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Pricing Under Distress
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ABSTRACT

We study price adjustment during Chile's October 2019 Social Uprising using VAT invoice data linking supermarket and supplier prices. Price-change frequency fell, adjustment size increased, and markups rose conditional on adjustment. Supplier pricing was unchanged, and supermarket responses did not vary with local riot intensity, weighing against upstream cost shocks and localized disruptions. We show that frequency and size alone cannot distinguish anticipated demand dispersion from higher menu costs. Combining the micro data with a calibrated Kimball menu-cost model, we find that both channels are needed to match the data and that both amplify monetary non-neutrality.

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1 Introduction

The pricing decision of firms is central in macroeconomics. The frequency and size of price changes help determine the effectiveness of monetary policy on real outcomes. Price setting is inherently forward looking, as firms anticipate that the price they set today will remain in place for some time. Expectations, and more broadly uncertainty about the future, are therefore a key ingredient of the price-setting problem. Understanding how firms respond to changes in uncertainty is essential not only for interpreting micro evidence on pricing but also for evaluating how nominal shocks transmit into the real economy.

Uncertainty is typically modeled as time variation in the dispersion of a fundamental that shapes firms' decisions. In the menu-cost framework of Vavra (2014), for example, the dispersion of firm-level productivity shocks changes over time. An increase in this dispersion has two distinct effects: (i) the distribution becomes more dispersed today and (ii) it is expected to remain more dispersed in the future. We refer to these as the *realization* and *anticipation* effects of uncertainty, respectively.[1] Empirical episodes studied in the uncertainty literature often move realized and expected future dispersion at the same time, making it difficult to discipline their relative roles in practice.

Menu-cost models make this distinction concrete. In these models, firms adjust prices only when the benefit of doing so exceeds a fixed adjustment cost. Realized higher dispersion pushes more firms away from their desired prices and tends to increase the frequency and size of price changes. News about higher future dispersion has a different implication: because firms anticipate that a price chosen today may become quickly suboptimal tomorrow, some firms prefer to wait, lowering current adjustment frequency and increasing the size of price changes conditional on adjustment. These two features of uncertainty therefore have opposite implications for nominal price rigidity.

A further challenge is that uncertainty episodes may also affect the cost of changing prices itself. If the episode raises the current cost of implementing price changes, firms may also delay adjustment, generating the same qualitative decline in adjustment frequency and increase in adjustment size as news about future dispersion. Appendix A.1 illustrates these forces in a simple Dixit (1991) menu-cost model and shows why frequency and size alone cannot distinguish anticipated future dispersion from an increase in the current menu cost.

We study these mechanisms in the context of Chile's 2019 Social Uprising (*"Estallido Social"*). On October 18, 2019, localized demonstrations over a subway fare increase unexpectedly escalated into a nationwide wave of protests, with widespread calls for deep political and institutional change. From the perspective of firms, this episode may have

[1] Bloom (2009) uses the terms uncertainty and volatility effects to describe these channels.

plausibly raised uncertainty about future economic and institutional conditions *before* any concrete reform took place, making it an environment in which anticipation effects could be salient. At the same time, these events could also have increased the fixed cost of changing prices, for instance, because immediate operational demands made price changes temporarily more costly to implement. The episode is therefore a useful laboratory for studying both anticipatory pricing behavior and menu-cost changes, and for asking how these forces can be distinguished in the data.

Our analysis uses a uniquely granular dataset built from electronic value-added tax invoices. These data allow us to observe daily retail prices for thousands of products across stores and regions. For a large matched subset, we also observe the prices paid to suppliers, which allows us to track costs and construct markups. We organize the empirical evidence around three pricing moments: the frequency of supermarket price adjustment, the size of supermarket price changes conditional on adjustment, and markups conditional on supermarket price adjustments. During the Social Uprising, these three pricing moments move sharply: (i) the frequency of price changes falls, (ii) the size of price changes conditional on adjustment rises, and (iii) markups rise conditional on supermarket price adjustments. Two additional pieces of evidence help discipline alternative explanations. Supplier pricing behavior does not exhibit comparable changes in frequency or size, and supermarkets located in municipalities where protests were more intense do not display stronger responses.

The markup behavior becomes central when considering anticipation and menu cost forces. In a general menu cost model, the reset price depends on the conditions the firm faces. In this type of model, a higher menu cost changes which firms adjust, but once a firm decides to adjust, the cost is sunk and does not directly affect the price it chooses. Instead, news about future dispersion changes the continuation value of the reset price and can therefore change the price chosen conditional on adjustment. Markups provide the empirical counterpart to this reset-price logic: for a given product and marginal cost, a higher reset price implies a higher markup. The markup response therefore provides additional empirical discipline on the mix of news and menu-cost changes that can jointly account for the frequency, size, and markup evidence.[2]

Together, these patterns make a pure realization-driven uncertainty shock or an upstream marginal-cost shock unlikely to be the main driver of the supermarket pricing response. The

[2]Appendix A.2 formalizes this reset-price distinction in a finite-horizon menu-cost model with persistent desired prices. In the random-walk limit, the model nests the Dixit (1991) logic and firms reset to their desired price. With a stationary desired-price process, as in our full quantitative model, the reset price depends on the firm's state. In this setting, the current menu cost affects the adjustment decision and the width of the inaction region, but drops out of the reset-price first-order condition conditional on adjustment. Future uncertainty enters through the continuation value and can therefore affect the reset price.

absence of stronger responses among supermarkets more exposed to local riot intensity also weighs against localized-disruption mechanisms that require pricing responses to vary with local exposure. They do not, however, rule out a broader increase in menu costs common across supermarkets.[3]

Given our focus on uncertainty and state-dependent adjustment, a natural benchmark for a quantitative model is Vavra (2014). We depart in two ways that are central for our empirical interpretation and for our application. First, we distinguish anticipation from realization and show why the anticipation mechanism is empirically hard to seperate from menu-cost changes using frequency and size alone. Second, because our candidate shock is about idiosyncratic demand rather than marginal costs, we need a demand system in which demand conditions affect desired prices and markups. Under CES demand, idiosyncratic demand shocks move quantities but not desired markups. We therefore use a Kimball (1995) aggregator, which generates variable markups and gives the markup moment empirical content.

We then use the model to quantify the relative roles of (i) news about future dispersion (anticipation) and (ii) menu-cost changes in explaining the three facts we identify during the Social Uprising. Both forces can generate a decline in frequency and an increase in size. The news channel alone generates a positive markup response and contributes to the frequency and size responses, but it cannot by itself match the full decline in frequency and increase in size observed in the data. By contrast, a menu-cost shock can generate large movements in frequency and size, but it does not directly move reset prices conditional on adjustment and cannot account for the observed markup response on its own. Quantitatively, we use the three empirical moments to discipline a baseline combined experiment in which both news and menu costs may move. We find that the two channels are complementary across moments: news is essential for matching the markup response, while menu costs account for much of the frequency and size responses. Together, they can account for all three moments. The resulting experiment features a 52 percent temporary increase in the menu cost today, together with news that idiosyncratic demand dispersion tomorrow will increase by a factor of 2.51 with 50 percent probability. We also provide evidence and additional discussion in an appendix on why other candidate explanations cannot account for the three moments.

Finally, we use the calibrated model to study monetary policy effectiveness. The main policy lesson is about timing and about which component of uncertainty is operative. When firms anticipate higher future dispersion but have not yet observed it, the delay in adjustment

[3] For example, the Social Uprising may have temporarily disrupted routine price monitoring, internal approval, or implementation processes at the chain level. It may also have led firms to prioritize staff safety, inventory management, damage prevention, and store operations over routine price changes. These mechanisms could affect pricing decisions broadly and need not vary one-for-one with a supermarket's exposure to local riot intensity.

implies larger real effects of nominal interventions on impact: in our calibrated experiment, the impact response is amplified by 51% relative to the steady-state benchmark. If the news is realized in the following period and dispersion increases, the opposite force emphasized by Vavra (2014) dominates: prices become more flexible, and monetary effectiveness is attenuated by 75% relative to the corresponding no-realization case. Moreover, holding fixed the decline in adjustment frequency, a pure menu-cost shock and a pure news shock have similar implications for monetary non-neutrality in our calibrated environment.

Beyond the Chilean episode, the broader implication is that many consequential economic events — financial crises, political transitions, trade disruptions, large policy shifts — operate first through expectations and uncertainty about the future, before materializing in current fundamentals. In such settings, the economy's response to anticipation need not resemble the response to realization. Failing to distinguish these phases risks misreading the timing, magnitude, and mechanism of any effect one hopes to study, with direct consequences for how we assess the effectiveness of policy interventions.

Literature review. Our paper contributes to several strands of the literature. A growing literature examines the macroeconomic effects of uncertainty. Bloom (2009, 2014) quantitatively show that uncertainty shocks can decrease investment and hiring through wait-and-see behavior.[4] Fernández-Villaverde et al. (2011) study real interest rate volatility fluctuations in emerging economies, while Fernández-Villaverde et al. (2015) study fiscal uncertainty, both in the absence of changes in means. In both cases, higher uncertainty dampens economic activity. These papers underscore that second-moment shocks, even in the absence of changes in means, can have large real effects. We build on this foundation by examining how uncertainty affects firms' pricing behavior in a setting where first-moment shocks are limited.

An empirical challenge in this literature is to distinguish the anticipation effect of higher uncertainty about future events from the realization effect of higher volatility of current shocks. Berger et al. (2019) provide evidence that innovations to realized volatility are contractionary, whereas shocks to expected future volatility have weaker macroeconomic effects. Related evidence from asset prices draws a similar distinction: Dew-Becker et al. (2017) study the term structure of variance claims and find that transitory realized variance is priced, while news about future variance is not priced in the same way. Other papers seeking to measure the anticipatory component of uncertainty include Baker et al. (2016), Jurado et al. (2015), and Kumar et al. (2023). This measurement problem is compounded by the fact that common proxies for uncertainty and beliefs may not trace the underlying shock

[4]The seminal work of Bernanke (1983), Dixit (1991), and Dixit and Pindyck (1994) theoretically shows how wait-and-see behavior arises under uncertainty for irreversible decisions.

at the same frequency as firm decisions: forecast disagreement is distinct from subjective uncertainty, and professional forecasts may adjust discretely and with delay (Bharadwaj, 2025; Baley and Turen, 2025). We contribute by studying a sharp episode in which pricing behavior changes without comparable changes in supplier prices or local disruption measures, allowing us to discipline the role of anticipation separately from realized volatility and menu cost shocks.

A related body of work explores the effect of uncertainty on firms' price-setting behavior in menu-cost models.[5] Vavra (2014) shows that price dispersion increases in recessions. Interpreting this finding as countercyclical idiosyncratic volatility, he shows that the realization effect typically dominates the anticipation effect in a menu-cost model, leading to countercyclical monetary policy effectiveness.[6] Drenik and Perez (2020) also empirically relate uncertainty to price dispersion. Baley and Blanco (2019) show that higher firm-level uncertainty increases the frequency and size of price changes at the micro level, while cross-sectional heterogeneity in firm-level uncertainty amplifies monetary non-neutrality. Klepacz (2021) shows that time-varying aggregate volatility affects pricing frequency and monetary transmission. We contribute to this literature by providing evidence on both the timing and magnitude of price changes around a sharp aggregate event. Critically, we use product-level input costs to discipline the marginal-cost process and to construct markups, which provide an additional moment for distinguishing news about future dispersion from menu-cost changes.[7]

From a different angle, Ilut et al. (2020) show that Knightian uncertainty can generate infrequent price adjustment. Other microfoundations for nominal price rigidity include customer anger (Rotemberg, 2005) and rational inattention (Maćkowiak et al., 2023). These papers provide alternative foundations for sluggish price adjustment, while our focus is on how news about future dispersion and menu-cost changes can generate similar frequency-size patterns but different markup implications.

There is also a literature on real rigidities in menu-cost models. For instance, Aruoba et al. (2025) and Gagliardone et al. (2025) use menu-cost models augmented with Kimball (1995) preferences. Aruoba et al. (2025) show that a menu-cost model with demand shocks

[5]Early work on menu-cost models, which jointly model the extensive and intensive margins of price adjustment, includes Barro (1972), Sheshinski and Weiss (1977), Caplin and Spulber (1987), Caballero and Engel (1993), and Dotsey et al. (1999); more recent contributions include Golosov and Lucas Jr (2007), Nakamura and Steinsson (2008), Midrigan (2011), Alvarez and Lippi (2014), and Alvarez et al. (2023).

[6]Alvarez and Lippi (2022) also show this result analytically in their Appendix C.

[7]A common practice in menu-cost models is to set the marginal-cost process to match the distribution of price changes. We instead discipline marginal costs using merged product-supermarket-location-level data on suppliers' prices, which allows us to separate supermarkets' price-setting behavior from movements in supplier prices. Eichenbaum et al. (2011) is the only paper we know using similar data; in their case, for a single supermarket in the U.S. and focusing on the pass-through of costs to prices.

and Kimball (1995) preferences can solve the tension between price dynamics and firm-level shocks highlighted by Klenow and Willis (2016). Our model shares the use of variable markups and idiosyncratic demand shocks, but departs in three ways. First, we introduce leptokurtic productivity shocks. These shocks are calibrated directly using our micro data. Second, we incorporate news about future idiosyncratic demand dispersion, generating a wait-and-see effect in pricing before the dispersion is realized. Third, we calibrate the model directly to micro-pricing facts from our data, including costs and markups.

A large empirical literature studies price setting during rare or disruptive events.[8] Hobijn et al. (2006) examine the introduction of the Euro, Gagnon (2009) studies exchange-rate pass-through during Mexico's 1994 crisis, and Alvarez et al. (2019) analyze pricing in Argentina's large inflation swings. During the COVID-19 period, Montag and Villar (2023) and Henkel et al. (2023) document reduced stickiness, while Jaravel and O'Connell (2020a,b) report increased use of sales. Cavallo et al. (2014) study supermarket prices and product availability after the 2010 earthquake in Chile and the 2011 earthquake in Japan, documenting severe disruptions in product availability together with relatively stable prices. In many of these settings, shocks reflect realized disruptions, supply shortages, lockdowns, or logistical bottlenecks, which affect current conditions directly and may also involve first-moment shocks. By contrast, the Chilean Social Uprising is useful for our purposes because the retail pricing response appears before comparable movements in supplier prices and does not vary systematically with local riot intensity. This makes the episode a useful laboratory for studying anticipatory pricing behavior and menu-cost changes in the absence of clear evidence for upstream repricing or localized disruption mechanisms.

The remainder of the paper is structured as follows. Section 2 describes our unique daily pricing panel data. Section 3 describes the Chilean Social Uprising that we use as a laboratory. Section 4 presents our empirical analysis showing the pricing effects of the Social Uprising. Section 5 presents the quantitative model, and Section 6 shows its calibration and the effects of demand uncertainty on pricing. Section 7 explores the policy implications of our findings. Finally, Section 8 concludes.

2 Data

We use a business-to-business (B2B) transaction-level dataset built from electronic invoices ("Factura Electrónica" in Spanish) collected by the Chilean Tax Authority (Servicio de

[8] More broadly on the effect of rare disasters, Barro (1972) and Gabaix (2012) study them theoretically. Empirical examples include Başkaya et al. (2024), who use the 1999 earthquake in Turkey; Acemoglu et al. (2018), who use the Arab Spring in the early 2010s; and Boehm et al. (2019) and Wieland (2019), who use the 2011 earthquake in Japan.

Impuestos Internos) and provided anonymously to the Central Bank of Chile. The coverage and granularity of the information in this dataset are unique, providing a record of the date, product description, buyer, seller, and prices for the universe of B2B transactions. We focus on the period from January 2015 to November 2019, ending the sample well before the Covid-related lockdown in March 2020 to avoid contamination from pandemic disruptions. Further details on the data are provided in Appendix B, where Section B.1 describes the construction of the dataset.

Our goal in the empirical part of the paper is to examine how the pricing behavior of firms in Chile responded to the Social Uprising. We focus on transactions at supermarkets, which are a common subject in both micro and macro studies of price setting. Supermarkets are ideal for this analysis because they post shelf prices for the goods they sell. Apart from occasional discounts, either general or conditional on a coupon or a loyalty program, they do not engage in price discrimination. Therefore, when we observe the maximum price for a good within a day, it typically corresponds to the posted shelf price. Since our dataset includes B2B transactions, we study the prices at which goods are purchased by firms in supermarkets. These transactions account for about 16% of total supermarket sales in Chile with the rest being recorded in the consumer-facing "Boleta Electrónica" system, which is only available since 2021. Prices recorded in the Factura data closely match those in the consumer-facing Boleta data for overlapping periods and products.[9] We do not use quantities in our analysis (e.g., we do not quantity-weight prices or changes). Instead, we use the detailed transaction records to observe posted prices and their changes over time.

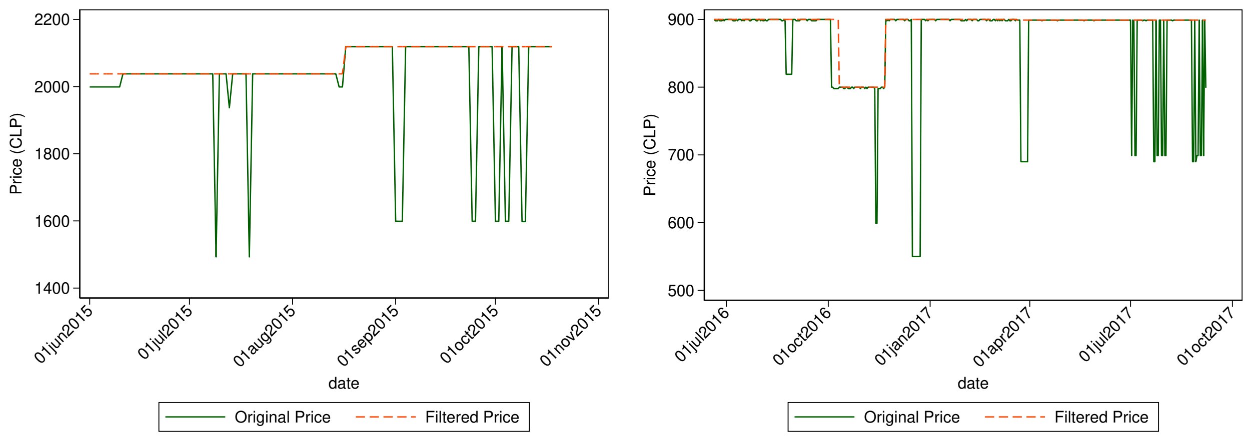
A product is defined as a unique triplet of a supermarket (seller's ID), a location, and a product description. We aggregate the transaction-level price data to daily frequency by taking the intra-day maximum price for each product triplet. This procedure filters out intra-day discounts that may be applied to some transactions but not others. We then apply the filter proposed by Kehoe and Midrigan (2015) to eliminate high-frequency variation, especially those that result from short-lived sales. Figure 1 shows the original and filtered daily prices for two randomly selected products. As expected, the filter removes transient spikes and reverts prices to their modal levels.

We also impose a continuity condition that retains products exhibiting at least one uninterrupted spell of 20 consecutive weeks, during which they are sold on no fewer than three days per week. This condition ensures that each product has a sufficiently dense set of observations to allow for precise identification of both price changes and periods of price

[9]In Appendix C.1.1 we show that for the year 2023, a period outside our main sample period but one where both data sources are available, on average 60% of products in Boleta data also appear in the Factura data, and for these products the simple correlation of prices we observe is 0.98.

Figure 1: Original and Filtered Prices: Two Products in the Dataset

(a) Product X (b) Product Y



Notes: The figure presents the original and filtered prices of two randomly selected products in the dataset. The original price is defined as the intra-day maximum price observed at a supermarket-branch location. The filtered price applies the method in Kehoe and Midrigan (2015) to remove short-term price fluctuations.

stability. Furthermore, because the COVID-19 pandemic introduced substantial disruptions to supermarket sales, we terminate the sample in November 2019 to maintain as balanced a sample as possible under the continuity requirement. These procedures yield our baseline sample, which includes 13.8 million product-day observations across 39,679 products sold in 183 supermarkets, spanning 766 locations, and covering the period from January 1, 2015, to November 17, 2019.

The granularity of the B2B invoice data allows us to complement these retail prices with information on the prices charged by suppliers. We do this by examining transactions in which supermarkets appear as buyers. Because the data lack standardized product codes (such as UPCs), we match supermarket products to supplier transactions using textual product descriptions. The procedure combines two complementary text-distance methods and retains only high-confidence matches; when a supermarket product can be matched to multiple suppliers, we keep the supplier with the longest overlap in the observation period. Appendix B.1 provides further details on the matching methodology. Each product in the matched sample is defined as a unique combination of a supermarket, a location, a product description, and a matched supplier ID. For each product in the matched sample, let p_{it} denote the filtered daily supermarket price and let c_{it} denote the matched supplier price. We define the log markup proxy as

$$m_{it} \equiv \log p_{it} - \log c_{it}.$$

In the regression analysis, we use the standardized log markup proxy

$$\tilde{m}_{it} = \frac{m_{it} - \bar{m}_{\text{pre}}}{s_{m,\text{pre}}},$$

where $\bar{m}_{\text{pre}}$ and $s_{m,\text{pre}}$ are the mean and standard deviation of the unstandardized log markup proxy in the matched sample during the pre-Social Uprising period.[10] For descriptive statistics and raw daily plots, we report changes in the unstandardized log markup proxy, Δm_{it}. The resulting matched sample includes 2 million daily price observations for 6,511 products, sold by 94 supermarkets across 490 locations, and matched to 295 distinct suppliers.

We also construct a suppliers sample to analyze the pricing decisions of the suppliers themselves. Here, products are defined as a triplet of supplier ID, buyer ID, and product description. Because the supermarket location is not recorded in supplier transactions, the location margin is collapsed on the supplier side. This sample consists of 2,016 products priced by the 295 suppliers included in the matched sample.

Table 1 presents descriptive statistics for the two supermarket samples, the baseline sample and the matched sample, as well as for the suppliers sample. The upper panel reports statistics commonly used to characterize price-setting behavior, beginning with the share of product-day observations in which a price change occurs, which we label breaks. This is then separated into positive and negative changes. We also report the average size and standard deviation of price changes, calculated using log differences. For example, Product Y in Figure 1 exhibits one positive and one negative break. The negative break corresponds to a price change of -0.1178, computed as $\log(800) - \log(900)$.

