and (Expected) Cost Changes



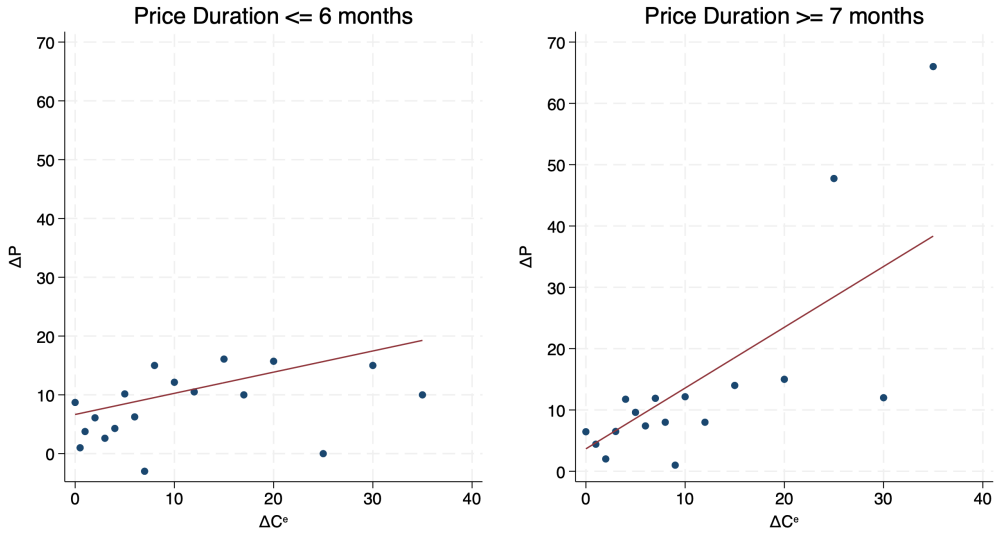
(a) Actual Contemporaneous Cost Changes (b) Expected Future Cost Changes

Note: The figure shows the relation between actual, reported price changes (vertical axis) and realized cost changes since the last price adjustment (left panel) and expected future price changes over the following 12 months (right panel), on the horizontal axis.

Figure A.5: Relationship between Actual Price Change and (Expected) Cost Changes (Split by Typical Price Duration)



(a) Actual Contemporaneous Cost Changes



(b) Expected Future Cost Changes

Note: The figure shows the relation between actual, reported price changes (vertical axis) and realized cost changes since the last price adjustment (upper panels) and expected future price changes over the following 12 months (lower panel), on the horizontal axis. The left panels show the relation for firms with an average reported price duration of 6 months or less, the right panels the for firms with an average reported price duration of 7 months or more.

Table A.3: Price Changes and (Expected) Cost Changes (November 2024 through January 2025 Changes)

	(1)	(2)	(3)	(4)
	OLS	IV	IV First Stages	
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.455***	0.846***		
	(0.095)	(0.133)		
ΔC_i^e	0.301***	-0.061		
	(0.062)	(0.094)		
Z_{1i}			0.457***	0.224***
			(0.099)	(0.077)
Z_{2i}			0.261***	0.873***
			(0.099)	(0.183)
Constant	2.702***	2.412***	3.090***	4.766***
	(0.731)	(0.769)	(0.545)	(0.594)
N	203	197	197	197
R^2	0.311	0.283	0.380	0.488
SW F-stats			21.71	20.02

Note: Columns (1) and (2) contain OLS and IV regressions of price changes on actual contemporaneous cost changes and expected future cost changes as in equation (2). The instruments used are Z_{1i} defined in equation (3) and Z_{2i} defined in equation (5). The analysis in this table is conducted only for price changes that occurred in November 2024, December 2024, or January 2025. Columns (3) and (4) are the first stage regressions from the IV, corresponding to equations (6) and (7). Both OLS and IV estimates are obtained using a jackknife procedure that excludes observations that are overly influential to our main coefficients of interest. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Price Changes and (Expected) Cost Changes (November 2024 through January 2025 Changes; Only Firms with Over 10 Employees)

	(1)	(2)	(3)	(4)
	OLS	IV	IV First Stages	
	ΔP_i	ΔP_i	ΔC_i	ΔC_i^e
ΔC_i	0.617***	0.481**		
	(0.133)	(0.243)		
ΔC_i^e	0.171***	0.261*		
	(0.057)	(0.141)		
Z_{1i}			0.610***	0.575***
			(0.091)	(0.096)
Z_{2i}			0.181	1.084***
			(0.126)	(0.106)
Constant	2.916***	2.965***	1.346**	3.199***
	(0.820)	(0.910)	(0.605)	(0.463)
N	130	121	121	121
R^2	0.317	0.289	0.534	0.798
SW F-stats			16.23	17.65