In the baseline sample, 1.17 percent of products change prices on an average day, with price increases occurring more frequently than price decreases. The average positive change is 11.5 percent, and the average negative change is 12.4 percent. The matched and supplier samples display similar patterns. In the matched sample, the average daily change in the log supermarket-price–supplier-price gap, conditional on a supermarket price adjustment, is 0.0023, with a standard deviation of 0.1577. Our dataset includes supermarkets across a broad range of regions and municipalities in Chile, with coverage in all regions. Our baseline sample includes information across 194 municipalities out of a total of 346 (56% coverage), 50 Provinces out of a total of 56 (89% coverage), and all 16 Regions. Appendix B.2 presents additional descriptive statistics and compares the properties of the Chilean data to results

[10] A practical concern is that the retail unit sold by the supermarket and the wholesale unit purchased from the supplier may differ (e.g., the supplier sells a 12-pack while the supermarket sells individual units). If the conversion factor between wholesale and retail units is constant over time within a matched product–supplier pair, then it enters $\log c_{it}$ as an additive constant and therefore is absorbed by product fixed effects in regressions. For the same reason, the descriptive statistics report changes in log markups, where product fixed effects are not directly applicable.

Table 1: Descriptive Statistics

	Baseline sample		Matched sample		Suppliers sample	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Price setting						
Total breaks	0.0117	0.1075	0.0127	0.1118	0.0106	0.1023
Positive breaks	0.0065	0.0801	0.0067	0.0815	0.0067	0.0814
Negative breaks	0.0053	0.0723	0.0060	0.0772	0.0039	0.0625
Size, positive	0.1150	0.1289	0.1001	0.1082	0.0941	0.1173
Size, negative	0.1237	0.1391	0.1056	0.1202	0.1254	0.1528
Markup change	-	-	0.0023	0.1577	-	-
Sample information						
Number of supermarkets	183		94		–	
Number of suppliers	–		295		295	
Number of supermarket locations	766		490		–	
Number of product IDs	39,679		6,511		2,016	
Number of product descriptions	13,682		1,920		1,923	
Number of observations	13,845,147		1,980,403		836,004	
Municipalities covered / Total	194 / 346		164 / 346		–	
Provinces covered / Total	50 / 56		48 / 56		–	
Regions covered / Total	16 / 16		16 / 16		16 / 16	

Notes: This table presents descriptive statistics for the three samples used in the analysis. The upper panel summarizes price-setting behavior, and the lower panel provides sample characteristics. Markup change is computed in the matched sample, conditional on a supermarket price adjustment, as the raw change in the log markup proxy, $\Delta m_{it} = \Delta \log p_{it} - \Delta \log c_{it}$. The period of analysis spans January 1, 2015 through November 17, 2019.

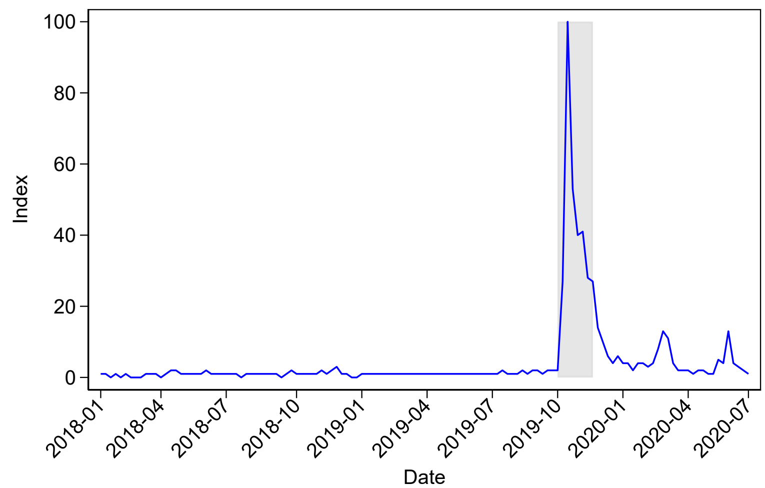
in the related literature.

3 Social Uprising as a Laboratory

On October 6, 2019, Santiago's subway fare was raised by 4 percent, equivalent to about \$0.05 USD. Students responded with peaceful demonstrations and some limited disruptions to the subway system. The situation changed drastically on October 18, when large disturbances erupted throughout the Santiago subway network. This date is identified as the start of the Social Uprising. Despite an early police response, by the morning of October 19, a significant portion of Santiago's metro infrastructure had been damaged. On November 15, roughly one month after the onset of the Social Uprising, a broad political agreement was reached among several parties to begin the process of constitutional reform. This agreement largely brought the unrest to an end.

While a detailed account of these events is beyond the scope of this paper, scholars agree

Figure 2: Google Trends for “Protestas” (Protests)



Notes: Figure shows a daily index of Google searches for “protestas” (protests) originating in Chile. The index is normalized so that the maximum value, on October 19, 2019, equals 100. The shaded area covers October 18 to November 17, 2019.

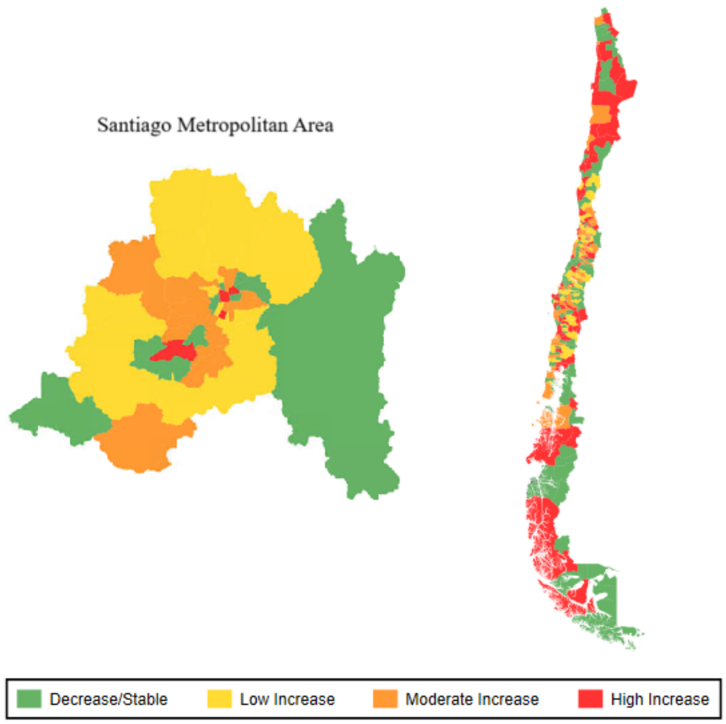
that the unrest was not only about the fare increase. Instead, it reflected deeper and more widespread dissatisfaction in society. The initial violence quickly evolved into a national movement, with leaders across sectors voicing demands related to education, health care, pensions, and wages. What began as student-led demonstrations transformed into a broad call for a new social contract, captured by the slogan “Chile cambió” (Chile changed). In response, political, social, and business leaders acknowledged the need for structural reform, which shifted expectations about Chile’s future.[11]

From the perspective of this study, two features of the Social Uprising are central. First, it was fully unexpected but relatively short-lived, making it suitable as a laboratory to study pricing when the environment facing firms changes abruptly. Figure 2 shows a daily index of Google searches for “protestas” (protests) originating in Chile. The index increases one hundred-fold between October 17 and October 19, indicating a sharp and sudden rise. By November 17, however, search volume had returned to near pre-Social Uprising levels. This also roughly coincides with the November 15 agreement. We treat this 31-day window, marked by the shaded area in the figure, as the most intense phase of the Social Uprising and use it as the period of interest in our empirical work.

Second, the Social Uprising was widespread, but the intensity of its violent component,

[11]See Joignant and Garrido-Vergara (2025) for a detailed account of the 2019 Uprising, tracing its roots in structural inequality, the range of groups involved, and the role of social media. They show how the protests, driven by discontent over education, pensions, health, and wages, ultimately catalyzed Chile’s constitutional reform process.

Figure 3: Geographical Distribution of Local Riot Intensity



Notes: The map on the right shows local riot intensity across all municipalities in Chile. The map on the left zooms into the Santiago Metropolitan Area. Local riot intensity is measured as the change in the number of police reports for public disorder in October and November 2019, relative to the same period in 2018, adjusted for population. Municipalities are grouped into four categories: green indicates no increase or a decline, yellow corresponds to the lowest third of increases, orange to the middle third, and red to the top third.

what we label as local riot intensity, varied significantly across locations. Figure 3 displays a municipality-level map of local riot intensity across Chile, with a close-up of the Santiago Metropolitan Area. Local riot intensity is measured by the increase in public disorder reports, a category that includes damage to both public and private property, relative to the same period in the previous year, adjusted for population. The map reveals substantial variation across and within regions, without a clear geographical pattern.

From the perspective of firms, the Social Uprising could have operated through more than one channel. On the one hand, the political nature of the episode plausibly shifted expectations about future economic and institutional conditions, raising uncertainty about future conditions relevant for product-level demand, costs, and profitability. On the other hand, the disruptions associated with protests and riots may have raised the effective cost of changing posted prices—for example through operational constraints or other factors that made price changes temporarily more costly to implement. The empirical analysis therefore begins by documenting how three supermarket pricing moments changed during the Social Uprising: the frequency of price changes, the size of price changes conditional on adjustment, and markup behavior conditional on supermarket price adjustments.

Before turning to our main empirical analysis, we illustrate the effect of the Social Uprising on pricing behavior using raw daily data. Figure 4 presents the three pricing moments throughout 2019. Panel (a) shows a clear and abrupt decline in the daily frequency of price changes during the 31-day period following October 18, marked by the shaded area. Panel (b) shows a simultaneous increase in the average absolute size of price changes. Panel (c), based on the matched sample, shows that when supermarkets change prices during the Social Uprising they increase their markup relative to when they adjust prices in normal times. Because of our continuity restriction, these results are based on products that remained continuously available throughout the Social Uprising. Therefore, the observed changes cannot be explained by store closures, inventory disruptions, or changes in product composition. In short, the raw data show a clear shift in pricing behavior along all three dimensions: frequency, size, and markups.[12]

4 Empirical Results

We now estimate how supermarkets' pricing strategies changed during the Social Uprising. We proceed in four steps. First, using the supermarket data, we estimate the effect of the Social Uprising on the three pricing moments: the frequency of price changes, the size of price changes conditional on adjustment, and markups conditional on supermarket price adjustments. Second, using the suppliers sample, we examine whether suppliers changed their own pricing dynamics during the same window. Third, exploiting geographic variation in riot intensity, we ask whether supermarkets with greater exposure to unrest experienced stronger pricing responses. Fourth, we report robustness checks and extensions that evaluate whether the results are sensitive to alternative specifications.

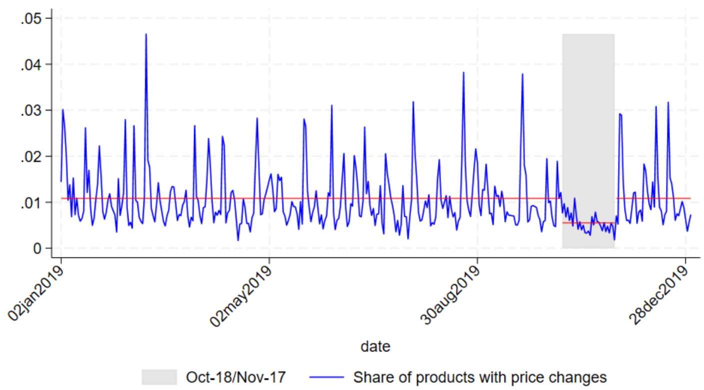
4.1 Baseline Results: Frequency, Size, and Markups

The unit of observation is a product-day. Each product is defined as a triplet of product description, supermarket chain, and store location. For example, "milk, in branch 5 of

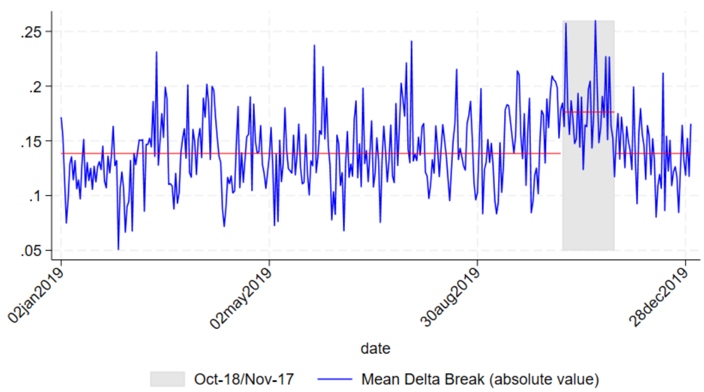
[12] Table A-6 in Appendix C.1.2 reports the share of prices that changed during this period, the distribution of price changes across percentiles, and the distribution of the standardized markup proxy. The distribution of price changes displays noticeably fatter tails during the Social Uprising, consistent with wider inaction bands and greater selection into large adjustments, while markups tend to increase during the episode.

Figure 4: Frequency, Size, and Markup Dynamics in 2019

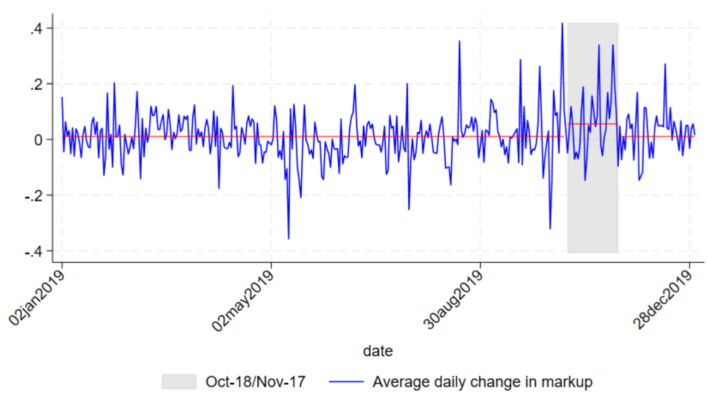
(a) Frequency of Price Changes



(b) Size of Price Changes



(c) Markup Change



Notes: Panel (a) shows the daily frequency of price changes in 2019, computed as the share of product prices that change on a given day. Panel (b) shows the average size of daily price changes in absolute value. Panels (a) and (b) are based on the baseline sample. Panel (c) shows the daily change in the log supermarket-price–supplier-price gap, conditional on a supermarket price adjustment, and is based on the matched sample. The shaded area covers the period from October 18 to November 17, 2019. The red horizontal lines report the average value of the series outside and during the Social Uprising period, corresponding to the non-shaded and shaded areas, respectively.

supermarket chain X" constitutes a distinct product. Our baseline empirical specification is

$$y_{it} = \text{Fixed Effects} + \beta D_t + \gamma_1 X_{1,it} + \gamma_2 X_{2,t} + \gamma_3 X_{3,s(i)t} + \varepsilon_{it}^{y}, \tag{1}$$

where D_t is a dummy equal to one during the 31-day Social Uprising period beginning on October 18, 2019. The coefficient of interest, β, captures the average change in pricing behavior during the Social Uprising. The vector $X_{1,it}$ includes time-varying product-level controls, $X_{2,t}$ includes an aggregate economic-activity control, and $X_{3,s(i)t}$ includes a supermarket-level economic-activity control, where $s(i)$ denotes the supermarket that sells product i.

We include product fixed effects, which control for all time-invariant characteristics at this level, including location, supermarket identity, and persistent product characteristics. As a result, identification comes from within-product changes for the same product at the same store over time, comparing before and during the Social Uprising period. The other fixed effects in (1) include day of the week, week of the month, month of the year, and non-mandatory holidays. These account for regular temporal variation in pricing, such as day-of-week cycles or seasonal patterns. The vector $X_{1,it}$ includes a third-order polynomial in the number of days since the last price change, along with a count of price changes for the product in the preceding 30 days. These controls capture state-dependent pricing dynamics. The vector $X_{2,t}$ includes total monthly retail sector sales, which controls for broad market trends. The vector $X_{3,s(i)t}$ includes total weekly purchases by each supermarket from its suppliers, capturing chain-level demand shifts. This measure is constant across all product-store combinations within a supermarket.

We estimate (1) for three main outcomes. The first is an indicator for whether the supermarket price changes on date t, which captures the frequency of price adjustment. The second is the absolute size of the log price change, conditional on a supermarket price adjustment. The third is the standardized log markup proxy, also conditional on a supermarket price adjustment. We cluster standard errors at the supermarket-location level to allow for location-specific serial correlation in pricing decisions.

Table 2 presents the baseline results. The first column shows that the frequency of supermarket price changes falls sharply during the Social Uprising. The coefficient implies a decline of roughly 0.57 percentage points, relative to an average daily frequency of about 1.17 percent. Thus, during the Social Uprising, supermarkets changed prices about half as often as in normal times.

The second column shows that, conditional on adjustment, price changes become larger. The average absolute size of price changes rises by about 3.8 percentage points, relative to a pre-Social Uprising average of 12 percent. Hence, the Social Uprising is associated with

Table 2: Change in Pricing Behavior During the Social Uprising

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0057***	0.0379***	0.0122**
	(0.0005)	(0.0093)	(0.0062)
Observations	13,845,147	155,471	23,977
Within R-squared	0.000	0.003	0.007
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200	-0.0027

Notes: This table reports estimates of β from Equation (1). The first column uses the baseline supermarket sample and the dependent variable is an indicator for a supermarket price change. The second column uses the baseline supermarket sample restricted to supermarket price adjustments and the dependent variable is the absolute size of the log price change. The third column uses the matched sample restricted to supermarket price adjustments and the dependent variable is the standardized log markup proxy defined in Section 2. The standardizing standard deviation is $s_{m,\mathrm{pre}} = 1.3548$, computed from the unstandardized log markup proxy in the pre-Social Uprising matched sample. Standard errors are clustered at the seller-location level. *** p<0.01, ** p<0.05, * p<0.1.

fewer price changes, but larger changes among the prices that do adjust.

The third column shows that markups conditional on supermarket price adjustments rise during the Social Uprising. The coefficient implies an increase of about 0.012 in the standardized log markup proxy conditional on supermarket price adjustments, or a 2.3. p.p. increase expressed in markup units.[13] This moment is central for the interpretation. Frequency and size alone cannot distinguish news about future dispersion from a temporary increase in menu costs, because both mechanisms can widen inaction regions and generate fewer but larger adjustments.

4.2 Supplier Pricing and Upstream Shocks

One explanation for the baseline results is that supermarkets may be responding mechanically to upstream repricing by their suppliers. To evaluate this hypothesis, we turn to the suppliers sample, which follows the same set of suppliers that provide goods to the supermarkets in our data. We estimate the analogue of (1) using this sample, with price changes defined at the supplier–supermarket–product level. In this supplier-side specification, the economic-activity control is each supplier's total monthly sales across all customers, rather than sales

[13]Since the standardizing standard deviation is $s_{m,\mathrm{pre}} = 1.3548$, this corresponds to a raw log-markup increase of about $0.0122 \times 1.3548 = 0.0165$. Expressed in markup units, a 37% markup prior to the Social Uprising would increase by about 2.3 p.p., to 39.3%.

Table 3: Change in Pricing Behavior During the Social Uprising, Suppliers Sample

Variable	(1) Breaks	(2) Abs Size
D	-0.0016	-0.0014
	(0.0010)	(0.0110)
Observations	836,004	8,471
Within R-squared	0.001	0.006
Controls	Yes	Yes
Economic Activity Controls	Yes	Yes
FE	Yes	Yes
Mean of Dependent Variable	0.0106	0.1060

Notes: This table reports estimates of β from Equation (1), using the suppliers sample. The first column uses an indicator for a supplier price change. The second column uses the absolute size of the log supplier price change, conditional on adjustment. The economic-activity control corresponds to each supplier's total monthly sales across all customers. Standard errors are clustered at the supplier–supermarket link level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

to the supermarkets in our matched sample.[14]

As shown in Table 3, we do not detect statistically significant changes in the frequency or size of supplier price adjustments during the Social Uprising period. The point estimates are small and statistically insignificant. These results imply that the supermarket response is unlikely to be explained by a simultaneous shift in supplier repricing behavior.

Importantly, the supplier evidence does not require the supplier prices to be literally constant day-to-day, nor does it rule out all cost pressures faced by supermarkets. Rather, it shows that the *pricing dynamics* upstream, measured by the frequency and size of supplier price changes in our invoice records, do not display a break during the Social Uprising comparable to the supermarket-side response.

4.3 Local Intensity of the Social Uprising: Local Disruptions vs National Mechanisms

Having shown that supplier repricing does not display a comparable break during the Social Uprising, we next ask whether the supermarket response varies with exposure to local unrest. If pricing behavior were driven mainly by localized contemporaneous disruptions that required local pricing responses, such as store damage, transport disruptions, or staffing shortages, we would expect supermarkets that are more exposed to local riot intensity to display stronger responses.

[14] One may wonder whether the baseline results also hold in the matched sample. Table A-7 in Appendix C.2.1 shows that the results are similar in this sample.

We start from municipality-level variation in local riot intensity, shown in Figure 3. Local riot intensity is measured as the change in police reports for public disorder in October and November 2019 relative to the same period in 2018, adjusted for population. Because supermarkets may coordinate pricing and operational decisions across locations (DellaVigna and Gentzkow, 2019), our main intensity measure aggregates this municipality-level variation to the supermarket level. Specifically, for each supermarket, we construct exposure to local riot intensity as a weighted average of local riot intensity across the municipalities in which the supermarket operates, using the supermarket's sales distribution across municipalities as weights. This measure captures the extent to which a supermarket is exposed to unrest through its geographic footprint. We refer to this variable as $\text{Intensity}_{s(i)}$ where $s(i)$ represents the supermarket that sells the product i.

To estimate whether the pricing response varies by exposure to local riot intensity, we interact this exposure measure with the Social Uprising period dummy and estimate

$$y_{it} = \text{Fixed Effects} + \beta D_t + \theta D_t \times \text{Intensity}_{s(i)} + \gamma_1 X_{1,it} + \gamma_2 X_{2,t} + \gamma_3 X_{3,s(i)t} + \varepsilon^y_{it}. \quad (2)$$

The direct effect of *Intensity* is absorbed by product fixed effects, since products are defined at the product–supermarket–location level. The controls $X_{1,it}$, $X_{2,t}$, and $X_{3,s(i)t}$ are defined as in (1).

Table 4 presents the results. The coefficient on the Social Uprising dummy remains significant and similar in sign to the baseline estimates in Table 2: frequency falls, size rises, and markups rise. In contrast, the interaction between the Social Uprising dummy and riot-intensity exposure is statistically insignificant across the three outcomes, and the point estimates are small relative to the baseline effects.[15]

4.4 Robustness and Extensions

Appendix C presents a series of robustness checks and extensions to our main empirical findings. These serve two purposes: to evaluate whether the estimated effects are sensitive to specification choices, and to explore whether alternative mechanisms, such as unmodeled costs or omitted shocks, could plausibly account for the results.

Raw data and controls. As shown in Figure 4, the drop in price-change frequency, the rise in average size, and the change in markup behavior are visible in the raw daily data. To assess the role of our control variables, we re-estimate Equation (1) removing all controls

[15] In Appendix C.3.3, we replicate this analysis using a municipality-level measure of local riot intensity assigned directly to each supermarket location. The main findings remain unchanged.

Table 4: Supermarket Analysis: Baseline Sample and Local Riot Intensity

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0070***	0.0453***	0.0209**
	(0.0012)	(0.0120)	(0.0081)
$D \times$ Intensity	0.0001	-0.0003	-0.0004
	(0.0000)	(0.0006)	(0.0003)
Observations	13,845,147	155,471	23,977
Within R-squared	0.000	0.003	0.007
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200	-0.0027

Notes: This table reports the estimated coefficients β and θ from Equation (2). Intensity is measured at the supermarket level as a sales-weighted average of municipality-level riot intensity across the municipalities where the supermarket operates. Municipality-level riot intensity is the change in public disorder reports in October–November 2019 relative to the same period in 2018, adjusted for population. The columns mirror Table 2: a pooled supermarket price-change indicator, absolute size conditional on a supermarket price adjustment, and the standardized log markup proxy from the matched sample conditional on a supermarket price adjustment. Standard errors are clustered at the seller-location level. *** p<0.01, ** p<0.05, * p<0.1.

except for the fixed effects. Appendix C.2.2 shows that the frequency, size, and markup results are robust: frequency and size effects remain similar, and markup effects are stronger when controls are excluded.

Balanced panel. Another check uses a balanced panel of products that pass a stricter continuity restriction for every week in the period September 23, 2019 to November 17, 2019. Appendix C.3.1 shows that the decline in frequency is about one-quarter smaller than in the baseline specification but still highly significant, while the estimated increases in the size of price changes and markups remain close to the baseline results.

Fixed effects and supermarket-wide pricing. Our baseline specification includes product fixed effects, where products are defined at the product–supermarket–location level. Thus, identification comes from within-product changes for the same product sold by the same supermarket at the same location. If supermarket chains coordinate pricing across stores, this specification already allows for persistent differences in pricing policies across supermarket–product–location combinations. As an additional check, Appendix C.3.2 interacts the Social Uprising dummy with the size of the supermarket location, measured by average monthly sales before the Social Uprising. The baseline effects remain significant, and the interaction terms are insignificant for frequency and size. For markups, the interaction is negative and statistically significant, suggesting that the markup increase was less pronounced in larger supermarket locations.

Additional controls. Finally, we augment the baseline regressions with additional controls. Appendix C.3.4 reports results controlling for the monthly log-difference of the CLP/USD exchange rate; Appendix C.3.5 controls for each supermarket's monthly wage bill; and Appendix C.3.6 controls for the most recent price change by the product's supplier in the matched sample. Across these specifications, the Social Uprising coefficient remains stable and statistically significant.

Taken together, these robustness checks reinforce the conclusion that the decline in frequency, the rise in size, and the increase in markups during the Social Uprising are not artifacts of controls, fixed effects, or compositional changes in products.

4.5 Summary of Empirical Results

During the 31-day period following the outbreak of the Social Uprising on October 18, 2019, supermarkets in Chile changed the way they set prices. They adjusted prices less often, made larger changes conditional on adjustment, and had higher markups conditional on adjusting prices. These facts are visible in the raw data and are robust to a wide set of controls and specifications.

These empirical patterns connect directly to the distinction between realization and anticipation discussed in the Introduction. A pure realization of higher current dispersion would tend to increase the frequency of price adjustment by pushing more firms outside their inaction bands. This is inconsistent with the decline in frequency that we observe. The joint decline in frequency and increase in size therefore points away from a pure realization channel and toward mechanisms that make supermarkets more willing to wait before changing prices.

Frequency and size alone, however, do not isolate anticipation. As discussed in the Introduction, an increase in menu costs can also widen inaction regions, reduce the frequency of adjustment, and increase the size of price changes conditional on adjustment. The evidence therefore leaves two plausible forces: news about future conditions and a temporary increase in menu costs. The supplier and riot-intensity results help narrow the interpretation. Suppliers do not display a comparable change in their own pricing dynamics, which makes upstream repricing or supplier-side cost shocks unlikely to be the main driver of the supermarket response. The supermarket response also does not vary with exposure to local riot intensity, which weighs against localized-disruption explanations that predict stronger pricing responses in more exposed locations. At the same time, these results remain consistent with national mechanisms, including both a nationally shared shift in expectations about future demand conditions and a nationwide increase in effective menu costs.

Markup dynamics provide the additional restriction. In the model, a menu-cost shock changes the extensive margin of adjustment and the selection of firms that adjust, but it does not directly move reset prices conditional on adjustment. News about future dispersion, instead, changes the continuation value of reset prices and can move markups. The next section therefore introduces a quantitative model with both forces, news about future idiosyncratic demand dispersion and temporary menu-cost changes, and uses the three empirical moments jointly to quantify their relative roles and study the implications for monetary policy.

5 Quantitative Model

In the rest of the paper, we turn to a calibrated quantitative model to accomplish two tasks. First, we use the model to quantify the relative roles of the two channels discussed so far in accounting for the three empirical moments documented during the Chilean Social Uprising: lower frequency of price changes, larger price changes conditional on adjustment, and higher markups conditional on supermarket price adjustments. The first channel is *news* about a possible increase in the future dispersion of idiosyncratic demand, which captures the anticipation effect. The second is a current increase in menu costs. The model also allows us to evaluate whether other candidate explanations can jointly account for the three empirical moments. Second, we use the calibrated model to study how these two channels influence the effectiveness of monetary policy.

Our model is a standard menu-cost model with two additional ingredients that are necessary for our application. First, we include idiosyncratic demand shocks in addition to productivity shocks. In normal times, which we use to calibrate the model, idiosyncratic demand follows an AR(1) process with a constant innovation variance. We model the anticipation effect during the Social Uprising as news about a possible future increase in the innovation variance of idiosyncratic demand. Second, we replace the standard constant elasticity of substitution (CES) aggregator with the Kimball (1995) aggregator, which generates variable markups and strategic complementarities in price setting.[16] This step is essential

[16]Non-CES aggregation such as Kimball is commonly used in international finance and trade, where constant markups and complete pass-through of costs are inconsistent with the data. See Gopinath and

for the demand-side mechanism. Under CES, idiosyncratic demand shocks affect quantities but not desired markups, so anticipated or realized changes in demand dispersion cannot generate systematic movements in reset prices *relative to cost*, which is one of the key empirical objects we study. Kimball demand breaks this neutrality by making the elasticity faced by a firm depend on its idiosyncratic demand state.

A final distinguishing feature of our approach is methodological: we observe both prices and input costs at the product level and directly calibrate the model to micro data from Chilean supermarkets and their suppliers. This allows us to discipline key pricing moments—including pass-through and markup dynamics, in addition to the more standard frequency and size of price changes—directly with the data.

Throughout this section, we use x, x' and x_{-1} to denote the value of a generic variable in the current, next and previous periods, respectively. Much of the detail is relegated to Appendix D, including the household's problem, which is entirely standard.[17]

5.1 Final Good Producer

A representative firm aggregates intermediate varieties y^i into a final good Y using the implicit aggregator introduced by Kimball (1995), defined as

$$\int_0^1 G\left(\frac{\nu^i y^i}{Y}\right) di = 1, \tag{3}$$

where ν^i is a variety-specific demand shifter that scales consumer preferences for good i. As in Aruoba et al. (2025), we allow ν^i to evolve stochastically and to affect not only the level but also the elasticity of demand.

We adopt the functional form for $G(\cdot)$ used in Dotsey and King (2005) and Harding et al. (2021)

$$G\left(\frac{\nu^i y^i}{Y}\right) = \frac{\omega}{1+\omega\psi}\left[(1+\psi)\frac{\nu^i y^i}{Y} - \psi\right]^{\frac{1+\omega\psi}{\omega(1+\psi)}} + 1 - \frac{\omega}{1+\omega\psi}, \tag{4}$$

where ω governs the baseline price elasticity of demand in the symmetric equilibrium, and $\psi \leq 0$ controls how that elasticity varies with quantity (i.e., the super-elasticity). The steady-state markup is jointly determined by both ω and ψ.

Given a vector of prices $\mathbf{p} = \{p^i\}_{i\in[0,1]}$, the price of the final good P, and total final output Y, the final-good producer chooses intermediate inputs $\{y^i\}$ to maximize profits, solving the

Itskhoki (2010) and Amiti et al. (2019) for recent applications.

[17] A representative household supplies labor to firms in exchange for wage payments, trades a complete set of Arrow-Debreu securities, and consumes a final good. It also owns all firms in the economy and receives all accrued profits.

problem

$$\max_{\{y^i \geq 0\}} \quad 1 - \int_0^1 \frac{p^i y^i}{PY} di \quad \text{subject to} \quad \int_0^1 G\left(\frac{\nu^i y^i}{Y}\right) di = 1. \tag{5}$$

The solution to this problem yields a system of implicit demand functions for each variety, $y^i = y(p^i, \nu^i; P, Y, \lambda)$, where the unit cost index $P(\mathbf{p})$ and the Lagrange multiplier $\lambda(\mathbf{p})$ both depend on the full vector of prices.[18]

When $\psi = 0$, the aggregator collapses to the familiar CES case. In this limit, ν^i enters demand purely as a multiplicative taste shifter: it affects quantities but not markups. This is exactly the structure analyzed in Redding and Weinstein (2020), where demand shocks scale revenue but leave pricing incentives unchanged. With $\psi < 0$, by contrast, the elasticity of demand decreases in ν^i—so that firms facing higher demand optimally charge higher markups. This feature is crucial for generating a pricing response to demand shocks in our model. Aruoba et al. (2025) provide a detailed description of how the Kimball (1995) aggregator compares to the more standard CES aggregator, in particular under idiosyncratic demand shocks.

5.2 Intermediate Producers

A continuum of intermediate producers, indexed by $i \in [0, 1]$, each produces a differentiated variety using linear technology: $y^i = z^i h^i$, where z^i is idiosyncratic productivity and h^i is labor input. Since all producers are ex-ante identical and we focus on a symmetric equilibrium, we omit the i superscript where convenient.

Idiosyncratic productivity z evolves according to a Poisson AR(1) process, as in Midrigan (2011) and Vavra (2014)

$$\log z = \begin{cases} \rho_z \log z_{-1} + \sigma_z \epsilon^z, \quad \epsilon^z \sim \mathcal{N}(0,1) & \text{with probability } p_z, \\ \log z_{-1} & \text{with probability } 1 - p_z. \end{cases} \tag{6}$$

Idiosyncratic demand ν follows a standard AR(1) process

$$\log \nu = \rho_\nu \log \nu_{-1} + \sigma_\nu \epsilon^\nu, \quad \epsilon^\nu \sim \mathcal{N}(0,1). \tag{7}$$

We separate the firm's problem into two stages. First, the firm chooses its nominal price p, taking as given the price of the final good P, aggregate output Y, the multiplier for the final-good problem λ, and the implied demand function $y(p, \nu; P, Y, \lambda)$. In solving this problem, the firm faces a fixed cost f expressed in terms of labor units to change prices.

[18] Under the Kimball specification, a single scalar price index does not suffice to summarize cross-variety interactions; see Matsuyama (2025) for a detailed discussion.

Thus, at the start of each period, the firm decides whether to re-optimize and pay f, or keep $p = p_{-1}$.[19] Second, conditional on the resulting quantity y, it hires labor to meet demand following $h = y/z$, which is the solution to a cost minimization problem of choosing inputs given a level of output.

The effect of demand ν on pricing operates through the Kimball aggregator discussed earlier: firms with higher ν face less elastic demand and charge higher markups. Under CES, this channel would be absent—prices would move one-for-one with marginal cost and desired markups would be constant. Under Kimball, both cost and demand fundamentals shape pricing, leading to incomplete pass-through and markup variation. This variable-elasticity structure creates strategic complementarities in price-setting: demand becomes more elastic above the average price and less elastic below it, making large deviations in either direction increasingly costly and pulling firms' optimal prices toward the aggregate. These interactions are central to the model's predictions about inertia and the effects of policy.

5.3 Equilibrium

We focus on a symmetric stationary equilibrium, as the model features no aggregate risk. Aggregate nominal spending is defined as $S \equiv PY$, where P is the price of the final good. We assume that S grows deterministically at a constant rate μ, such that $\log(S) = \mu + \log(S_{-1})$. Given this deterministic growth path, equilibrium consists of a time-invariant distribution over firm states (ν, z, p) and associated pricing decisions that jointly satisfy firms' optimality, the aggregation constraint, and market clearing. A formal definition of equilibrium is provided in Appendix D.4, and the full solution algorithm for the steady state is described in Appendix D.5.1.

6 Quantitative Results

We now bring the model to the data in two steps. First, we calibrate the model using Chilean microdata from normal times, excluding the Social Uprising period. The data include both retail and supplier prices, which allows us to discipline cost-side processes and retail pricing behavior directly. Second, we introduce the Social Uprising into the model in a way that is disciplined by our empirical evidence. The next subsection details our calibration strategy.

[19] Unlike CES, there may be states in which the firm finds no profitable price that yields positive sales. In such cases, the firm remains dormant and earns zero profits. That is, if for a given (ν, z) no interior solution exists that yields $y > 0$, the firm sets $y = 0$. We treat this as a dormancy state. For our calibration, dormancy occurs with very low probability and has negligible impact on aggregate outcomes.

Table 5: External Calibration

Parameter	Description	Value	Source
β	Discount Rate	0.997	3.67% Real rate per annum
μ	Trend Inflation	0.37%	Nominal and Real GDP Growth
p_z	Prob. change in idio. TFP	0.19	Supplier price change frequency
ρ_z	Idio. TFP persistence	0.33	Supplier price AR(1) estimate
σ_z	Idio. TFP innovation	0.10	Supplier price AR(1) estimate
ξ	Labor disutility	1.0	Normalization

Notes: This table reports externally calibrated parameters and the empirical source or identifying moment used for each.

6.1 Calibration

Our calibration strategy takes full advantage of the rich Chilean microdata, especially the matched supplier-supermarket price data. This allows us to go beyond the standard practice of targeting only retail price-setting moments. We directly use supplier price dynamics to discipline the leptokurtic idiosyncratic productivity process, and we use matched retail and supplier prices to discipline markups and pass-through. This direct measurement of both prices and input costs is a distinctive feature of our approach and constitutes a contribution to the quantitative menu-cost literature. We set the model frequency to monthly and when necessary, we aggregate our daily dataset to the monthly level to construct the calibration targets.

We begin by externally calibrating a subset of parameters, shown in Table 5. The discount factor is set to $\beta = 0.997$, consistent with a 3.67% annual real interest rate, and the labor disutility parameter ξ is normalized to unity. We set the trend growth rate of nominal expenditure μ to 0.37%, based on the average monthly difference between nominal and real GDP growth in Chile from 1996 to 2021.

We use the matched supermarket-supplier data to discipline the idiosyncratic productivity process. Assuming that the marginal cost of a product equals the supplier price of the product, we treat the inverse of the supplier price as the firm's TFP. The probability of receiving a productivity shock, p_z, is calibrated to match the observed monthly probability of a supplier price change, 0.19. Conditional on a price change, we estimate the AR(1) parameters of the productivity process by regressing the log inverse of supplier prices on its lag using the Arellano and Bond (1991) panel estimator with supplier fixed effects. This yields $\rho_z = 0.33$ and $\sigma_z = 0.10$.

We then jointly calibrate the remaining parameters $(\omega, \psi, \rho_\nu, \sigma_\nu, f)$ to match five empirical moments: the average markup, cost pass-through, the fraction of price changes that are increases, the average size of price changes, and the monthly frequency of price changes. The

Table 6: Internal Calibration

Parameter	Description	Value	Target Moment	Model	Data
ω	Kimball elasticity	1.32	Avg. Markup	0.37	0.37
ψ	Super-elasticity	-1.68	Cost Pass-through	0.31	0.31
ρ_ν	Demand AR(1) persistence	0.76	Fraction up	0.53	0.53
σ_ν	Demand AR(1) innovation	0.088	Size of change	0.11	0.11
f	Menu Cost	0.042	Frequency	0.26	0.26

Notes: The table reports internally calibrated parameters along with the model and empirical values of their associated target moments.

calibrated values and moment matches are shown in Table 6. The model reproduces all five targeted moments exactly up to two decimal points.

The Kimball parameters (ω, ψ) control the curvature of demand and thus shape both markups and pass-through. We compute the average markup as the ratio between the observed supermarket price and the supplier price for matched products. To avoid unit mismeasurement (e.g., bulk versus per-unit pricing), we exclude cases where the supermarket price is below the supplier price. The average markup is 37% in the data.

To estimate the pass-through, we regress changes in log supermarket prices on changes in log supplier prices, conditional on observing a price change:

$$\Delta \log\left(p_t^i\right) = \beta \cdot \Delta \log\left(c_t^i\right) + \text{Product FE}_i + \epsilon_t^i, \tag{8}$$

where c_t^i is the matched supplier price. We find $\beta = 0.31$, consistent with short-run pass-through estimates in the literature (e.g., Burstein and Gopinath (2014)). The model, via $\psi < 0$, replicates this incomplete pass-through exactly.

The menu cost f is pinned down by the frequency of price changes, which is 26% per month in the data. Finally, the idiosyncratic demand parameters (ρ_ν, σ_ν) are jointly chosen to match the average size of price changes, 11%, and the fraction of increases, 53%. With $(\rho_\nu, \sigma_\nu) = (0.76, 0.088)$, the model hits both targets precisely.

6.2 Introducing the Social Uprising into the Model

With the model calibrated to normal times, we introduce the Social Uprising as a combination of two changes: news about a possible future increase in idiosyncratic demand dispersion, and a contemporaneous increase in the cost of changing prices. We assume that prior to period $t = 0$ the economy is at the steady state. At $t = 0$, firms learn that the standard deviation of idiosyncratic demand innovations at $t = 1$ may be higher by a factor of $\mathcal{D}$ with probability $\mathcal{P}$. Specifically, this news leads to the following $t = 1$ law of motion for ν:

$$\log \nu_1 = \rho_\nu \log \nu_0 + u\,\sigma_\nu \varepsilon_1^\nu, \qquad u = \begin{cases} \mathcal{D} & \text{with prob. } \mathcal{P}, \\ 1 & \text{with prob. } 1 - \mathcal{P}. \end{cases} \tag{9}$$

From $t \geq 2$ onward, the economy reverts to the baseline process with innovation standard deviation σ_ν.

We also assume that in period $t = 0$ the fixed cost of adjusting prices temporarily changes according to

$$f_t = \begin{cases} \mathcal{M} \times f & \text{if } t = 0, \\ f & \text{if } t > 0. \end{cases} \tag{10}$$

In other words, the menu cost temporarily increases in period $t = 0$ and immediately returns to normal from the next period onward.[20] Thus, the Social Uprising is introduced into the model as a combination of three parameters, $(\mathcal{D}, \mathcal{P}, \mathcal{M})$. As special cases, if $D = 1$ then the only change is an increase in the menu cost, and if $M = 1$ then the only change is news about future demand dispersion.

The change in fixed costs moves the economy off the stationary equilibrium. Similarly, although the arrival of news affects the economy only through beliefs in $t = 0$, it still creates a departure from the stationary distribution that persists as the economy converges back. Because the shock may or may not be realized in $t = 1$, we compute the dynamics under both scenarios. We use a shooting algorithm to solve for the transitional dynamics of the full economy starting at the steady state. Further details are provided in Appendix D.5.2.

We discipline the $(\mathcal{D}, \mathcal{P}, \mathcal{M})$ combination by having the model match the three key moments identified in the empirical analysis: the decline in the frequency of price changes, the increase in the size of price changes conditional on adjustment, and the increase in the standardized log markup proxy, which are shown in the first row of Table 7. These numbers are based on a monthly aggregation of our data in order to match the frequency of the model and hence differ somewhat from the daily estimates reported in Table 2. Details about these estimates are provided in Appendix C.5. We run a comprehensive search in the $(\mathcal{D}, \mathcal{P}, \mathcal{M})$ space to find the combination that best matches these three targets. We arrive at the combination $\mathcal{D} = 2.51$, $\mathcal{P} = 0.5$, and $\mathcal{M} = 1.52$, which means that firms expect a 2.51-fold increase in demand dispersion tomorrow with 50% probability, while the menu cost increases by 52% today. The second row of Table 7 shows that the model, with this configuration, captures the three empirical moments well.

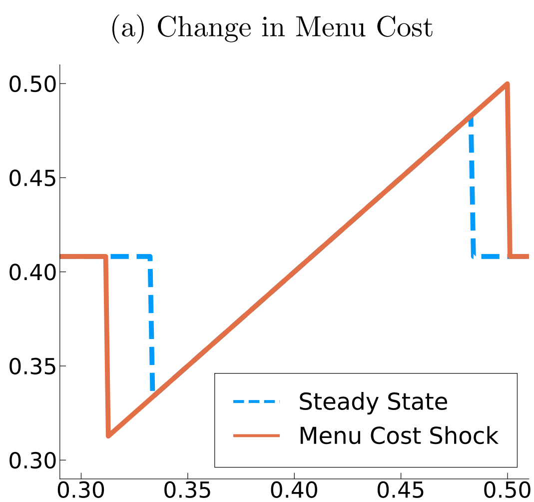
[20] We experimented with different durations of the increase in menu cost, from lasting for a few periods to being permanent. In terms of the impact on period $t = 0$ outcomes, these alternatives lead to very similar, though weaker results. This is because these enter the continuation values for adjusting and not adjusting symmetrically and almost fully cancel out. See Appendix E.1 for details.