Note: Columns (1) and (2) contain OLS and IV regressions of price changes on actual contemporaneous cost changes and expected future cost changes as in equation (2). The instruments used are Z_{1i} defined in equation (3) and Z_{2i} defined in equation (5). The analysis in this table is conducted only for price changes that occurred in November 2024, December 2024, or January 2025 and includes only firms with over 10 employees (owner included). Columns (3) and (4) are the first stage regressions from the IV, corresponding to equations (6) and (7). Both OLS and IV estimates are obtained using a jackknife procedure that excludes observations that are overly influential to our main coefficients of interest. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Survey Appendix

MCSMB320: Please consider your most important product or service, for a typical customer. On average, how often does the price for this product or service change, and when did it last change?

On average, the price changes every ...	▽ 0 months (1) ... more than 24 months (26)
The last time the price changed was ...	▽ 0 months (1) ... more than 24 months (26)

MCSMB800: Which of the following trade policies have already meaningfully increased or are expected to meaningfully increase your firm's costs? Please select all that apply.

- ◯ Tariffs on imports from China
- ◯ Tariffs on imports from Canada
- ◯ Tariffs on imports from Mexico
- ◯ Tariffs on imports from the EU
- ◯ Tariffs on imports from other Asian countries
- ◯ Tariffs on steel and aluminum
- ◯ Tariffs on autos and auto parts
- ◯ Ending of the de minimis provision (tariff exemption for low-value packages of $800 or less)
- ◯ Other tariffs or trade policies
- ◯ Non of the above. My costs are not affected by trade policies.

MCSMB801: For how long do you expect new tariffs or trade policies to affect your firms' costs?

▽ Less than 1 month (1) ... more than 4 years (15)

MCSMB802: Please think of your main product or service and the most recent price change for it. By how much did the price change?

- ◯ Price increased by _____ %
- ◯ Price decreased by _____ %

MCSMB803: Now please think back to the most recent time you adjusted your price. We are interested in how your firm's costs have changed between the most recent and previous price adjustments, and how recent trade policy may have contributed to those cost changes. Think about any changes—upward, downward or none—in your firm's costs over this period, and how much of those changes were related to trade policy. Please enter your responses as percentages. Use 0 if there was no change.

	Costs increase by %	No cost change (please write 0)	Costs decreased by %
Change in costs between the most recent *price* adjustment and the previous one	◯ ____	◯	◯ ____
Change in costs between the most recent *price* adjustment and the previous one, **only due to trade policy**	◯ ____	◯	◯ ____

MCSMB804: Now, please continue thinking back to the most recent time you adjusted your price. What were your expectations back then of how costs and prices would change in the future? Please enter your responses as percentages, using negative values for decreases.

	Average change in %	Lowest possible change in %	Highest possible change in %
As of the time you most recently adjusted your price, expected change in *costs* over the following 12 months	◯ ____	◯ ____	◯ ____
As of the time you most recently adjusted your price, expected change in *costs* over the following 12 months, **only due to trade policy**	◯ ____	◯ ____	◯ ____
As of the time you most recently adjusted your price, expected change in *prices* over the following 12 months	◯ ____	◯ ____	◯ ____

Please take a moment to think about your business in January 2025. Specifically, we would like you to reflect on the situation facing your firm during that month. Consider how your business was performing, any changes in costs or prices you had experienced around that time, and whether external factors—such as trade policy—may have influenced your decisions.

MCSMB807: Please think of your main product or service again, for a typical customer. Now, **looking back to January 2025**, in that month, by how much did you

adjust its price? Please enter your responses as percentages. Use 0 if there was no change.

	Increased by %	No change (please write 0)	Decreased by %
Price change	◯ ____	◯	◯ ____

MCSMB808: We would like to ask you a bit more about the price change you made in January 2025. As before, we are interested in how your firm's costs evolved since the previous price adjustment leading up to January, and how recent trade policy contributed to those changes. Please provide your answers as percentages. Use 0 if there was no change.

	Costs increased by %	No cost change (please write 0)	Costs decreased by %
Change in costs between the previous price change until January 2025	◯ ____	◯ ____	◯ ____
Change in costs between the previous price change until January 2025, **only due to trade policy**	◯ ____	◯ ____	◯ ____

MCSMB809: Also thinking back to January 2025: What were your expectations back then of how costs and prices would change in the future? Please enter your responses as percentages, using negative values for decreases. using negative values for decreases.

	Average change in %	Lowest possible change in %	Highest possible change in %
January 2025 expected change in *costs* over the following 12 months	◯ ____	◯ ____	◯ ____
January 2025 expected change in *costs* over the following 12 months, **only due to trade policy**	◯ ____	◯ ____	◯ ____
January 2025 expected change in *prices* over the following 12 months	◯ ____	◯ ____	◯ ____

MCSMB810: What was the average tariff rate in percent that you paid to US customs, if any, for the goods and services you had imported?

	in January was %	in June was %
Average tariff paid	◯ ———	◯ ———

C Model Appendix

Appendix A.1 General LQ problem (FOC and survival representation)

Consider the problem of choosing the reset price in period t:

$$\hat{p}_t^* \;=\; \arg\min_{p}\; \mathbb{E}_t\left[\sum_{k=0}^{\tau-1} \beta^k \left(p - \hat{p}_{t+k}^{\dagger}\right)^2\right],$$

where τ is the (random) time until the next reset and $\beta \in (0,1)$.

First-order condition. Define the objective $L(p) \equiv \mathbb{E}_t\big[\sum_{k=0}^{\tau-1} \beta^k (p - \hat{p}_{t+k}^{\dagger})^2\big]$. Differentiating and setting the derivative to zero:

$$\frac{\partial L(p)}{\partial p} = \mathbb{E}_t\left[\sum_{k=0}^{\tau-1} 2\,\beta^k \left(p - \hat{p}_{t+k}^{\dagger}\right)\right] = 0 \quad\Longrightarrow\quad \mathbb{E}_t\left[\sum_{k=0}^{\tau-1} \beta^k\, p\right] = \mathbb{E}_t\left[\sum_{k=0}^{\tau-1} \beta^k\, \hat{p}_{t+k}^{\dagger}\right].$$

Hence,

$$\hat{p}_t^* = \frac{\mathbb{E}_t\Big[\sum_{k=0}^{\tau-1} \beta^k\, \hat{p}_{t+k}^{\dagger}\Big]}{\mathbb{E}_t\big[\sum_{k=0}^{\tau-1} \beta^k\big]}. \tag{16}$$

Survival representation. Let $S_k \equiv \Pr_t(\tau > k)$ denote the survival probability. Using

$$\mathbb{E}_t\left[\sum_{k=0}^{\tau-1} \beta^k\right] = \sum_{k\geq 0} \beta^k\, S_k, \qquad \mathbb{E}_t\left[\sum_{k=0}^{\tau-1} \beta^k\, \hat{p}_{t+k}^{\dagger}\right] = \sum_{k\geq 0} \beta^k\, S_k\, \mathbb{E}_t \hat{p}_{t+k}^{\dagger},$$

equation (16) becomes

$$\hat{p}_t^* = \frac{\sum_{k\geq 0} \beta^k\, S_k\, \mathbb{E}_t \hat{p}_{t+k}^{\dagger}}{\sum_{k\geq 0} \beta^k\, S_k}. \tag{17}$$

With $\hat{p}_{t+k}^{\dagger} = \hat{mc}_{t+k}$, differentiating (17) with respect to $\mathbb{E}_t \hat{mc}_{t+j}$ yields the general weight formula

$$\frac{\partial \hat{p}_t^*}{\partial\, \mathbb{E}_t \hat{mc}_{t+j}} \;=\; \frac{\beta^j\, S_j}{\sum_{k\geq 0} \beta^k\, S_k}, \qquad j = 0, 1, 2, \ldots$$

which is used throughout the main text.

A.2 Calvo and Taylor. For Calvo pricing, $S_j = \theta^j$, so $\sum_k \beta^k S_k = (1-\beta\theta)^{-1}$ and $w_j = (1-\beta\theta)(\beta\theta)^j$. For Taylor contracts, $S_j = 1$ for $j \leq N-1$ and zero thereafter, giving $\sum_k \beta^k S_k = (1-\beta^N)/(1-\beta)$ and $w_j = (1-\beta)\beta^j/(1-\beta^N)$.

A.3 Menu-cost environments. In continuous time, with Poisson opportunities at rate ν and cost draws $K \sim F$, let $a(x) = V(x) - V(0)$ denote the gain from adjusting. In the inaction region, a satisfies the Hamilton–Jacobi–Bellman equation

$$\rho a(x) = cx^2 + \tfrac{\sigma^2}{2} a''(x) - \nu\, \Phi(a(x)), \qquad \Phi(a) = \mathbb{E}(a - K)^+.$$

Adjustment occurs when $K \leq a(x)$, implying $\lambda(x) = \nu F(a(x))$. For many common F (e.g., uniform or exponential), Φ admits closed form. Near the origin, $a(x) \propto |x|$ so that $\lambda(x) \approx \lambda_1 |x|$. Under Gaussian AR(1) targets, the expected hazard $\bar{\lambda}_k = \mathbb{E}\lambda(X_k)$ yields the survival patterns summarized in Proposition 6: geometric decay in the stationary AR(1) case, stretched-exponential decay in the random-walk case, and saturation at $\lambda(x) \to \nu$ for large gaps.