Table 7: **Model Configurations and Moments**

Configuration	$\mathcal{D}$	$\mathcal{P}$	$\mathcal{M}$	**Frequency**	**Size**	**Markup**
Data	–	–	–	−0.135	0.021	0.025
Baseline	2.51	0.50	1.52	−0.122	0.022	0.026
News Only	2.51	0.50	1.00	−0.025	0.006	0.019
Menu Cost Only	1.00	1.00	1.52	−0.102	0.016	NS
News Only (5 p.p. decline in frequency)	2.80	1.00	1.00	−0.050	0.013	0.046
Menu Cost Only (5 p.p. decline in frequency)	1.00	1.00	1.22	−0.051	0.007	NS

Notes: The table shows how Frequency, Size and Markup changes relative to the steady state in a period where news about an increase in future demand dispersion arrives (news, increase $\mathcal{D}$-fold with probability $\mathcal{P}$), where the menu cost increases for the current period (menu cost, increase $\mathcal{M}$-fold) or both (baseline), along with their monthly data counterparts. "NS" indicates that the change was not significant based on the criteria explained in Appendix E.1.

Figure 5: Decision Rule Comparison: Menu Cost versus News



Notes: The plotted decision rule is the optimal price $p(p_{-1}, \nu, z)$ versus p_{-1}, with p and p_{-1} in logs. State variables are fixed at $\nu = 1.081$ and $z = 0.826$. Panel (a): increase in menu cost by 52%. Panel (b): arrival of news with $(\mathcal{D}, \mathcal{P}) = (2.51, 0.5)$.

6.3 Discussion of the Economic Mechanism

In the previous subsection, we showed that the Social Uprising can be introduced into the model as a combination of two mechanisms: (i) the arrival of news about future idiosyncratic demand volatility, and (ii) a contemporaneous, temporary increase in the fixed cost of adjusting prices. We now explain why a combination of the two mechanisms is needed.

To illustrate the distinction between the two mechanisms, Figure 5 compares firms' price-setting rules under a higher menu cost, Panel (a), and under a news shock, Panel (b), holding (ν, z) fixed and varying p_{-1}. The 45-degree segments show the inaction region; the flat portions correspond to reset prices when the firm adjusts. In both cases, the inaction region expands, as firms become less likely to adjust prices. However, only the news shock leads to a change in the reset price itself.

A higher menu cost today makes price adjustment less likely today by widening the inaction region. Conditional on adjusting, however, firms choose the same reset price as in the baseline for a given state. This is because the fixed cost drops out of the within-period optimization problem once the firm decides to adjust. By contrast, when firms anticipate greater future dispersion in idiosyncratic demand, they factor that into their price-setting decision today. As a result, firms that adjust choose a reset price that reflects the expected volatility ahead. The news shock therefore affects both the width of the inaction band and the level of the reset price.[21]

The discussion so far makes clear that both mechanisms can generate a decline in adjustment frequency and an increase in the average size of adjustments. The key difference is on the intensive margin. A pure menu-cost shock affects the decision of *whether* to adjust but, holding fundamentals fixed, does not directly affect the optimal *reset* price. Its effect on average size comes from selection: when adjustment becomes more costly, only firms with larger price gaps adjust. In contrast, news about future dispersion changes the distribution of future demand states and can therefore shift the optimal reset price itself. In the news case, both selection into adjustment and the reset price can move.

In Appendix E.2 we report results for experiments in which we search over $\mathcal{D} > 1$ with $\mathcal{M} = 1$, that is, news-only experiments, and over $\mathcal{M}$ with $\mathcal{D} = 1$, that is, menu-cost-only experiments. Two key results guide our conclusion that a combination of the two mechanisms is necessary to match all three data moments. First, both channels are able to match frequency and size qualitatively, but the news-only channel can deliver a maximum decline of about 5.5 p.p. in frequency and a maximum increase of about 1.4 p.p. in size, which are 41% and 67% of their data counterparts, respectively. As we explain further in Appendix E.2, this is because firms with sufficiently large current price gaps still adjust, even when future dispersion rises. The menu-cost-only channel, in contrast, can match the data values exactly. Second, the markup moment is what separates the two channels. The news-

[21] Equation (A-39) in Appendix D shows that the problem of a firm adjusting its price does not depend directly on f. Under a pure menu-cost shock, reset prices are unchanged for a given state, although aggregate markup moments can still move through selection into adjustment. Under a news shock, by contrast, the expected increase in dispersion tomorrow enters through the expectation term. Since the value function is nonlinear, higher expected dispersion can affect the choice of the optimal reset price. In general, reset prices in our model respond to news shocks, though the direction and magnitude vary with the state variables.

only channel generates a positive and significant markup response, while the menu-cost-only channel does not. The third and fourth rows of Table 7 also show that news contributes to the frequency and size responses, but menu costs account for about 80% of those two moments. In the joint experiment, the channels are not additive: news changes reset-price incentives, while menu costs change the set of firms that adjust. This selection effect can amplify the markup response to news, allowing the model to match frequency, size, and markups simultaneously.

For a given set of fundamentals, including the cost or TFP of the firm, differences in reset prices translate into differences in markups. Under CES aggregation, the desired markup is constant. Demand shifters scale quantities but do not affect desired markups, and changes in the dispersion of demand shocks–anticipated or realized–do not generate systematic movements in reset markups relative to cost. By contrast, under Kimball preferences with $\psi < 0$, demand becomes less elastic in high-demand states, so that firms optimally charge higher markups when ν is high. This introduces variable markups and implies that changes in the dispersion of future ν' can shift the expected desired markup and therefore the optimal reset markup. Thus, Kimball aggregation, or more generally a deviation from CES, is crucial for matching the markup target.

Having explained the distinct roles of news and menu-cost changes in matching the three moments, we next discuss the empirical plausibility of each channel in the Chilean episode. For the news channel, Appendix C.4 reports aggregate forecast-dispersion measures from the Central Bank of Chile's Economic Expectations Survey, as well as the World Uncertainty Index for Chile. Forecast dispersion rises sharply at the outset of the Social Uprising: disagreement about real activity forecasts increases roughly threefold, and disagreement about inflation forecasts increases roughly fivefold. We interpret this evidence as suggestive of a shift in beliefs about future economic conditions during the episode. At the same time, forecast disagreement is not a direct measure of supermarket-level idiosyncratic demand uncertainty.[22]

Turning to a sudden and temporary increase in the menu cost f during the Social Uprising, in Section 4.3, we showed that the changes in pricing behavior were not correlated with the local intensity of the riots. If higher f reflected physical or logistical disruptions that required local pricing responses, such as staffing shortages, delivery delays, or local security

[22] There are additional caveats to using this evidence to infer an increase in uncertainty. The survey concerns aggregate variables rather than product-level idiosyncratic demand, and respondents are professional forecasters rather than price setters. We therefore interpret the evidence as suggestive and do not use it directly for calibration. Bharadwaj (2025) emphasizes that forecast disagreement is an imperfect proxy for subjective uncertainty. Baley and Turen (2025) show that professional forecasts adjust lumpily and with delay. In the context of the Social Uprising, this means that measured disagreement may jump with the shock but decline more gradually than the episode itself or the high-frequency pricing response.

concerns, we would expect firms in more affected municipalities to behave differently. The absence of such heterogeneity weighs against this narrow interpretation. We interpret the temporary rise in the menu cost more broadly: not as a literal increase in the physical cost of changing a price tag, but capturing any force that triggers a national increase in the cost of implementing price changes during a turbulent period.[23] For example, staff safety, inventory control, damage prevention, and store operations may have taken priority over routine price changes, increasing the effective cost of implementing price changes. This interpretation is related to models in which firms allocate attention across tasks and adjust prices infrequently, as in Turen (2023). In the model, these forces are summarized by a higher menu cost, which raises the inaction threshold and makes firms adjust only when price gaps are sufficiently large.

6.4 Alternative Explanations

Before turning to the policy implications, we use the model to evaluate other mechanisms that may deliver the three empirical observations. We treat the parameters $(\beta, \xi, \omega, \psi)$ as structural and fixed throughout, and the previous subsection already considered a change in the menu cost f. This leaves changes, or expected changes, in the stochastic properties of idiosyncratic shocks, as well as changes in the level of aggregate demand growth S through μ, as plausible mechanisms through which the Social Uprising could affect pricing. We consider both contemporaneous changes at $t = 0$ and news about changes arriving at $t = 0$ but taking effect in $t = 1$, in line with the structure used in the main experiment. All changes we consider, whether contemporaneous or in the future, last for one period and revert to their baseline value in the following period.

Specifically, we examine five contemporaneous experiments: increases in $\mathbb{E}[\log z]$, $\mathbb{E}[\log \nu]$, $\text{Var}[\log z]$, $\text{Var}[\log \nu]$, and μ. We also examine five forward-looking experiments with a news structure: increases in $\mathbb{E}[\log z]$, $\mathbb{E}[\log \nu]$, $\text{Var}[\log z]$, and μ, as well as a decrease in f, which is the direction that induces firms to wait. We also consider two variants of the menu-cost-only experiment: one in which the increase in the menu cost lasts for five periods instead of one, and one in which it is permanent. None of the changes we consider, with one caveat discussed below, is able to match all three empirical facts. Detailed results are reported in Appendix E.1.

[23] Since the Social Uprising started with an increase in a salient price, one may think that supermarkets became reluctant to increase prices but behaved normally when decreasing prices. Appendix C.2.3 reports the baseline results separately by sign, and Appendix C.2.4 reports formal symmetry tests. The frequency of both price increases and price decreases falls, and the size of both positive and negative changes rises. The formal tests do not reject symmetry for size and provide only weak evidence against exact symmetry for frequency. This evidence helps rule out explanations based on one-sided reluctance to adjust prices.

The caveat concerns news about future TFP dispersion. In our baseline model, z follows the leptokurtic process in (6), with p_z calibrated to 0.19. Thus, with probability 81%, a firm's z does not change from yesterday to today. As a result, news about the future innovation variance of z has little effect on behavior today, because most firms are unlikely to draw a new productivity shock in the next period. In Appendix E.1, we consider an alternative specification in which z follows a regular AR(1) process, just like ν, calibrated to match the original properties of the baseline z process. Under this specification, news about a future increase in TFP dispersion has the same qualitative effect as our baseline news experiment. This shows that the anticipation effect need not operate only through demand; it could also arise from the supply side. Our empirical finding that supplier pricing does not respond during the Social Uprising, together with the availability of rich micro-data to discipline the leptokurtic process for z, guides our choice to introduce news about idiosyncratic demand rather than idiosyncratic productivity in the baseline experiment.

7 Policy Implications

In this section we examine the policy implications of an episode like the Social Uprising in Chile. In particular, we study how the effectiveness of monetary policy in stimulating real activity is affected when firms receive news about future uncertainty and, at the same time, face a temporary increase in effective menu costs. Prior work, notably Vavra (2014), shows that realized increases in idiosyncratic volatility make prices more flexible by raising the frequency of adjustment, thereby dampening the real effects of monetary shocks. When shocks become more dispersed today, more firms find themselves far from their optimal price and choose to adjust. In Appendix E.1, we replicate this mechanism: a contemporaneous increase in dispersion leads to more frequent and larger price changes.

Our empirical results point to a different force on impact. During the Social Uprising, the frequency of adjustment fell, even as the size of adjustments rose, and markups increased conditional on adjustment. Through the lens of the model, matching all three moments requires news about future dispersion together with a temporary increase in the cost of adjustment. This differs from the realization effect emphasized by Vavra (2014), where current dispersion rises, more firms move far from their desired prices, and adjustment frequency increases. The policy implications of these two changes, jointly and individually, are therefore not immediate. They depend on timing: whether monetary policy arrives when volatility is anticipated but not yet realized, or after the anticipated dispersion has materialized.

We operationalize monetary policy as a one-time, unanticipated shock to nominal aggre-

Table 8: Output Response to MP Shock

	$t=0$	$t=1$	CIR
Monetary Policy in $t=0$			
No News or Change in Menu Cost	0.458	0.216	0.793
News (realized) + Menu Cost	0.691	0.067	0.805
News (not realized) + Menu Cost	0.691	0.270	1.229
Menu Cost Only (5 p.p. decline in frequency)	0.542	0.223	0.901
News Only (not realized, 5 p.p. decline in frequency)	0.602	0.268	1.077
Monetary Policy in $t=1$			
No News or Change in Menu Cost	-	0.458	0.793
News (realized) + Menu Cost	-	0.081	0.127
News (not realized) + Menu Cost	-	0.385	0.687

Notes: Output is expressed as a fraction of the nominal expenditure shock. "Realized" means the news about higher dispersion materializes in $t=1$; "not realized" means it does not. "5 p.p. decline in frequency" refers to parameterizations of the news-only and menu-cost-only shocks chosen to generate the same 5 percentage point decline in the period-$t=0$ price-adjustment frequency.

gate expenditure, which may arrive in period $t=0$ or $t=1$.[24] Output response is measured as a fraction of the nominal expenditure shock. If prices are fully flexible, the entire shock is absorbed by P and C does not change. If prices are fully rigid, the entire shock is passed through to C. Recall that in the model $S = P \cdot C$, where P is the aggregate price level and C is consumption. Previously, S grew deterministically at rate μ, so that $\log(S) = \log(S_{-1}) + \mu$. Here we introduce a one-time increase in S_0 or S_1 equal to $3 \times \mu$ (about 1.11%), mimicking a monetary expansion. From the next period onward, S resumes its deterministic path. The policy shock pushes the economy out of its steady state, and we use a shooting algorithm to solve for the full transition, as described in Appendix D.5.3.

We report three output responses: (i) the immediate response in $t=0$, (ii) the response in $t=1$, and (iii) the cumulative impulse response (CIR), which aggregates the effect over the full adjustment path. Since our model has no explicit propagation mechanism, the impact response at $t=0$ also represents the peak effect. The impact response and the CIR offer tractable and interpretable measures of magnitude and duration of the effect, respectively.

Table 8 presents the results. The first panel shows what happens if monetary policy is

[24]Following the menu-cost literature, for example Golosov and Lucas Jr (2007), Midrigan (2011), and Alvarez and Lippi (2014), this way to implement monetary policy shocks avoids the need to model the nominal interest rate directly as a policy instrument. In practice, central banks adjust a short-term policy rate, such as the federal funds rate, in order to influence credit conditions and demand. In our framework, we capture the effect of such interventions as an exogenous change in nominal expenditure. Given the simplicity of the model, it is not possible to distinguish between a monetary policy shock and other shocks to aggregate nominal expenditures.

implemented in period $t = 0$, the period when the news arrives and the menu cost temporarily increases. The second panel shows the effects of a policy implemented in period $t = 1$, when the increase in demand dispersion may or may not be realized.

Turning to the first panel, the first row shows the baseline case with no news or menu-cost shock—a textbook monetary expansion. The output response peaks at 0.458 and dissipates quickly, with a CIR of 0.793. These magnitudes are broadly consistent with prior estimates, though care is warranted in comparing across countries.[25]

The next two rows introduce the news shock in period $t = 0$ together with the temporary increase in the fixed cost of adjustment, keeping monetary policy timing unchanged. Because firms are cautious in response to the news and because the cost of adjustment is higher today, they delay adjustment, increasing the initial effectiveness of the policy. Intuitively, when firms expect a wider range of possible optimal prices tomorrow, they become more reluctant to pay the menu cost to adjust today, especially when that cost is also temporarily higher. The resulting expansion of inaction raises nominal rigidity precisely when the policy shock hits. The impact response is amplified by 51% relative to the baseline, rising from 0.458 to 0.691.

The subsequent dynamics depend on whether the dispersion increase is realized in $t = 1$. If it is *not* realized, the economy remains closer to the high-inaction configuration induced by the news, and rigidity persists longer, amplifying the CIR by 55% relative to the baseline. If it *is* realized, the economy experiences a one-period surge in dispersion, which pushes many firms far from their desired prices and triggers a wave of adjustment in $t = 1$. In this case 56% of firms adjust in $t = 1$ (versus the steady-state value of 26%), absorbing more of the nominal stimulus and sharply reducing the continuation response from 0.270 to 0.067, a decline of 75%. As a result, the CIR falls to 0.805, so the total effect of monetary policy is attenuated by 34% relative to the non-realization case. This pattern reflects a temporary amplification followed by rapid neutralization, recovering the familiar Vavra (2014) force: once dispersion is realized in the cross section, prices become more flexible and monetary policy becomes less effective.

A central message of the paper is that *news shocks* and *menu-cost shocks* can generate similar movements in frequency and size, while differing in their implications for reset prices and markups. It is therefore natural to ask whether they also differ in their implications for monetary policy. The final two rows in the first panel address this question by comparing the

[25] For example, Alvarez et al. (2016) show that the real effect of monetary shocks is roughly proportional to the ratio of the kurtosis of price changes to the frequency of price adjustment. In our Chilean data, frequency is higher than in U.S. data (0.26 in monthly frequency, versus 0.11 as reported, for example, in Vavra (2014)) and kurtosis is similar to the values obtained in the U.S. data, implying a smaller CIR under standard calibrations.

two mechanisms in isolation. To make the comparison meaningful, we choose parameters so that each mechanism delivers the same 5 p.p. decline in price-adjustment frequency in period $t = 0$; for the news-only case, we report the non-realization state. These two specifications are shown at the bottom of Table 7. The results show that both mechanisms increase short-run monetary non-neutrality once they are scaled to generate the same decline in frequency. The menu-cost-only shock raises the impact response from 0.458 to 0.542, and the news-only shock raises it to 0.602. Thus, holding fixed the decline in the adjustment frequency, both channels operate through the same broad force: fewer firms adjust on impact, so a larger share of the nominal expenditure shock passes through to real activity.

The second panel of Table 8 shows the results when the monetary expansion occurs not at the time of the news shock ($t = 0$), but one period later ($t = 1$). In that case, if the news is realized, monetary policy becomes virtually ineffective. This again aligns with the result in Vavra (2014): realized dispersion increases price flexibility and neutralizes the real effects of policy. If the news is not realized, the intervention retains stronger effects, mirroring the findings in the contemporaneous case.

Three lessons regarding the link between uncertainty and monetary policy effectiveness emerge. First, monetary policy is more effective when uncertainty about the future leads firms to delay price adjustments, temporarily increasing nominal rigidity. Second, the ultimate real effect depends on whether the anticipated volatility materializes. If it does, firms reoptimize more aggressively, absorbing a larger share of the nominal stimulus and weakening the real response. If it does not, rigidity persists and output gains are larger. Third, once the frequency decline is held fixed, news and menu-cost shocks have similar implications for short-run monetary non-neutrality, even though they differ in their implications for reset prices and markups.

8 Conclusion

Periods of heightened uncertainty often generate large changes in firm behavior, but distinguishing realized volatility, anticipated future volatility, and changes in adjustment costs is empirically difficult. In this paper, we use the October 2019 Social Uprising in Chile and a high-frequency dataset of supermarket prices and costs to study how pricing behavior changes when firms may face both news about future conditions and higher effective menu costs. We document three changes in supermarket pricing behavior. During the 31-day window following the onset of the Social Uprising, the frequency of price changes fell by about 0.57 percentage points per day, the absolute size of price changes conditional on adjustment rose by about 3.8 percentage points, and the standardized markup proxy rose by about 0.012. These changes occurred on the supermarket side of the price chain: supplier pricing behavior did not display a comparable break during the episode. Moreover, the supermarket response was not stronger for supermarkets more exposed to local riot intensity. These facts narrow the set of plausible explanations. They make pure upstream-cost shocks unlikely and weigh against purely local disruption stories that require stronger pricing responses in more exposed locations, while leaving room for national mechanisms operating through expectations, higher effective menu costs, or both.

The empirical pattern highlights why multiple pricing moments are needed. The joint decline in frequency and increase in size is inconsistent with a pure realization effect of higher current dispersion, which would tend to push more firms outside their inaction bands and raise adjustment frequency. However, frequency and size alone do not distinguish between news about future dispersion and an increase in menu costs. Both forces can widen inaction regions, lower the frequency of adjustment, and increase the size of price changes conditional on adjustment. Markups provide the additional discipline. Once a firm pays the fixed cost and resets its price, the current menu cost is sunk and does not directly enter the reset-price decision. News about future dispersion, in contrast, changes continuation values and can move reset prices and markups. The observed increase in markups conditional on supermarket price adjustments is therefore informative about the role of news, while the frequency and size responses also point to a role for menu-cost changes.

We quantify these forces in a menu-cost model calibrated directly to the Chilean microdata. The model combines two ingredients that are essential for our application: idiosyncratic demand shocks and Kimball demand, which makes desired markups respond to demand conditions. We discipline the model using normal-times moments from supermarket and supplier prices, including pass-through and markup behavior. We then introduce the Social Uprising as a combination of news about future idiosyncratic demand dispersion and a temporary increase in effective menu costs. The two channels are complementary. News alone generates the markup response but fails to account for the bulk of the frequency and size responses. Menu-cost changes help match the decline in frequency and the increase in size, but on their own do not generate the observed markup response. The combined experiment closely matches all three empirical moments.

The model also clarifies the implications for monetary policy. A key object for short-run monetary non-neutrality is the frequency of price adjustment. When firms delay adjustment–whether because they anticipate greater future dispersion or because effective menu costs rise–nominal rigidities increase and monetary policy has larger real effects on impact. This contrasts with the realization effect emphasized by Vavra (2014): once dispersion materializes in the cross section, more firms are pushed far from their desired prices, adjustment frequency rises, and monetary policy becomes less effective. Thus, the policy implication is not that monetary policy is more powerful only under a pure news shock. Rather, monetary policy is more powerful when the relevant shock induces firms to wait, and less powerful when the shock induces firms to reprice.

The broader lesson is that episodes of social, political, or institutional distress can affect prices before the underlying fundamentals fully materialize. In such environments, firms may respond both to news about future demand conditions and to disruptions that raise effective menu costs. Distinguishing these forces requires more than measuring how often prices change and by how much. Matched cost data and markup behavior provide crucial additional information about reset prices and the mechanisms behind price adjustment. This distinction matters for interpreting micro pricing evidence and for assessing how monetary policy transmits during periods of heightened uncertainty and operational stress.

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Online Appendix to "Pricing Under Distress"
Not for Publication

A Simple Models

This appendix collects two simple models referenced in the main text. Section A.1 presents a tractable Dixit-style impulse-control model that illustrates realization and anticipation effects. Section A.2 presents a three-period model that formalizes the reset-price distinction used to interpret the markup evidence.

A.1 Dixit (1991) Model

This section summarizes the key results of the quadratic menu-cost model in Dixit (1991). A firm faces a quadratic flow loss kx^2, where $k > 0$ and x is the log price gap relative to the firm's ideal log price. Every instant, the gap follows

$$dx = \sigma dz,$$

where z is a standard Wiener process. The firm's ideal gap is $x = 0$, but it must pay a fixed cost $f > 0$ to reset the gap.

The firm solves the problem

$$V(x) = \min E \left\{ \int_0^\infty k x_t^2 e^{-rt} dt + \sum_i f e^{-rt_i} \,\middle|\, x_0 = x \right\}, \tag{A-1}$$

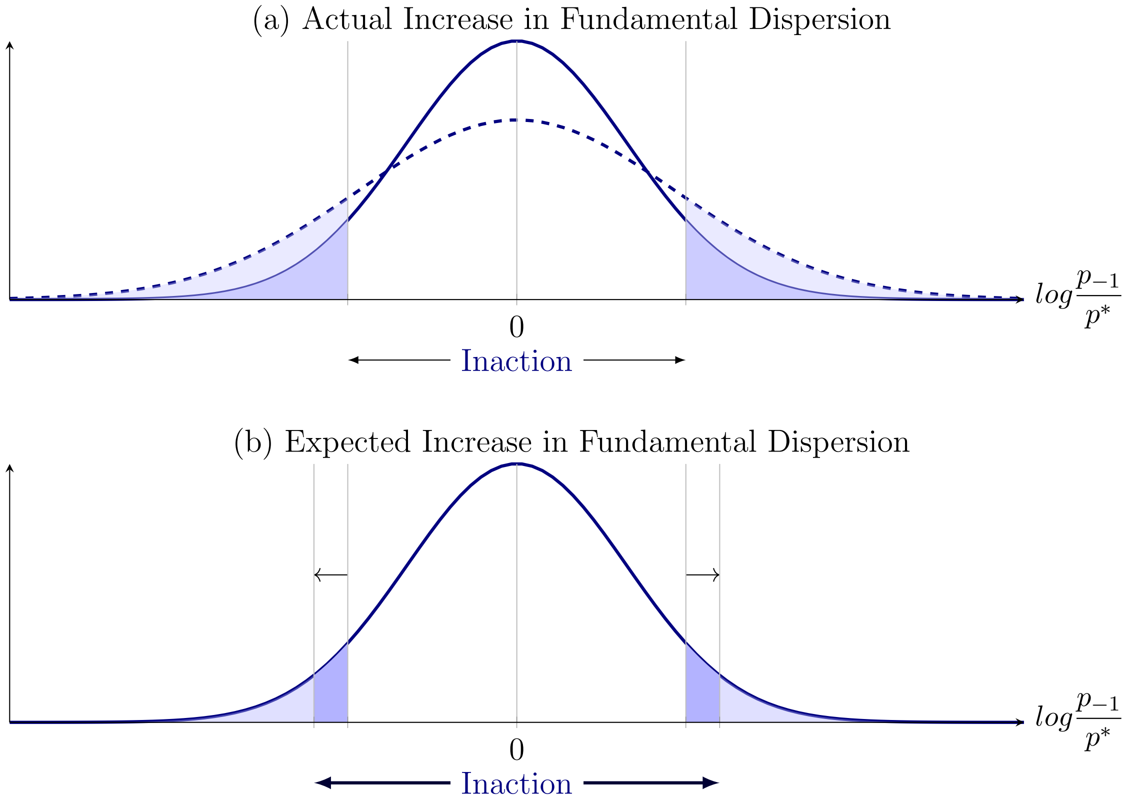
where t_i denotes the instants where the control is exercised. The solution to this problem is characterized by $\{x_1, x_2, x_3\}$ with $x_1 < x_2 < x_3$, $x_1 = -\bar{x}$, $x_2 = 0$, and $x_3 = \bar{x}$, such that as long as $x_t \in [x_1, x_3]$ no control is exercised and if x_t is outside this range the firm resets the gap to $x_t = 0$ and pays the cost f. For small enough menu cost f, the half-width of the inaction region is

$$\bar{x} = \left(\frac{6\sigma^2 f}{k} \right)^{1/4}. \tag{A-2}$$

Equation (A-2) shows that the inaction region widens with both the volatility of future price gaps, σ, and the menu cost, f.

The solid-blue distribution in both panels of Figure A-1 shows the price-gap distribution under the baseline dispersion. Firms whose price gaps fall in the blue shaded areas at the two ends of the distribution adjust their prices, while firms in the white region between

Figure A-1: Distribution of Desired Price Changes in a Stylized Menu Cost Model



Notes: Panel (a) shows the effects of an increase in the current price-gap distribution, going from the less dispersed solid-blue distribution to the more dispersed dashed-blue distribution. All else is held equal, including expectations about future states, so the inaction region remains fixed at $[-1, 1]$. The grey vertical lines represent the inaction bands. The dark-blue and light-shaded areas represent the mass of firms adjusting prices under the two distributions, respectively. Panel (b) shows an increase in future dispersion of idiosyncratic states, holding the current distribution of desired price gaps constant. This induces a wider inaction region, depicted by the shift in the grey vertical lines from $[-1, 1]$ to $[-1.2, 1.2]$. The light-blue shaded areas represent the mass of firms adjusting, whereas the dark-blue shaded areas represent the mass of firms that choose not to adjust after the shock to future dispersion. The figures are drawn with: $k = 1$, $f = 0.3945$, $\sigma = 0.65$ for the solid-blue distribution and $\sigma = 0.936$ for the dashed-blue distribution.

the adjustment thresholds do not adjust. In the first exercise shown in Panel (a), initially the log price gap is drawn from a distribution with dispersion σ, which is the solid-blue distribution. Suddenly, in the current instant, the firm faces draws from a more dispersed distribution, understanding that in the next instant log price gaps will again be drawn from the original distribution. Because the inaction bands reflect the dispersion the firm will face in the future, they remain unchanged. Therefore, only the current distribution becomes more dispersed. The wider dashed-blue distribution has more mass in the tails relative to the baseline distribution; therefore, more firms adjust and the average adjustment size rises. This is the *realization* effect of higher dispersion.

In Panel (b), dispersion is instead expected to increase starting in the next instant, with no change in the distribution in the current instant. Because the current distribution does not change, the distribution of desired price gaps is unchanged. The key mechanism is forward-looking: a firm near the edge of the inaction region anticipates that higher dispersion in the next instant makes it more likely that any price it sets now will become quickly suboptimal, potentially requiring another menu cost payment. As shown by equation (A-2), higher expected future dispersion raises the half-width of the inaction region. As a result, the firm prefers to wait until the state in the next instant is revealed. This enlarges the inaction region now, reducing the frequency of price changes and increasing adjustment size conditional on changing. This is the *anticipation* effect isolated from realization.

Equation (A-2) also shows why the frequency-size pattern is not by itself diagnostic of the underlying mechanism. Holding current price gaps fixed, an increase in expected future dispersion widens the inaction region because firms prefer to wait before paying the menu cost. Holding dispersion fixed, an increase in the current menu cost also widens the inaction region. Both forces reduce the frequency of adjustment and increase the average size of price changes conditional on adjustment. Thus, frequency and size alone cannot distinguish news about future dispersion from an increase in the current menu cost.

A.2 Three-Period Discrete-Time Model

We consider a firm facing a three-period horizon $t = 1, 2, 3$. This is a simplified version of the full model with a finite horizon, a pricing target instead of an explicit cost structure, and no quantity (or input) choice.

The desired log price for the firm is x_t and it follows an AR(1) process

$$x_{t+1} = \rho x_t + \varepsilon_{t+1},$$

where

$$\varepsilon_1 \sim \mathcal{N}(0, \sigma^2), \qquad \varepsilon_2 \sim \mathcal{N}(0, \sigma_2^2), \qquad \varepsilon_3 \sim \mathcal{N}(0, \sigma^2),$$

with all innovations independent. The firm chooses a price p_t in each period and incurs the period loss $(p_t - x_t)^2$. The firm starts period $t = 1$ with an inherited price p_0 and desired price x_1. Changing price in period 1 costs f_1. Changing price in periods 2 and 3 costs f. There is no continuation value after period 3.

Define the inherited price gap at the beginning of period t by

$$z_t = p_{t-1} - x_t,$$

and define the post-adjustment gap chosen in period t by

$$y_t = p_t - x_t.$$

Changing price in period t is therefore equivalent to choosing $y_t \neq z_t$. The next-period inherited gap is

$$z_{t+1} = p_t - x_{t+1}.$$

Using $p_t = x_t + y_t$ and $x_{t+1} = \rho x_t + \varepsilon_{t+1}$,

$$z_{t+1} = y_t + (1-\rho)x_t - \varepsilon_{t+1}.$$

This is the key law of motion. When $\rho = 1$, the level x_t drops out and the price gap is a sufficient state variable. When $\rho \neq 1$, the level x_t remains a state variable.

The terminal value in period 3 is

$$W_3(z_3, x_3) = \min\{z_3^2, f\},$$

since the firm either keeps the inherited gap z_3 or pays f and resets the gap to zero. The period-2 value is therefore

$$W_2(z_2, x_2) = \min_{y_2} \left\{ y_2^2 + f\mathbf{1}_{\{y_2 \neq z_2\}} + \beta \mathbb{E}_{\varepsilon_3} \left[W_3\left(y_2 + (1-\rho)x_2 - \varepsilon_3, \rho x_2 + \varepsilon_3\right)\right] \right\},$$

where $\varepsilon_3 \sim \mathcal{N}(0, \sigma^2)$. This recursively defines the continuation value from period 2 onward without requiring us to characterize the period-2 inaction region explicitly.

For the period-1 problem, define

$$\Omega(y_1, x_1; \sigma_2) = \mathbb{E}_{\varepsilon_2}\left[W_2\left(y_1 + (1-\rho)x_1 - \varepsilon_2, \rho x_1 + \varepsilon_2\right)\right],$$

where $\varepsilon_2 \sim \mathcal{N}(0, \sigma_2^2)$. The period-1 Bellman equation is

$$W_1(z_1, x_1, f_1) = \min_{y_1} \left\{ y_1^2 + f_1 \mathbf{1}_{\{y_1 \neq z_1\}} + \beta \Omega(y_1, x_1; \sigma_2) \right\}.$$

If the firm does not adjust, then $y_1 = z_1$ and the value is

$$N(z_1, x_1; \sigma_2) = z_1^2 + \beta \Omega(z_1, x_1; \sigma_2).$$

If the firm adjusts, it solves

$$\min_{y_1} \left\{ y_1^2 + f_1 + \beta\Omega(y_1, x_1; \sigma_2) \right\}.$$

Since f_1 is constant with respect to y_1, it drops out of the reset-price decision. Let

$$A(x_1; \sigma_2) = \min_{y} \left\{ y^2 + \beta\Omega(y, x_1; \sigma_2) \right\}.$$

Then the value from adjustment is $f_1 + A(x_1; \sigma_2)$. If the adjusted-price problem has an interior solution, the optimal adjusted gap y_1^A solves

$$2y_1^A + \beta\Omega_y(y_1^A, x_1; \sigma_2) = 0.$$

Therefore, the optimal period-1 reset price is

$$p_1^A = x_1 + y_1^A.$$

This expression shows that the period-1 reset price generally depends on σ_2 through the continuation function Ω, but it does not depend on f_1 conditional on adjustment.

The firm does not adjust in period 1 if and only if

$$N(z_1, x_1; \sigma_2) \leq f_1 + A(x_1; \sigma_2).$$

Equivalently, defining the gross gain from adjustment before paying f_1 as

$$D(z_1, x_1; \sigma_2) = N(z_1, x_1; \sigma_2) - A(x_1; \sigma_2),$$

the inaction condition is

$$D(z_1, x_1; \sigma_2) \leq f_1.$$

Proposition A.1. *In the finite-horizon menu-cost model described above, the following statements hold.*

1. *If $\rho = 1$, the model has the same gap-state structure as the canonical Dixit impulse-control problem. In the corresponding continuous-time infinite-horizon impulse-control problem, the reset gap is zero, so in original price variables the reset price is*

$$p^A = x.$$

2. *Conditional on adjustment in period 1, the current menu cost f_1 does not affect the optimal reset price p_1^A.*

3. *An increase in f_1 weakly widens the period-1 inaction region.*

4. *The future uncertainty parameter σ_2 affects the period-1 continuation value and therefore generally affects the period-1 inaction region. The direction of this effect is generally ambiguous.*

5. *When $\rho \neq 1$, the future uncertainty parameter σ_2 generically affects the period-1 reset price. When $\rho = 1$, the price gap is a sufficient state variable and symmetry implies $p_1^A = x_1$, so σ_2 affects the inaction region but not the reset price.*

Proof For item 1, when $\rho = 1$, the desired price follows a random walk and the gap law of motion becomes

$$z_{t+1} = y_t - \varepsilon_{t+1}.$$

Thus the level of x_t drops out and the gap is a sufficient state variable. In the corresponding continuous-time infinite-horizon impulse-control problem, the value function is symmetric around a zero gap. Therefore, conditional on adjustment, the firm resets the gap to zero. In original price variables this implies $p^A = x$.

For item 2, conditional on adjustment in period 1, the firm solves

$$\min_{y_1} \left\{ y_1^2 + f_1 + \beta\Omega(y_1, x_1; \sigma_2) \right\}.$$

The term f_1 is constant with respect to the choice variable y_1. Hence it drops out of the reset-price problem. The adjusted gap solves

$$2y_1^A + \beta\Omega_y(y_1^A, x_1; \sigma_2) = 0,$$

whenever the solution is interior. Thus $p_1^A = x_1 + y_1^A$ does not depend on f_1, conditional on adjustment.

For item 3, the firm does not adjust if and only if

$$D(z_1, x_1; \sigma_2) \leq f_1.$$

For fixed (x_1, σ_2), if $f_1' > f_1$, then

$$\{z_1 : D(z_1, x_1; \sigma_2) \leq f_1\} \subseteq \{z_1 : D(z_1, x_1; \sigma_2) \leq f_1'\}.$$

Therefore, an increase in f_1 weakly widens the period-1 inaction region.

For item 4, σ_2 changes the distribution of ε_2 inside the expectation defining Ω. Since Ω enters both $N(z_1, x_1; \sigma_2)$ and $A(x_1; \sigma_2)$, it generally shifts the inaction region. The sign is not pinned down because σ_2 affects both the no-adjustment value and the adjustment value.

For item 5, the period-1 reset gap satisfies

$$2y_1^A + \beta\Omega_y(y_1^A, x_1; \sigma_2) = 0.$$

Since σ_2 changes the distribution inside the expectation defining Ω, it generically changes Ω_y and therefore the solution y_1^A when $\rho \neq 1$. When $\rho = 1$, however, the gap evolves according to

$$z_{t+1} = y_t - \varepsilon_{t+1},$$

so the level x_t drops out of the state transition. The continuation value is symmetric in the reset gap, and the adjusted-price problem is minimized at $y_1^A = 0$. Therefore $p_1^A = x_1$. In this random-walk case, σ_2 can affect the value of waiting and hence the inaction region, but it does not affect the reset price.

This distinction is the reset-price logic used in the main text. A current menu-cost increase changes which firms adjust, but for a given state it does not directly change the reset price chosen conditional on adjustment. News about future dispersion can instead change the reset price through the continuation value. Since the empirical markup proxy is the retail price relative to the supplier price, reset-price movements provide the model counterpart to markup movements conditional on adjustment.

B Pricing Data

Appendix B describes details of how the datasets used for the empirical analysis in the main text were constructed and compares the properties of the underlying pricing data in Chile with two well-known studies that use U.S. data (Nakamura and Steinsson, 2008 and Eichenbaum et al., 2014).

B.1 Construction of Datasets

Our core data source is the register of the universe of business-to-business transactions reported by Chilean firms in the electronic VAT invoices ("Factura Electronica") to the Chilean Tax Authority ("Servicio de Impuestos Internos"). This electronic reporting became mandatory on November 1st, 2014 for relatively large firms and was later gradually extended to all other firms. Most of the supermarkets that we study fall under the category of large firms, which is why their data are available from January 2015. Each VAT invoice records the date, seller and buyer's tax ID, seller's branch code, the municipality code where sellers and buyers are located. It also includes a description of each of the products in the invoice, together with information on the quantities sold and the price paid for each of them. We have access to this register through the Central Bank of Chile's repository of anonymous administrative data.

When purchasing goods in Chile, it is common practice to ask the buyer if the purchase is made on behalf of a firm or a final consumer, giving rise to the issuance of a VAT invoice or a regular receipt ("Boleta Electrónica"), respectively. All VAT invoice transactions are recorded in the dataset we study. Sales to final consumers in the Boleta data are not observable at the same granular level before 2021. Only daily sales aggregates at the firm level are available, which we use to compute the share of total sales of supermarkets that correspond to business-to-business transactions.

To focus on supermarkets, we only consider invoices in which the seller or the buyer were classified under the main economic activity "retail trades in non-specialized stores". Then, we focused on firms that report annual sales higher than 1 million U.S. dollars, which is the threshold used by the Central Bank of Chile to denote large firms (i.e "estrato" 3 and 4, in the classification of the Central Bank of Chile). Given that the economic activity classification was not sufficiently restrictive to exclude non-supermarket retailers—such as warehouses or department stores—we implemented an additional filter. Using the internal product classification developed by the Central Bank of Chile, which is based on product descriptions in the VAT Invoices, we keep only those establishments for which food and non-alcoholic beverages constitute the largest share of total sales. After the restrictions we mentioned are applied, the raw Factura data captures about 16% of supermarkets' total sales, which is the sum of the Factura and Boleta sales.

Our unit of analysis consists of products sold by supermarkets at specific locations. A key challenge is that firms do not always report location information accurately (if at all), and the tax authority does not systematically audit this field. To address this, we adopt two complementary strategies. First, for supermarkets that consistently report branch codes—7- to 8-digit identifiers for specific stores—we use these codes as location identifiers and validate them using the official registry provided by the Chilean tax authority, which also includes geographic information. Second, for supermarkets with largely missing or unverifiable branch codes in their VAT invoices, we rely on the municipality of origin field to define a location ID. We incorporate this alternative only after applying a strict verification procedure to ensure its accuracy. In particular, we require that at least half of the buyers in a given

Table A-1: Examples of fuzzy matching of product descriptions

	Product Description From Supermarket	Product Description From Supplier	Cosine Distance	Q-gram Distance
Successful matches	Pimiento Rojo UND	Pimiento Rojo UND	$\in [0, 0.01]$	≤ 1
	Berros Hidroponic	Berro Hidroponico	> 0.03	$\in [2, 3]$
	Lechuga Escarola Bolsa Un	Lechuga Escarola Bolsa	$\in [0.02, 0.03]$	$\in [2, 3]$
Unsuccessful matches	Atun Lomito Agua	Consumo Agua Potable Punta	> 0.05	> 5
	Platano Granel	Papas Granel	> 0.05	> 5

Notes: This table illustrates five examples from the fuzzy matching procedure used to construct the matched sample. The first three rows show successful matches that satisfy at least one of the following conditions: (i) cosine distance ≤ 0.03; (ii) q-gram distance ≤ 3; or (iii) cosine distance ≤ 0.05 and q-gram distance ≤ 5. The last two rows show unsuccessful matches that did not meet these thresholds.

week report being located in the same municipality. Our continuity filter ensures that only products with stable and verified location identifiers over time are included in the baseline sample.[A-1] Out of the total number of observations in our baseline sample (13,845,147), 44 percent were validated using our first approach, and the remaining share was done using the second approach.

Given the correct identification of a product as a triplet, (supermarket, valid location, and product description) we build its daily price as the intra-day maximum. To consider a product in our analysis we require that it was sold 3 days or more per week over 20 or more consecutive weeks. For each product spell for which this continuity restriction is satisfied, we fill any gaps using the last observed daily price. It is important to point out that, the vast majority of price changes we observe are obtained by actual price changes on two consecutive days. In other words, for these price changes we accurately identify the day of the price change precisely. Next, we apply the procedure proposed by Kehoe and Midrigan (2015) to filter out short-lived price changes, which are likely to be discounts. We compute a filtered price of a product for a given day t equal to the modal price observed between $t - 21$ and $t + 21$. Then, we follow their iterative process to align changes in the modal price with changes in the actual price.

To construct the matched sample, where products are matched between supermarkets and their suppliers, two parallel methods of fuzzy matching were used: cosine similarity and 1-gram distance. To validate a match, we require either of the following three alternative conditions to be satisfied: cosine distance is less than or equal to 0.03, q-gram distance is less than or equal to 3, or cosine distance is less or equal than 0.05 and q-gram distance less or equal than 5. These parameters were calibrated following various explorations. They deliver

[A-1]Regarding the supplier sample, the continuity filter was relaxed to consider the lower frequency of supermarkets' purchases. Specifically, to consider a product in this case, we require that it was sold at least 1 day per month over 6 or more consecutive months

Table A-2: 10 Most Traded Products

#	Baseline Sample	Matched Sample
1	Azucar granulada XXXXX 1 KG	Aceite vegetal XXXXX 900 CC
2	Aceite vegetal XXXXX 900 CC	Azucar granulada XXXXX 1 KG
3	Marraqueta	Arroz G2 largo delgado XXXXX 1 KG
4	Hallulla KG	Pan hot dog KG
5	Sal de mesa XXXXX 1 KG	Sal fina XXXXX 1 KG
6	Aceite vegetal XXXXX 900 CC	Tomate primera granel
7	Champiñon	Aceite vegetal XXXXX 5 LT
8	Marraqueta KG	Sal de mesa XXXXX 1 KG
9	Sal fina XXXXX 1 KG	Tomate primera KG
10	Azucar granulada XXXXX 1 KG	Tomate larga vida

Notes: This table presents the most frequently traded products in each sample. Column (1) corresponds to the baseline sample, and column (2) to the matched sample. The transaction count is calculated as the total number of daily observations, aggregated at the product description level. All brand names have been anonymized and replaced with "XXXXX".

a matching rate of about 14% (i.e. $1,920$ products from the $13,682$ in the baseline sample). We preferred a stricter criterion that led to a relatively low matching rate but with a higher probability of successful matches. Table A-1 shows one example of successful matching according to each matching criterion as well as two unsuccessfully matched products.

Table A-2 shows a sample of the 10 most traded products in the two datasets. The most traded products in the baseline sample are two different brands of sugar ("azucar granulada"), three types of bread ("hallulla KG", "marraqueta" and "marraqueta KG"), two brands of salt ("sal de mesa", "sal fina"), and two brands of cooking oil ("aceite vegetal 900 CC"), and a type of edible mushroom ("champiñon"). Likewise, in the matched sample, fruits, vegetables, rice, salt, bread and oil enter as the most traded products too. Therefore, the two samples we study contain everyday groceries that are important in the price basket of any country.

B.2 Comparing the Chilean Pricing Data with the U.S.

Table A-3 benchmarks the Chilean pricing data to the US data by replicating Nakamura and Steinsson (2008)'s monthly statistics. For this exercise, we focus on the pre-Social Uprising period by ending the analyzed sample on September 30, 2019. For comparison purposes, we also report statistics for the daily baseline sample (which we also report at the monthly frequency) as well as those used when calibrating the model, which come from the matched sample. We do this to provide some basic information about the Chilean data. Naturally since there are many differences between the Chilean and the U.S. economies

Table A-3: Frequency of Price Change (Nakamura and Steinsson, 2008)

Statistic	N&S - Monthly Data Processed food	N&S - Monthly Data Unprocessed food	From Baseline Sample Monthly Data	From Baseline Sample Daily Data	From Calibration Sample Monthly Data
Median Freq	25.9	37.3	23.0	1.0	25.8
Median Implied Duration	3.3	2.1	3.8	3.3	3.3
Mean Freq	25.6	39.5	22.8	1.1	25.5

Note: The column N&S corresponds to the Nakamura and Steinsson (2008)'s results for the groups of products "Processed food" and "Unprocessed food", when sales and substitutions are included in the calculations. The other two columns present statistics from the Chilean data used in our work, both restricted to the pre-Social Uprising period ending on September 30, 2019: the baseline daily and monthly samples, and the monthly matched sample used in model calibration. Frequencies are calculated as the share of products that change prices within a given month (or day), averaged over the pre-Social Uprising period. Implied durations are computed using the formula $d = -1/\log(1-f)$, where f denotes the median frequency. Duration is always reported in months.

(average inflation being the most important one), we do not expect the results to match across countries.

In Table A-4, we run a second exercise in which we replicate some of the results of Eichenbaum et al. (2014) with the Chilean data. We calculate the fraction of price changes that are smaller in absolute value than 1, 2.5, and 5 percent – the same bins considered in their work. To do so, we consider two subsamples, one with no adjustments and another one in which only price changes bigger than $1CLP were considered.[A-2] Columns 2 and 3 show the results using the daily and monthly versions of this comparison price panel, respectively.[A-3]

C Additional Empirical Results

Appendix C presents additional empirical analysis that was not presented in the main text due to space constraints. It is divided into four subsections. The first presents additional descriptive statistics from the dataset. The second presents robustness exercises that simplify the baseline specification or examine sign-specific price changes. The third presents additional robustness analyses and extensions, including stricter continuity restrictions, size heterogeneity, local riot intensity, and additional controls. The fourth presents forecast-dispersion evidence around the Social Uprising.

[A-2]The Chilean exchange rate fluctuated between 587 and 859 CLP per US dollar during the period of analysis (2015 to 2019), which makes $1CLP around $0.001 USD.

[A-3]The frequency of price changes differs from Table A-3 because we are not imposing any restriction to consider a price change. We imposed these restrictions before as we were following the data construction in Nakamura and Steinsson (2008).

Table A-4: Small Price Changes (Eichenbaum et al, 2014)

	Eichenbaum et al (2014)		Chilean Data - Daily		Chilean Data - Monthly	
Total number of prices	4,791,569		18,029,931		542,944	
Total number of price changes	1,047,547		177,497		145,468	
Frequency of Price changes	21.9		0.98		26.79	
	Total number	% of all price changes	Total number	% of all price changes	Total number	% of all price changes
Price changes smaller than 1 percent in absolute value						
No adjustment	69,720	6.7	26,223	14.8	14,204	9.8
Remove price changes that are less than a US penny (1 CLP)	61,017	5.9	8,534	4.8	6,250	4.3
Price changes smaller than 2.5 percent in absolute value						
No adjustment	142,822	13.6	47,567	26.8	32,052	22.0
Remove price changes that are less than a US penny (1 CLP)	132,935	12.8	29,820	16.8	24,040	16.5
Price changes smaller than 5 percent in absolute value						
No adjustment	256,303	24.5	77,079	43.4	58,336	40.1
Remove price changes that are less than a US penny (1 CLP)	245,519	24.3	59,313	33.4	50,310	34.6

Note: Column (1) reports the share of price changes falling below absolute thresholds of 1%, 2.5%, and 5%, as documented in Table 1 of Eichenbaum et al. (2014) for the unweighted price changes case. Columns (2) and (3) present the corresponding shares from the Chilean data, using the daily and monthly versions of the price panel constructed for this comparison. This panel is broader than the baseline regression sample because it is constructed before dropping filled observations; therefore, the total number of prices is not directly comparable to the product-day count in Table 1. For each case, we compute the fraction of price changes smaller than the stated thresholds, with and without excluding changes below one US penny (1 CLP).

C.1 Additional Descriptive Statistics

C.1.1 Validating Price Analysis in Factura with Boleta

Our dataset is obtained from electronic VAT invoices from B2B transactions, and hence represent only a share of the universe of transactions. The latter would be the sum of the B2B transactions plus those in the Boleta data made to non-firms by supermarkets. It is therefore informative to assess the extent to which the price dynamics in the Factura data that we study are correlated with those coming from Boleta. This can be done only after 2023 when data from Boleta started arriving at the Central Bank of Chile's repository at the product-location level. Table A-5 compares daily product-level prices recorded in VAT invoices from Factura and regular receipts from Boleta during 2023, a period in which both electronic forms are available for the entire year. Across these datasets, a product is

Table A-5: Boleta vs Factura

Panel A: Prices	
Variables	Log Price in Regular Tickets
Log Price in VAT Invoices	0.9577***
	(0.0000)
Observations	16,987,326
R-squared	0.9658
Simple Correlation Log Prices	0.983
Panel B: Products	
Avg. share of products in Factura vs. Boleta	0.596

Note: This table compares daily product-level records from VAT invoices ("Factura Electrónica") and regular receipts ("Boleta Electrónica") in 2023, when both electronic systems are available year-round. A product is defined by the triplet seller ID × location ID (municipality of issuance/origin) × product description. For each source and product–day, we take the maximum recorded price. Panel A reports the coefficient from regressing log(max price from Boleta) on log(max price from Factura) for matched product–day observations; we also report the simple correlation between these two variables. Panel B reports, across supermarkets' locations, the average ratio of distinct products observed in Factura to those observed in Boleta (i.e., No. products in Factura / No. products in Boleta). *** p<0.01, ** p<0.05, * p<0.1.

defined as the triplet of seller ID, location ID (municipality of issuance/origin), and product description. Panel A reports the coefficient from a regression of the log of daily total prices recorded in Boleta receipts on the corresponding prices from VAT-invoices. Additionally, we report the simple correlation between these two variables. As can be seen, the correlation and R-squared are virtually unity, 0.98 and 0.97, respectively. And the estimated coefficient is very close to unity (0.96). Therefore, price dynamics in the Factura data closely track those in the Boleta data, providing further validation of our analysis with the former.

Despite the previous analysis, another possible concern is that, while prices in the Factura and Boleta data are closely related, this may come from a relatively small sample of products from the universe of products in the Boleta data. This is in fact not the case as depicted in Panel B of Table A-5. As documented, around 60 percent of the universe of products in the Boleta data can be recovered in the Factura data, further providing validation for the analysis we do with the Factura data.

C.1.2 Distributions of Price and Markup Changes

Table A-6 complements the descriptive evidence on the frequency and size of price changes and markups in Figures 4 and A-2. Panel A reports the share of prices that changed before and during the Social Uprising. Panel B reports the distribution of price changes using several percentiles. Panel C reports the distribution of markup changes for the pre-Social Uprising period. For markup changes, due to confidentiality requirements from the Central

Bank of Chile, specific values for the Social Uprising period cannot be reported. Nonetheless, the distribution shifts toward higher values across most of its support, with the lower-middle part becoming less negative and the upper-middle part increasing, while the extreme tails remain broadly similar.

The distributional evidence is informative about the mechanism. For price changes, the model's implication is direct. When the inaction region widens, fewer firms adjust prices, and the firms that still adjust are those farther from their reset target. Thus, conditional on adjustment, price changes should become larger in absolute value and the distribution of price changes should display fatter tails. Panel B of Table A-6 shows this pattern during the Social Uprising.

For markup changes, the implication is less mechanical because two forces are at work. A higher menu cost changes selection into adjustment, but does not by itself raise reset markups. News about future idiosyncratic demand dispersion, in contrast, changes reset-price incentives under Kimball demand and can raise markups conditional on adjustment. The descriptive shift of the markup-change distribution toward higher values is consistent with this reset-markup force. This distributional evidence is therefore in line with the baseline results and Figure A-1: the frequency of price changes falls sharply during the Social Uprising, the distribution of price changes displays fatter tails, and markups tend to increase during the episode.

C.2 Robustness: Alternative Specifications

This subsection first tests the symmetry of the baseline results with respect to price increases and decreases, and then repeats the baseline analysis using the matched sample in Table A-7. Next, it undertakes a series of robustness tests by dropping some of the covariates from the baseline estimation. Table A-8 presents results when all controls are removed except for the fixed effects. Lastly, Table A-9 presents results when one runs the baseline estimation, distinguishing the sign of the price breaks. The main findings of our baseline specification are largely robust to all of these modifications.

C.2.1 Baseline Results Using the Matched Sample

An important check to validate the representativeness of the matched sample is to verify whether the baseline results in Table 2, obtained using the baseline sample, are recovered when using the smaller matched sample. This is corroborated in Table A-7.

Table A-6: Frequency of Price Changes and Size Distribution

Statistic	(1) Before Social Uprising	(2) During Social Uprising
Panel A: Breaks		
Frequency of price changes	0.012	0.006
Panel B: Price Changes		
B.1: Raw data		
p1/p99	-0.527/0.525	-0.708/0.691
p5/p95	-0.283/0.285	-0.413/0.418
p10/p90	-0.183/0.190	-0.278/0.311
p25/p75	-0.065/0.081	-0.092/0.124
B.2: Residuals		
p1/p99	-0.517/0.511	-0.698/0.665
p5/p95	-0.277/0.269	-0.386/0.441
p10/p90	-0.183/0.178	-0.253/0.288
p25/p75	-0.071/0.072	-0.091/0.104
C: Markup Change		
p1/p99	-0.459/0.436	*/*
p5/p95	-0.262/0.258	*/*
p10/p90	-0.168/0.171	*/*
p25/p75	-0.061/0.066	*/*

Note: Panel A presents the share of prices that changed in the baseline sample in the corresponding period. Panel B shows the distribution of price changes: subpanel B.1 reports this distribution using raw price changes, while subpanel B.2 presents the distribution of residuals from a regression of price changes as the dependent variable in the baseline specification (1) without the Social Uprising dummy. Panel C shows the distribution of the markup changes, reported only for the pre-Social Uprising period due to confidentiality requirements from the Central Bank of Chile; * indicates that specific values cannot be reported. Column (1) reports statistics for the pre-Social Uprising period, while column (2) corresponds to the 31-day Social Uprising period that starts on October 18, 2019.

Table A-7: Baseline Estimation: Matched Sample

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0068***	0.0266***	0.0122**
	(0.0010)	(0.0071)	(0.0062)
Observations	1,980,403	23,977	23,977
Within R-squared	0.001	0.006	0.007
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0127	0.1060	-0.0027

Note: The table reports the estimated coefficient β in Regression (1) associated with the Social Uprising dummy when using the Matched sample. Clustered standard errors at seller-location level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C.2.2 Baseline Results Excluding All Controls Except for Fixed Effects

See Table A-8 for the results.

Table A-8: Baseline Estimation Excluding All Controls: Baseline Sample

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0052***	0.0348***	0.0162***
	(0.0004)	(0.0092)	(0.0056)
Observations	13,845,174	155,473	23,979
Within R-squared	0.000	0.001	0.000
Controls	No	No	No
Economic Activity Controls	No	No	No
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200	-0.0026

Note: This table reports the estimated coefficient β from the baseline specification described in Regression (1), excluding all product-level controls and economic activity controls (see main text for the entire list). The full set of fixed effects is maintained. The baseline sample is used. Clustered standard errors at seller-location level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A-9: Baseline Estimation Separating Positive and Negative Price Changes: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0026***	-0.0031***	0.0338***	0.0488***
	(0.0003)	(0.0002)	(0.0129)	(0.0097)
Observations	13,845,147	13,845,147	79,576	63,588
Adjusted R-squared	0.002	0.002	0.425	0.471
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.0065	0.0053	0.1150	0.1237

Note: This table reports estimates of β from Equation (1), using the baseline sample and separating positive and negative price changes. Each column corresponds to a different dependent variable: the frequency or size of positive and negative price changes, as indicated. Standard errors are clustered at the seller-location level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.2.3 Baseline Estimation Separating Positive and Negative Price Changes

See Table A-9 for the results.

C.2.4 Test of Symmetry for the Baseline Results

To formally assess the symmetry of the Social Uprising's effects on positive and negative breaks, both outcomes must be included in the same equation. For the case of the size of price changes, this can be implemented directly by estimating:

$$|\text{Size}|_{it} = \text{Fixed Effects} + \beta_1 D_t + \beta_2 \text{Positive}_{it} + \beta_3 (D_t \times \text{Positive}_{it}) + \gamma_1 X_{1,it} + \gamma_2 X_{2,t} + \gamma_3 X_{3,s(i)t} + \varepsilon^y_{it}, \tag{A-3}$$

where D_t is the Social Uprising dummy and Positive_{it} is an indicator equal to one when the price change is positive and zero otherwise.[A-4] The controls $X_{1,it}$, $X_{2,t}$, and $X_{3,s(i)t}$ are defined as in (1). In this specification, β_3 is the coefficient of interest, providing the formal test of symmetry. It is important to note that β_1 and $\beta_1 + \beta_3$ exactly correspond to the results in Table A-9. Panel A of Table A-10 reports an estimate of $\beta_3 = -0.0149$ (s.e. 0.0103), showing that the interaction is not statistically significant. Thus, the null hypothesis of symmetry cannot be rejected.

For the frequency of breaks, the analysis requires additional considerations. The outcome takes three values—no change, positive break, and negative break—so symmetry cannot be evaluated with a simple interaction. Moreover, approaches that jointly model multiple outcomes are not feasible in our context, given the large number of product fixed effects. Our strategy is therefore to partial out fixed effects and controls from the dependent variables (positive and negative breaks) as well as from the Social Uprising dummy, and then perform a routine of seemingly unrelated regressions, clustering standard errors at the location level, to jointly model the residualized outcomes. The results, shown in Panel B of Table A-10, indicate that the estimated coefficients for positive and negative breaks are very similar to those reported in Table A-9, confirming that our residualization approach delivers comparable estimates. Turning to the symmetry test, $D_{negative} = D_{positive}$, it yields a p-value of 0.0557, providing evidence against symmetry only at the 10% significance level.

C.2.5 Residuals from Figure 4

Figure A-2 presents an alternative to Figure 4 by reporting average residuals from the baseline regression (1) estimated without the Social Uprising dummy, instead of averages from the raw data. As can be seen, the same clear change in the pricing pattern of products that were sold before, and during the Social Uprising documented in Figure 4 is found.

[A-4] All control variables and fixed effects are also interacted with Positive_{it}.

Table A-10: Test of Symmetry of the Baseline results

Panel A: Size	
Variables	Abs Size
D	0.0488***
	(0.0097)
D * Positive Break	-0.0149
	(0.0103)
Observations	143,164
Adjusted R-squared	0.321
Controls	Yes
Economic Activity Controls	Yes
FE	Yes
Mean of Dependent Variable	0.1188
Panel B: Breaks	
$D_{negative}$	-0.0031
	(0.0002)
$D_{positive}$	-0.0026
	(0.0003)
Observations	13,845,147
Test of symmetry	
Chi2(1)	3.66
Prob > chi2	0.0557

Note: Panel A reports the estimation of equation (A-3) for the absolute size of price changes. Panel B reports the results of an alternative approach applied to test the symmetry between the effects of the Social Uprising on the frequency of negative and positive breaks. The approach deals with the huge dimension of our panel partialling out fixed effects and controls from the dependent variables as well as from the Social Uprising dummy, and then jointly estimating the residualized equations using seemingly unrelated regressions. Finally testing $D_{positive} = D_{negative}$ directly. *** p<0.01, ** p<0.05, * p<0.1.

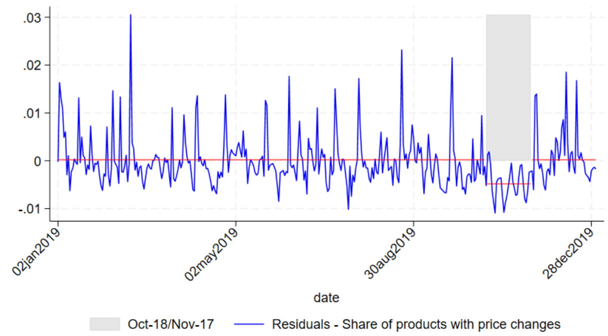
C.3 Additional robustness analysis and extensions

C.3.1 Baseline results: Products with Continuous Availability Before and During the Social Uprising

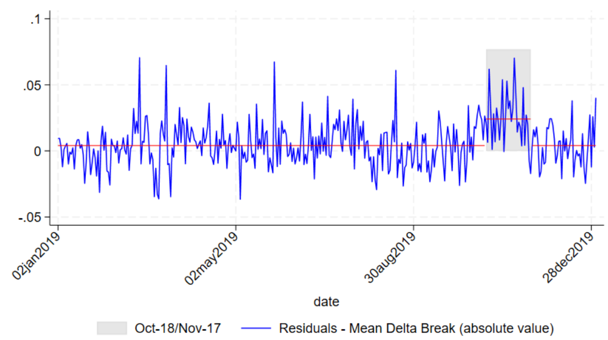
Another robustness check uses a balanced panel of products that pass our continuity filter restriction (see Appendix B.1) in every week between September 23 and November 17, 2019. Table A-11 shows the results for 6,973 products in the baseline sample that satisfy this criterion, while the markup specification uses 700 products from the matched sample that satisfy the same restriction. The decline in frequency is roughly one-quarter smaller than in the baseline results, though still highly significant, while the estimated increases in the size

Figure A-2: Frequency, Size, and Markup Dynamics in 2019 (Residuals)

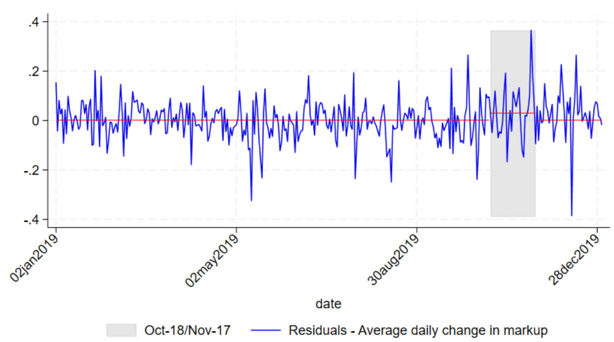
(a) Frequency of Price Changes



(b) Size of Price Changes



(c) Markup Change



Notes: Panel (a) presents the daily average residuals from our baseline regression specification (1), estimated using the frequency of price changes as the dependent variable and excluding the Social Uprising dummy. Panel (b) shows the corresponding residuals when the dependent variable is the size of price changes. Panels (a) and (b) are based on the baseline sample. Panel (c) shows the corresponding residuals when the dependent variable is the daily change in the log supermarket-price–supplier-price gap, conditional on a supermarket price adjustment, and is based on the matched sample. In all panels, the residuals reflect variation net of fixed effects and controls. The shaded area covers the Social Uprising period from October 18 to November 17, 2019, inclusive. The red horizontal lines report the average value of the residual series outside and during the Social Uprising period, corresponding to the non-shaded and shaded areas, respectively.

of price changes and markups remain close to the baseline results.

Table A-11: Baseline results: Products with Continuous Availability Before and During the Social Uprising

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0043***	0.0359***	0.0148**
	(0.0005)	(0.0098)	(0.0074)
Observations	4,021,785	43,648	7,040
Within R-squared	0.000	0.006	0.010
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0111	0.1220	-0.0288

Note: This table presents the baseline estimation when restricting the sample to products that satisfy the continuity filter (see Appendix B.1) in every week between September 23 and November 17, 2019. Clustered standard errors at seller-location level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C.3.2 Size Heterogeneity

We explored if the effects of the Social Uprising on price-setting behavior are driven by the heterogeneity of the size of supermarkets' locations. We conduct this analysis using average monthly sales during the pre-Social Uprising period as a measure of size. In Table A-12, we separately present the results of including an interaction of the Social Uprising dummy with this measure. The baseline results from Table 2 remain robust. The interaction terms are generally insignificant, with only one exception: markups, suggesting that the increase in the log supermarket-price–supplier-price gap was less pronounced among larger supermarket locations.

C.3.3 Intensity of Riots at the Supermarket-location Level

Table A-13 extends the analysis in Table 4 by exploiting a more granular local riot intensity measure. Rather than assigning a single supermarket-level value—computed as a sales-weighted average of intensity across all municipalities where the supermarket operates—the measure used here assigns a local riot intensity measure to each location. The results are broadly consistent with the baseline. For the frequency and size of price changes, the coefficients on the Social Uprising dummy remain statistically significant and of comparable magnitude to those in Table 2, while the interaction with local riot intensity remains insignificant. For markups, the point estimate is stable, though the reduced sample size widens the confidence intervals. Taken together, these findings continue to show no evidence that su-

Table A-12: Results with Supermarket Location Size Interaction: Baseline Sample

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0049***	0.0305***	0.0187***
	(0.0005)	(0.0077)	(0.0072)
D * Big Supermarket location	-0.0000	0.0001	-0.0000**
	(0.0000)	(0.0001)	(0.0000)
Observations	13,845,147	155,471	23,977
Within R-squared	0.000	0.003	0.007
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200	-0.0027

Note: The size of a supermarket's location is measured as its average monthly sales (in million CLP) during the pre-Social Uprising period. Clustered standard errors at seller-location level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-13: Riot's Intensity at the Supermarket-Location Level: Baseline Sample

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0065***	0.0346***	0.0135
	(0.0008)	(0.0113)	(0.0096)
$D \times$ Intensity	0.0000	0.0001	-0.0001
	(0.0000)	(0.0003)	(0.0003)
Observations	13,845,147	155,471	23,977
Within R-squared	0.000	0.003	0.007
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200	-0.0027

Notes: The table reports the estimated coefficients β and θ from Regression (2), corresponding to the Social Uprising dummy and its interaction with a proxy for riots intensity at the municipality level. This proxy is the change in public disorders reports in October-November 2019 relative to the same period in 2018, adjusted by municipality population. Clustered standard errors at seller-location level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

permarkets' pricing behavior varied systematically with the local severity of unrest during the Social Uprising.

C.3.4 Baseline Estimation with the Exchange Rate as a Control

Table A-14 presents our baseline specification augmented with the monthly log-difference of the CLP to USD exchange rate as an additional control. Baseline results are robust to this additional control.

Table A-14: Baseline Estimation with Exchange Rate Control: Baseline Sample

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0058***	0.0364***	0.0137**
	(0.0005)	(0.0091)	(0.0064)
Exchange Rate	0.0028	0.0479**	-0.0450
	(0.0020)	(0.0200)	(0.0406)
Observations	13,845,147	155,471	23,977
Within R-squared	0.000	0.003	0.007
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200	-0.0027

Note: This table presents the baseline results controlled by the monthly log-difference of the Chilean exchange rate to the USD. Clustered standard errors at seller-location level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.3.5 Controlling for Labor Costs

In the main text, we control for the wholesale cost of merchandises using data on supermarket suppliers and conclude that the response of pricing behavior to the Social Uprising is not driven by any changes in the supplier prices nor the way supermarkets respond to a given change in the wholesale cost. To isolate another potential supply-side channel related to changes in labor costs, we test whether our baseline estimates are robust to including wage rates as a control. In Table A-15, we control for the monthly logarithm of Wage Bill calculated as the total sum of taxable income across all the workers reported by firms to the Chilean Tax Authority through form DJ1887. Our baseline results continue to be robust after including these additional labor costs as controls.

C.3.6 Cost of Re-stocking as a Control

Table A-16 presents the results of the baseline estimation on the matched sample when we control for the cost of recent re-stocking. Specifically, we test if our estimates are robust to controlling for price changes made by the supplier during the previous 15 days when selling

Table A-15: Baseline Estimation with wage bill: Baseline Sample

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0055***	0.0352***	0.0120**
	(0.0005)	(0.0092)	(0.0060)
log Monthly Wage Bill	-0.0014	0.0209***	0.0015
	(0.0009)	(0.0054)	(0.0237)
Observations	13,811,108	155,300	23,975
Within R-squared	0.000	0.003	0.007
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200	-0.0028

Note: This table reports baseline results controlling for the supermarket's monthly log wage bill. Information on workers' wages is reported directly by firms to the Chilean Tax Authority through form DJ1887. The baseline sample is used. Clustered standard errors at seller-location level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

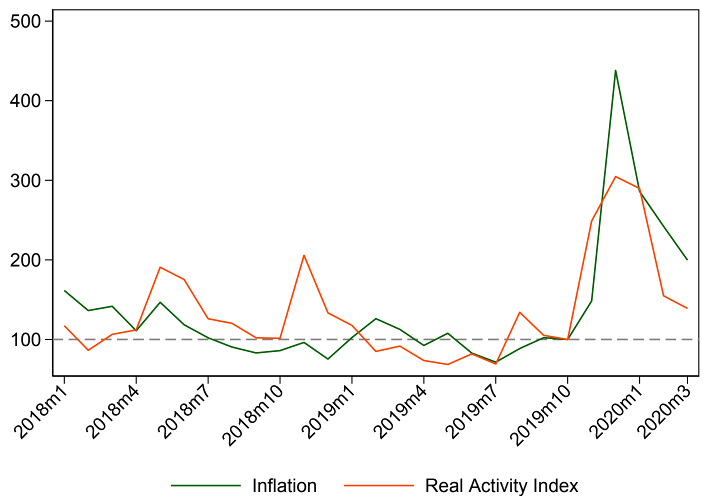
Table A-16: Baseline Estimation Controlling for Cost of Re-stocking: Matched Sample

Variable	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.0069***	0.0265***	0.0215***
	(0.0010)	(0.0072)	(0.0064)
Recent supplier's price change	0.0047***	-0.0455***	-0.2743***
	(0.0013)	(0.0148)	(0.0129)
Observations	1,941,661	23,690	23,690
Within R-squared	0.001	0.008	0.050
Controls	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.0128	0.1060	-0.0028

Note: This table reports baseline results controlling for re-stocking costs, measured as the change in the supplier's price over the past 15 days. The model is estimated on the matched sample. Clustered standard errors at seller-location level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

to each supermarket. Our baseline results in terms of the sign and significance of the Social Uprising dummy remain robust to controlling for the cost of re-stocking.

Figure A-3: Forecast Dispersion During the Social Uprising



Notes: The figure shows the monthly standard deviation of two forecasts from the "Encuesta de Expectativas Económicas" (Economic Expectations Survey) conducted by the Central Bank of Chile. The two variables are inflation expectations for December of the current year and the expected 12-month change in the IMACEC index, a monthly measure of economic activity, excluding mining. The standard deviations are normalized to 100 just prior to the Social Uprising.

C.4 Forecast Dispersion During the Social Uprising

Figure A-3 reports the monthly standard deviation across individual forecasts in the Central Bank of Chile's Economic Expectations Survey for two variables: inflation expected by year-end and the expected 12-month growth rate of the IMACEC index excluding mining. Both forecast-dispersion measures rise sharply during the Social Uprising. For real activity, the cross-sectional standard deviation triples. For inflation, it increases nearly five times. These levels are without precedent in the historical series and are consistent with the view that the episode shifted beliefs about future economic conditions.

The same pattern appears in a broader text-based proxy for uncertainty. Extending Baker et al. (2016), Ahir et al. (2022) build a World Uncertainty Index (WUI) for a large set of countries using the frequency of the word "uncertainty" in the quarterly Economist Intelligence Unit country reports. The WUI for Chile, available on FRED with code WUICHL, averages 0.18 for 2010Q1–2019Q3 and jumps to 1.07 in 2019Q4, the quarter that includes the Social Uprising. We use these measures only as contextual evidence of a shift in beliefs; the model parameters governing news and menu-cost changes are disciplined by the pricing moments in the main text.

Table A-17: Baseline estimation with Monthly Data

Variables	(1) Breaks	(2) Abs Size	(3) Markup
D	-0.135***	0.0207**	0.0254***
	(0.0337)	(0.0101)	(0.0076)
Observations	77,101	21,118	21,118
Within R-squared	0.001	0.005	0.008
Controls	No	No	No
Economic Activity Controls	No	No	No
FE	Yes	Yes	Yes
Mean of Dependent Variable	0.2890	0.1100	-0.0025

Note: This table reports estimates based on the monthly aggregation of the matched sample used to construct the empirical moments that discipline the model. The specification keeps the baseline fixed effects, omits the remaining baseline controls, and includes a linear monthly trend. The markup column uses the standardized log markup proxy $\tilde{m}_{it}$ defined in Section 2. Clustered standard errors at the seller-location level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C.5 Baseline estimation with Monthly Data

Table A-17 reports the monthly estimates used to discipline the model. We aggregate the matched sample to the monthly frequency by keeping, for each month, the observation from the first Friday after the fourth calendar day, or the nearest weekday if that Friday is a holiday. The specification keeps the baseline fixed effects, omits the remaining controls, and includes a linear monthly trend. The estimates preserve the qualitative pattern of the baseline results in Table 2: the Social Uprising is associated with a lower frequency of price changes, a larger absolute size of price changes conditional on adjustment, and a higher standardized log markup proxy. The monthly markup estimate uses the same standardized variable $\tilde{m}_{it}$ defined in Section 2.

D Model Appendix

D.1 Households

A representative household supplies labor to firms in exchange for wage payments, trades a complete set of Arrow-Debreu securities, and consumes a final good, C_t. It also owns all firms in the economy and receives all accrued profits. The household solves the problem

$$\max_{C_t, h_t, \mathbf{B_{t+1}}} \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log\left(C_t\right) - \xi h_t\right], \tag{A-4}$$

subject to the budget constraint

$$P_t C_t + \mathbf{Q_t} \cdot \mathbf{B_{t+1}} \leq B_t + W_t h_t + \Pi_t, \tag{A-5}$$

where $\mathbf{B_{t+1}}$ is a vector that captures the payments from a set of state-contingent assets purchased in period t and they are priced using vector $\mathbf{Q_t}$. P_t and W_t are the price of final good and nominal wage, respectively, both of which are taken as given by the household. Π_t denotes the total dividends received by the household. The solution to the household's problem yields the optimality conditions

$$1 = P_t C_t \Lambda_t \tag{A-6}$$

$$\frac{W_t}{P_t} = \xi C_t, \tag{A-7}$$

where Λ_t is the Lagrange multiplier, and the household's stochastic discount factor

$$\Xi_{t,t+1} \equiv \beta \frac{C_t}{C_{t+1}}. \tag{A-8}$$

D.2 Final Good Producer

A representative firm combines intermediate varieties y^i to produce the final good Y, using the Kimball (1995) aggregator. This aggregator is defined implicitly as

$$\int_0^1 G\left(\frac{\nu^i y^i}{Y}\right) di = 1, \tag{A-9}$$

where ν^i represents an idiosyncratic variety-specific preference shifter. Following Dotsey and King (2005) and Harding et al. (2021), we use the following specification for $G(\cdot)$

$$G\left(\frac{\nu y}{Y}\right) = \frac{\omega}{1+\omega\psi}\left[(1+\psi)\frac{\nu y}{Y} - \psi\right]^{\frac{1+\omega\psi}{\omega(1+\psi)}} + 1 - \frac{\omega}{1+\omega\psi}. \tag{A-10}$$

The parameter $\psi \leq 0$ is the super-elasticity parameter and it controls the curvature of the demand curve, or equivalently, the degree of strategic complementarity in pricing between intermediate firms. Together with ψ, the parameter ω determines the gross markup of firms. From here on, we reparameterize the problem with $\omega_p \equiv \frac{\omega(1+\psi)}{1+\omega\psi}$.

Taking as given variety prices p^i, as well as P, ν^i and aggregate demand Y, the final-good producer chooses y^i to maximize profits

$$\max_{y^i \geq 0} \quad 1 - \int_0^1 \frac{p^i y^i}{PY} di \quad \text{subject to} \quad \int_0^1 G\left(\frac{\nu^i y^i}{Y}\right) di = 1. \tag{A-11}$$

Using y^i/Y as the choice variable and taking the first-order condition with respect to this yields the optimal demand schedule for each variety

$$\begin{aligned}
\frac{p^i}{P} &= \lambda \nu^i G'\left(\frac{\nu^i y^i}{Y}\right) && \text{(A-12)} \\
\frac{p^i}{P} &= \lambda \nu^i \left[(1+\psi)\frac{\nu^i y^i}{Y} - \psi\right]^{\frac{1-\omega_p}{\omega_p}} && \text{(A-13)} \\
\left(\frac{p^i}{\lambda \nu^i P}\right)^{\frac{\omega_p}{1-\omega_p}} &= (1+\psi)\frac{\nu^i y^i}{Y} - \psi && \text{(A-14)} \\
\frac{\nu^i y^i}{Y} &= \frac{1}{1+\psi}\left(\left(\frac{p^i}{\lambda \nu^i P}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right), && \text{(A-15)}
\end{aligned}$$

where λ is the Lagrange multiplier on the constraint in (A-11). This multiplier can be obtained by substituting the optimal demand into (A-9)

$$\begin{aligned}
1 &= \int \left\{\frac{\omega_p}{1+\psi}\left[(1+\psi)\frac{\nu^i y^i}{Y} - \psi\right]^{\frac{1}{\omega_p}} + 1 - \frac{\omega_p}{1+\psi}\right\} di && \text{(A-16)} \\
1 &= \int \left\{\frac{\omega_p}{1+\psi}\left[\left(\frac{p^i}{\lambda \nu^i P}\right)^{\frac{\omega_p}{1-\omega_p}}\right]^{\frac{1}{\omega_p}} + 1 - \frac{\omega_p}{1+\psi}\right\} di && \text{(A-17)} \\
1 &= \frac{\omega_p}{1+\psi} \cdot \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p^i}{\nu^i P}\right)^{\frac{1}{1-\omega_p}} di + \int 1 di - \int \frac{\omega_p}{1+\psi} di && \text{(A-18)} \\
\frac{\omega_p}{1+\psi} &= \frac{\omega_p}{1+\psi} \cdot \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p^i}{\nu^i P}\right)^{\frac{1}{1-\omega_p}} di && \text{(A-19)} \\
1 &= \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p^i}{\nu^i P}\right)^{\frac{1}{1-\omega_p}} di && \text{(A-20)} \\
\lambda^{\frac{1}{1-\omega_p}} &= \int \left(\frac{p^i}{\nu^i P}\right)^{\frac{1}{1-\omega_p}} di && \text{(A-21)} \\
\lambda &= \left[\int \left(\frac{p^i}{\nu^i P}\right)^{\frac{1}{1-\omega_p}} di\right]^{1-\omega_p}. && \text{(A-22)}
\end{aligned}$$

The solution to the problem of the final-goods producer is, then, (A-15), along with (A-22), which implicitly define the demand for each variety, y^i, as a function of prices, the idiosyncratic demand shock and aggregate demand.

The aggregate price index can be obtained from the zero-profit condition for the final-good producer

$$1 = \int \frac{p^i y^i}{PY} di \tag{A-23}$$

$$1 = \int \frac{p^i}{P} \left[\frac{1}{\nu^i} \frac{1}{1+\psi} \left(\left(\frac{p^i}{\lambda \nu^i P} \right)^{\frac{\omega_p}{1-\omega_p}} + \psi \right) \right] di \tag{A-24}$$

$$1 = \int \frac{p^i}{P} \left[\frac{1}{\nu^i} \frac{1}{1+\psi} \left(\frac{p^i}{\lambda \nu^i P} \right)^{\frac{\omega_p}{1-\omega_p}} + \frac{1}{\nu^i} \frac{\psi}{1+\psi} \right] di \tag{A-25}$$

$$1 = \lambda^{\frac{-\omega_p}{1-\omega_p}} \frac{1}{1+\psi} \int \left(\frac{p^i}{\nu^i P} \right)^{\frac{1}{1-\omega_p}} di + \frac{\psi}{1+\psi} \int \frac{p^i}{\nu^i P} di \tag{A-26}$$

$$1 = \frac{1}{1+\psi} \left[\int \left(\frac{p^i}{\nu^i P} \right)^{\frac{1}{1-\omega_p}} di \right]^{1-\omega_p} + \frac{\psi}{1+\psi} \int \frac{p^i}{\nu^i P} di \tag{A-27}$$

$$P = \frac{1}{1+\psi} \left[\int \left(\frac{p^i}{\nu^i} \right)^{\frac{1}{1-\omega_p}} di \right]^{1-\omega_p} + \frac{\psi}{1+\psi} \int \frac{p^i}{\nu^i} di. \tag{A-28}$$

Note that when $\psi = 0$, $G(\cdot)$ collapses to the Dixit-Stiglitz CES aggregator, yielding the familiar expressions

$$y^i = (\nu^i)^{\frac{1}{\omega-1}} \left(\frac{p^i}{P} \right)^{\frac{\omega}{1-\omega}} Y, \tag{A-29}$$

$$P = \left[\int \left(\frac{p^i}{\nu^i} \right)^{\frac{1}{1-\omega}} di \right]^{1-\omega}, \tag{A-30}$$

along with $\lambda = 1$.

D.3 Intermediate Producers

A continuum of intermediate producers produce a differentiated variety of goods indexed by i using a linear production technology with labor as the only input

$$y^i = z^i h^i. \tag{A-31}$$

The processes for z^i and idiosyncratic demand ν^i are defined in (6) and (7).

We can split the intermediate-good producers into two independent problems. In the first problem the firm chooses the price it charges for the current period. In the second problem, its price and other things it takes as given, including the amount to be supplied to the final-good producer, the firm chooses how much labor to hire. The latter problem is a static one and can be solved as $h^i = y^i/z^i$. Using this condition, as well as the demand of the final-good producer, for a given price p the profits of the firm (gross of adjustment cost) are given by

$$\pi = \left(\frac{p}{P} - \frac{W}{zP}\right)\frac{C}{\nu} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p}{\lambda\nu P}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right] \tag{A-32}$$

$$= \left(\frac{p/S}{P/S} - \frac{\xi C}{z}\right)\frac{C}{\nu} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p/S}{\lambda\nu\,(P/S)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right] \tag{A-33}$$

$$= \left(\frac{p/S}{P/S} - \frac{\xi S}{zP}\right) \cdot \frac{(P/S)^{-1}}{\nu} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p/S}{\lambda\nu\,(P/S)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right] \tag{A-34}$$

$$= \left(\frac{p/S}{P/S} - \frac{\xi}{z\,(P/S)}\right) \cdot \frac{(P/S)^{-1}}{\nu} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p/S}{\lambda\nu\,(P/S)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right]. \tag{A-35}$$

In the first equality, we replace Y with C because they are equal in equilibrium. In the second equality, we substitute the household optimality condition to replace the real wage. In the third equality, we use the fact that $S = P \cdot C$. We also normalize all nominal prices by S to remove S as a variable.

Turning to the pricing problem, at the beginning of each period, intermediate producers decide whether or not to adjust their nominal prices, and if so, by how much. With Kimball (1995) demand, it is possible for demand to be non-positive. In other words, for some finite positive price the solution to the final good producer's problem (A-15) may yield $y^i < 0$. Following Aruoba et al. (2025), we address this by introducing a "dormancy" state in which firms optimally choose not to produce. A firm may remain in this state until its idiosyncratic shocks change such that the optimal price implies a strictly positive quantity. At our calibrated parameters, fewer than 1% of firms are in the dormancy state in steady state, so the quantitative results are essentially unaffected. Nominal price adjustments are subject to a fixed cost f in terms of labor. We write the firm's pricing problem recursively. To keep the state space of the problem bounded, all nominal prices ($\{p\}$ and P) are normalized by total nominal expenditures $S \equiv PY$. We assume that nominal aggregate expenditure grows deterministically at a fixed rate μ

$$\log(S) = \mu + \log(S_{-1}). \tag{A-36}$$

At the beginning of the period, a firm chooses among the available actions given its inherited price p_{-1} from the previous period, fixed adjustment cost f, and dormancy status

D. If the firm is active ($D = 0$), it may either keep its existing price, adjust its price, or become dormant. If the firm is already dormant ($D = 1$), it chooses between reactivating and adjusting its price or remaining dormant. The firm's value is therefore given by

$$V\left(D, \frac{p_{-1}}{S}, \nu, z; \frac{P}{S}, \lambda\right) = \begin{cases} \max\left\{V_N\left(\frac{p_{-1}}{S}, \nu, z; \frac{P}{S}, \lambda\right), V_A\left(\nu, z; \frac{P}{S}, \lambda\right), V_D\left(\nu, z; \frac{P}{S}, \lambda\right)\right\}, & D = 0, \\ \max\left\{V_A\left(\nu, z; \frac{P}{S}, \lambda\right), V_D\left(\nu, z; \frac{P}{S}, \lambda\right)\right\}, & D = 1. \end{cases} \tag{A-37}$$

The value of not adjusting its price is simply the flow profit at the existing price p_{-1}/S plus the continuation value

$$\begin{aligned} V_N\left(\frac{p_{-1}}{S}, \nu, z; \frac{P}{S}, \lambda\right) &= \pi\left(\frac{p_{-1}}{S}, \nu, z, \frac{P}{S}, \lambda\right) \\ &+ \mathbb{E}\left[\Xi V\left(0, \frac{p_{-1}}{S}\frac{1}{e^{\mu}}, \nu', z'; \frac{P'}{S}\frac{1}{e^{\mu}}, \lambda'\right)\right]. \end{aligned} \tag{A-38}$$

where Ξ is the households' stochastic discount factor (A-8), and $\pi(\cdot)$ denotes flow profits as a function of the price charged and the other state variables following (A-35).

Should the firm decide to adjust its price, it earns profits at the newly chosen price p/S but pays the adjustment cost

$$\begin{aligned} V_A\left(\nu, z; \frac{P}{S}, \lambda\right) = &-f\frac{W}{P} \\ &+ \max_{\frac{p}{S}}\left\{\pi\left(\frac{p}{S}, \nu, z, \frac{P}{S}, \lambda\right) + \mathbb{E}\left[\Xi V\left(0, \frac{p}{S}\frac{1}{e^{\mu}}, \nu', z'; \frac{P'}{S}\frac{1}{e^{\mu}}, \lambda'\right)\right]\right\}. \end{aligned} \tag{A-39}$$

Finally, the value of dormancy is

$$V_D\left(\nu, z; \frac{P}{S}, \lambda\right) = \pi_D\left(\nu, z, \frac{P}{S}, \lambda\right) + \mathbb{E}\left[\Xi V\left(1, \frac{p_{-1}}{S}\frac{1}{e^{\mu}}, \nu', z'; \frac{P'}{S}\frac{1}{e^{\mu}}, \lambda'\right)\right], \tag{A-40}$$

where $\pi_D(\cdot)$ denotes the flow payoff associated with remaining dormant. The intermediate producer's problem is otherwise standard, except for the introduction of the Kimball aggregator instead of the more common CES aggregator.

D.4 Equilibrium

We focus on a stationary equilibrium as our model features no aggregate risk. An equilibrium can be defined as follows.

Definition D.1. *A stationary recursive competitive equilibrium is a collection of (a) value functions $V(\cdot)$, $V_A(\cdot), V_N(\cdot)$ and $V_D(\cdot)$ and a pricing function $p^i/S(\cdot)$, (b) final good demand of each variety $y^i(\cdot)$, (c) labor demand by intermediate-good firms $h(\cdot)$ (d) time-invariant household decisions C, Ξ, h, (e) aggregate prices and other constants $\frac{W}{P}$, $\frac{P}{S}$, λ, Π, Y and (f) a time-invariant distribution $H(D^i, \frac{p^i}{S}, z^i, \nu^i)$ such that:*

1. *Given Π and W/P, households optimization using (A-5) along with*

$$\begin{aligned} \frac{W}{P} &= \xi C, && \text{(A-41)} \\ \Xi &= \beta && \text{(A-42)} \end{aligned}$$

   yield C, Ξ and h.

2. *Final-good producer problem yields $y^i(\cdot)$ following (A-15). Zero-profit condition (A-28) yields P/S and λ follows from (A-22).*

3. *Given P/S, λ, Y and W/P, the intermediate-good firms optimization yields value functions $V(\cdot)$, $V_A(\cdot)$, $V_N(\cdot)$, $V_D(\cdot)$ and decision rules $h(\cdot)$ as well as $p^i/S(\cdot)$ satisfying (A-37), (A-38), (A-39) as well as the optimization problem on the right hand side of (A-39). The sum of their profits yields Π.*

4. *Market clearing and consistency*

$$\begin{aligned} h &= \int_{y_i>0} h(\cdot)H(\cdot)di && \text{(A-43)} \\ 1 &= \int_0^1 \frac{\omega}{1+\omega\psi}\left[(1+\psi)\frac{\nu_i y_i}{Y} - \psi\right]^{\frac{1+\omega\psi}{\omega(1+\psi)}} + 1 - \frac{\omega}{1+\omega\psi} di && \text{(A-44)} \\ C &= Y && \text{(A-45)} \\ \frac{S}{P} &= Y. && \text{(A-46)} \end{aligned}$$

5. *The distribution $H(\cdot)$ is time-invariant and consistent with the optimizing decisions of the household and firms.*

D.5 Solution Method and Algorithms

D.5.1 Stationary Equilibrium

1. Construct discrete grids for idiosyncratic productivity z, idiosyncratic demand ν, and firm price $\frac{p^i}{S}$. We use the Tauchen method to construct the z and ν grids. For firm price, we use an equi-spaced grid.

2. Initialize guesses for aggregate prices $\left(\frac{\hat{P}}{S}, \hat{\lambda}\right)$.

3. Given $\left(\frac{\hat{P}}{S}, \hat{\lambda}\right)$, solve the intermediate producer's optimization problem using value function iteration. This yields the optimal pricing decision rules $\frac{p}{S}^{*}\left(D, \frac{p_{-1}}{S}, z, \nu; \frac{\hat{P}}{S}, \hat{\lambda}\right)$.

4. Initialize a firm distribution $H_0\left(D, \frac{p_{-1}}{S}, z, \nu\right)$ over intermediate producers' idiosyncratic states. Using the law of motion of z and ν, as well as the pricing decision rule $\frac{p}{S}^{*}$, iterate forward on the distribution until the implied aggregates are sufficiently stable. This yields a stationary distribution $H^{*}\left(D, \frac{p_{-1}}{S}, z, \nu; \frac{\hat{P}}{S}, \hat{\lambda}\right)$.

5. Compute $\frac{P}{S}$ and λ using equations (A-22) and (A-28) at the stationary distribution $H^{*}(\cdot; \frac{\hat{P}}{S}, \hat{\lambda})$. Compute the absolute difference between the guesses $(\frac{\hat{P}}{S}, \hat{\lambda})$ and the implied values $(\frac{P}{S}, \lambda)$. If the differences are larger than a pre-determined tolerance level, update the guesses using a convex combination of the original guess and the implied value and repeat from step (3) until the differences are sufficiently small.

D.5.2 Transition with News Shock in $t = 0$

The following describes the solution algorithm for solving for a transition in which the economy, initially at the stationary equilibrium, receives a one-time unanticipated news shock in period $t = 0$.

1. Construct discrete grids for idiosyncratic productivity z, idiosyncratic demand ν, and firm price $\frac{p^i}{S}$.

2. Set the number of transition periods, denoted by T. By assumption, the economy returns to the stationary equilibrium T periods after the arrival of the news shock. Adjust T as required.

3. Solve for the stationary equilibrium of the economy. Save the value functions $V_A^{*}(\cdot)$, $V_N^{*}(\cdot)$, $V_D^{*}(\cdot)$, $V^{*}(\cdot)$, pricing decision rule $\frac{p}{S}^{*}(\cdot)$, and stationary distribution in equilibrium $G^{*}(\cdot)$

4. Initialize two sequences of guesses for $\frac{P}{S}$ and λ. The first sequence, $\{\frac{\tilde{P}_t}{S_t}, \tilde{\lambda}_t\}_{t=0}^{T-1}$, is the guess for the case when the news shock is not realized. The second sequence, $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=0}^{T-1}$, is for when the news shock is realized.

5. Assume that in period T, the economy is at the stationary equilibrium with time-invariant value function $V^{*}(\cdot)$. For the case where the news shock is realized in $t = 1$, solve backwards for the value functions at each period t:

(a) In period $T-1$, solve equations (A-37, A-38, A-39) for $\hat{V}_A(\cdot;T-1), \hat{V}_N(\cdot;T-1), \hat{V}_D(\cdot;T-1), \hat{V}(\cdot;T-1)$ and the pricing decision rule $\hat{\frac{p}{S}}^*(\cdot;T-1)$ using the guesses $(\hat{\frac{P_{T-1}}{S_{T-1}}}, \hat{\lambda}_{T-1})$ and $V^*(\cdot)$ as continuation value.

(b) Iterate backward by repeating the step above for $t = T-2, ..., 1$, using the guesses $(\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t)$ and $\hat{V}(\cdot;t+1)$ as the continuation value.

(c) Obtain $\{\hat{V}_A(\cdot;t), \hat{V}_N(\cdot;t), \hat{V}_D(\cdot;t), \hat{V}(\cdot;t), \hat{\frac{p^*}{S}}(\cdot;t)\}_{t=1}^{T-1}$

6. Repeat the step above for the case where the news shock is not realized to obtain $\{\tilde{V}_A(\cdot;t), \tilde{V}_N(\cdot;t), \tilde{V}_D(\cdot;t), \tilde{V}(\cdot;t), \frac{p}{S}^*(\cdot;t)\}_{t=1}^{T-1}$

7. In period $t = 0$, solve equations (A-37, A-38, A-39) using the guesses $(\frac{\hat{P}_0}{S_0}, \hat{\lambda}_0)$ and $V(\cdot) = \mathcal{P}\hat{V}(\cdot;1) + (1-\mathcal{P})\,\tilde{V}(\cdot;1)$ as the continuation value, yielding $\{\hat{V}_A(\cdot;0), \hat{V}_N(\cdot;0), \hat{V}_D(\cdot;0), \hat{V}(\cdot;0), \hat{\frac{p}{S}}^*(\cdot;0)\}$.[A-5]

8. Assume that the economy is initially at the stationary equilibrium before the arrival of the news shock in period 0. For the case where the news shock is realized, iterate the firm distribution forward at each period t:

(a) Starting from the stationary distribution $H^*(\cdot)$, use the law of motion for (z, ν, S) and the pricing decision rule $\hat{\frac{p}{S}}^*(\cdot;0)$ to obtain the firm distribution in period 0 $\hat{H}(\cdot;0)$.

(b) For each $t = 1, ..., T-1$, iterate the lagged distribution $\hat{H}(\cdot;t-1)$ forward using the law of motion for (z, ν, S) and the pricing decision $\hat{\frac{p}{S}}^*(\cdot;t)$ for $\hat{H}(\cdot;t)$. In particular, the shocks to ν are more dispersed in period 1 when the news shock is realized.

(c) Obtain $\{\hat{H}(\cdot;t)\}_{t=0}^{T-1}$

9. Repeat the step above for the case where the news shock is not realized and obtain $\{\tilde{H}(\cdot;t)\}_{t=0}^{T-1}$

10. Compute the implied sequence of aggregate prices $\{\hat{\hat{\frac{P_t}{S_t}}}, \hat{\hat{\lambda}}_t\}_{t=0}^{T-1}$ period-by-period from equations (A-22) and (A-28) using the implied sequence of firm distributions $\{\hat{H}(\cdot;t)\}_{t=0}^{T-1}$ for the case where the news shock is realized. Similarly, compute $\{\tilde{\tilde{\frac{P}{S}}}, \tilde{\tilde{\lambda}}_t\}_{t=0}^{T-1}$ for the case where the news shock is not realized.

11. Compute the absolute difference between the guessed sequences $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=0}^{T-1}, \{\frac{\tilde{P}_t}{S_t}, \tilde{\lambda}_t\}_{t=0}^{T-1}$ and the implied sequences $\{\frac{\hat{\hat{P}}_t}{S_t}, \hat{\hat{\lambda}}_t\}_{t=0}^{T-1}, \{\frac{\tilde{\tilde{P}}_t}{S_t}, \tilde{\tilde{\lambda}}_t\}_{t=0}^{T-1}$ period-by-period. If the differences

[A-5] Note that in $t = 0$, the two cases (shock realizing and not realizing) coincide so that $\tilde{V} = \hat{V}$.

are larger than a pre-determined tolerance level, update the guesses using a convex combination of the original guesses and the implied sequence. Repeat from step (5) until the differences are sufficiently small.

We use model-simulated data to obtain the model responses of frequency, average size of price changes, and markups to the arrival of news. The exact procedure is as follows. In our simulation, we use $N = 100,000$ and $B = 200$.

1. Simulate N firms in the stationary equilibrium for B periods after sufficient burn in.
2. Starting from the period B cross-section, introduce a news shock in period $B+1$ and simulate one additional period.
3. Construct a dummy variable *adjust* that takes the value one if there is a price adjustment and takes the value zero otherwise. In addition, record the size of each price change in a variable size.
4. Generate a dummy variable *social uprising* that takes value of zero for periods 1 to B and one for period $B+1$.
5. Regress *adjust* and *size* respectively on *social uprising* to obtain the model responses of the change in frequency and size to the news shock.

D.5.3 Monetary Policy Shock

Monetary Policy Shock at $t = 0$

The following describes the solution algorithm for solving for a transition in which the economy, initially at the stationary equilibrium, receives a one-time unanticipated monetary policy shock in period $t = 0$.

1. Construct discrete grids for idiosyncratic productivity z, idiosyncratic demand ν, and firm price $\frac{p^i}{S}$.
2. Set the number of periods that the transition takes denoted by T. By assumption, the economy returns to the stationary equilibrium T periods after the arrival of the news shock. Adjust T as required.
3. Solve for the stationary equilibrium of the economy. Save the value functions $V_A^*(\cdot), V_N^*(\cdot), V_D^*(\cdot), V^*(\cdot)$, pricing decision rule $\frac{p}{S}^*(\cdot)$, and stationary distribution in equilibrium $G^*(\cdot)$
4. Initialize a sequence of guesses for $\frac{P}{S}$ and λ, labeled $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=0}^{T-1}$.

5. Assume that in period T, the economy is at the stationary equilibrium with time-invariant value function $V^*(\cdot)$. Solve backwards for the value functions at each period t:

   (a) In period $T-1$, solve equations (A-37, A-38, A-39) for $\hat{V}_A(\cdot;T-1), \hat{V}_N(\cdot;T-1), \hat{V}_D(\cdot;T-1), \hat{V}(\cdot;T-1)$ and the pricing decision rule $\hat{\frac{p}{S}}^*(\cdot;T-1)$ using the guesses $(\hat{\frac{P_{T-1}}{S_{T-1}}}, \hat{\lambda}_{T-1})$ and $V^*(\cdot)$ as continuation value.

   (b) Iterate backward by repeating the step above for $t = T-2, ..., 0$, using the guesses $(\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t)$ and $\hat{V}(\cdot;t+1)$ as the continuation value.

   (c) Obtain $\{\hat{V}_A(\cdot;t), \hat{V}_N(\cdot;t), \hat{V}_D(\cdot;t), \hat{V}(\cdot;t), \hat{\frac{p^*}{S}}(\cdot;t)\}_{t=0}^{T-1}$

6. Assume that the economy is initially at the stationary equilibrium before the arrival of the monetary policy shock in period 0. Then iterate the firm distribution forward at each period t:

   (a) Starting from the stationary distribution $H^*(\cdot)$, use the law of motion for (z, ν, S) and the pricing decision rule $\hat{\frac{p}{S}}^*(\cdot;0)$ to obtain the firm distribution in period 0 $\hat{H}(\cdot;0)$.

   (b) For each $t = 1, ..., T-1$, iterate the lagged distribution $\hat{H}(\cdot;t-1)$ forward using the law of motion for (z, ν, S) and the pricing decision $\hat{\frac{p}{S}}^*(\cdot;t)$ for $\hat{H}(\cdot;t)$.

   (c) Obtain $\{\hat{H}(\cdot;t)\}_{t=0}^{T-1}$

7. Compute the implied sequence of aggregate prices $\{\hat{\hat{\frac{P_t}{S_t}}}, \hat{\hat{\lambda}}_t\}_{t=0}^{T-1}$ period-by-period from equations (A-22) and (A-28) using implied sequence of firm distributions $\{\hat{H}(\cdot;t)\}_{t=0}^{T-1}$.

8. Compute the absolute difference between the guessed sequences $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=0}^{T-1}$ and the implied sequences $\{\hat{\hat{\frac{P_t}{S_t}}}, \hat{\hat{\lambda}}_t\}_{t=0}^{T-1}$ period-by-period. If the differences are larger than a pre-determined tolerance level, update the guesses using a convex combination of the original guesses and the implied sequence. Repeat from step (5) until the differences are sufficiently small.

Monetary Policy Shock and News Shock at $t = 0$

The algorithm in Appendix (D.5.2) can also be applied to solve for the transition in which the economy, initially at the stationary equilibrium, receives a one-time unanticipated news shock and monetary policy shock concurrently in period $t = 0$.

News Shock at $t = 0$ and Monetary Policy Shock at $t = 1$

The following describes the solution algorithm for solving for a transition in which the economy, initially at the stationary equilibrium, receives a one-time unanticipated news shock in period $t = 0$ and subsequently another unanticipated monetary policy shock in period $t = 1$.

1. Use the algorithm in Appendix (D.5.2) to first solve for the transition in which the economy receives only a one-time unanticipated news shock in period $t = 0$. Save the firm distribution in $t = 0$ as $H_0(\cdot)$ as well as the equilibrium aggregate prices $(\frac{P_0}{S_0}, \lambda_0)$.

2. Initialize two sequences of guesses for $\frac{P}{S}$ and λ. The first sequence, $\{\frac{\tilde{P}_t}{S_t}, \tilde{\lambda}_t\}_{t=1}^{T-1}$, is the guess for the case when the news shock is not realized. The second sequence, $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=1}^{T-1}$, is for when the news shock is realized.

3. Assume that in period T, the economy is at the stationary equilibrium with time-invariant value function $V^*(\cdot)$. For the case where the news shock is realized in $t = 1$, solve backwards for the value functions at each period t:

   (a) In period $T - 1$, solve equations (A-37, A-38, A-39) for $\hat{V}_A(\cdot; T-1), \hat{V}_N(\cdot; T-1), \hat{V}_D(\cdot; T-1), \hat{V}(\cdot; T-1)$ and the pricing decision rule $\hat{\frac{p}{S}}^*(\cdot; T-1)$ using the guesses $(\widehat{\frac{P_{T-1}}{S_{T-1}}}, \hat{\lambda}_{T-1})$ and $V^*(\cdot)$ as continuation value.

   (b) Iterate backward by repeating the step above for $t = T-2, ..., 1$, using the guesses $(\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t)$ and $\hat{V}(\cdot; t+1)$ as the continuation value.

   (c) Obtain $\{\hat{V}_A(\cdot; t), \hat{V}_N(\cdot; t), \hat{V}_D(\cdot; t), \hat{V}(\cdot; t), \hat{\frac{p}{S}}^*(\cdot; t)\}_{t=1}^{T-1}$

4. Repeat the step above for the case where the news shock is not realized to obtain $\{\tilde{V}_A(\cdot; t), \tilde{V}_N(\cdot; t), \tilde{V}_D(\cdot; t), \tilde{V}(\cdot; t), \frac{\tilde{p}^*}{S}(\cdot; t)\}_{t=1}^{T-1}$

5. In period $t = 0$, the firm distribution over idiosyncratic states is given by $H_0(\cdot)$. Set $\hat{H}(\cdot; 0) = \tilde{H}(\cdot; 0) = H_0(\cdot)$ as a result. For the case where the news shock is realized, iterate the firm distribution forward at each period $t = 1, ..., T-1$ while incorporating the monetary policy shock in period $t = 1$:

   (a) Iterate the lagged distribution $\hat{H}(\cdot; t-1)$ forward using the law of motion for (z, ν, S) and the pricing decision $\hat{\frac{p^*}{S}}(\cdot; t)$ for $\hat{H}(\cdot; t)$ to obtain $\{\hat{H}(\cdot; t)\}_{t=1}^{T-1}$. In particular, the shocks to ν are more dispersed in period 1 when the news shock is realized.

6. Repeat the step above for the case where the news shock is not realized and obtain $\{\tilde{H}(\cdot; t)\}_{t=1}^{T-1}$

7. Compute the implied sequence of aggregate prices $\{\frac{\hat{\hat{P}}_t}{S_t}, \hat{\hat{\lambda}}_t\}_{t=1}^{T-1}$ period-by-period from equations (A-22) and (A-28) using implied sequence of firm distributions $\{\hat{H}(\cdot; t)\}_{t=1}^{T-1}$

for the case where the news shock is realized. Similarly, compute $\{\tilde{\tilde{\frac{P}{S}}}, \tilde{\tilde{\lambda}}_t\}_{t=1}^{T-1}$ for the case where the news shock is not realized.

8. Compute the absolute difference between the guessed sequences $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=1}^{T-1}, \{\frac{\tilde{P}_t}{S_t}, \tilde{\lambda}_t\}_{t=1}^{T-1}$ and the implied sequences $\{\frac{\hat{\hat{P}}_t}{S_t}, \hat{\hat{\lambda}}_t\}_{t=1}^{T-1}, \{\frac{\tilde{\tilde{P}}_t}{S_t}, \tilde{\tilde{\lambda}}_t\}_{t=1}^{T-1}$ period-by-period. If the differences are larger than a pre-determined tolerance level, update the guesses using a convex combination of the original guesses and the implied sequence. Repeat from step (3) until the differences are sufficiently small.

Table 8 reports the model response of output to nominal expenditure shocks under different realizations of the news shock, which are constructed as follows. In all exercises, we set the length of the transition to $T = 40$. The solution algorithms can be found in Section (D.5.2) and Section (D.5.3).

Row 1: The output response is computed as the difference between (i) a transition with no news and a one-time nominal shock in period $t = 0$ and (ii) a transition with no news and no nominal shock.

Row 2: The output response is computed as the difference between (i) a transition with a one-time news shock in period $t = 0$ which is realized in period $t = 1$, a menu cost shock in period $t = 0$, and a one-time nominal shock in period $t = 0$ and (ii) a transition with a one-time news shock at period $t = 0$ which is realized in period $t = 1$ and a menu cost shock in period $t = 0$ in the absence of nominal shocks.

Row 3: The output response is computed as the difference between (i) a transition with a one-time news shock in period $t = 0$ which is not realized in period $t = 1$, a menu cost shock in period $t = 0$, and a one-time nominal shock in period $t = 0$ and (ii) a transition with a one-time news shock at period $t = 0$ which is not realized in period $t = 1$ and a menu cost shock in period $t = 0$ in the absence of nominal shocks.

Row 4: The output response is computed as the difference between (i) a transition with a menu cost shock in period $t = 0$ (calibrated to a 5 percentage point decline in frequency in period $t = 0$) and a one-time nominal shock in period $t = 0$ and (ii) a transition with a menu cost shock in period $t = 0$ (calibrated to a 5 percentage point decline in frequency in period $t = 0$) in the absence of nominal shocks.

Row 5: The output response is computed as the difference between (i) a transition with a one-time news shock at period $t = 0$ (calibrated to a 5 percentage point decline in frequency in period $t = 0$) which is realized in period $t = 1$ and a one-time nominal shock in period $t = 0$ and (ii) a transition with a one-time news shock at period $t = 0$ (calibrated to a 5 percentage point decline in frequency in period $t = 0$) which is realized in period $t = 1$ in the absence of nominal shocks.

Row 6: The output response is computed as the difference between (i) a transition with no news and a one-time nominal shock in period $t = 1$ and (ii) a transition with no news and no nominal shock.

Row 7: The output response is computed as the difference between (i) a transition with a one-time news shock in period $t = 0$ which is realized in period $t = 1$, a menu cost shock in period $t = 0$, and a one-time nominal shock in period $t = 1$ and (ii) a transition with a one-time news shock at period $t = 0$ which is realized in period $t = 1$ and a menu cost shock in period $t = 0$ in the absence of nominal shocks.

Row 8: The output response is computed as the difference between (i) a transition with a one-time news shock in period $t = 0$ which is not realized in period $t = 1$, a menu cost shock in period $t = 0$, and a one-time nominal shock in period $t = 1$ and (ii) a transition with a one-time news shock at period $t = 0$ which is not realized in period $t = 1$ and a menu cost shock in period $t = 0$ in the absence of nominal shocks.

In all rows, the cumulative impulse response is computed as the cumulative differences between two transitions.

E More Quantitative Results from the Model

E.1 Alternative Explanations

In this appendix we examine alternative model experiments beyond the two channels emphasized in the main text: news about future idiosyncratic demand dispersion and a one-period increase in the menu cost. The goal is not to exhaust every possible mechanism, but to ask whether other natural changes in the model can reproduce the three qualitative moments observed during the Social Uprising: a decline in adjustment frequency, an increase in adjustment size conditional on adjustment, and an increase in markups conditional on adjustment.

We consider contemporaneous changes in the mean or dispersion of the idiosyncratic shocks, changes in aggregate nominal spending growth, and variants of the menu-cost experiment. Specifically, we examine increases in $\mathbb{E}[\log z]$, $\mathbb{E}[\log \nu]$, $\mathrm{Var}[\log \nu]$, $\mathrm{Var}[\log z]$, and μ, as well as two variants of the menu-cost experiment in which the increase in f lasts for

Table A-18: Alternative Explanations

	Change in Frequency	Change in Size	Change in Markup
Data	−	+	+
Change Today ($t = 0$)			
Increase in $\mathbb{E}[\log z]$	+	0	+
Increase in $\mathbb{E}[\log \nu]$	0	0	0
Increase in $\text{Var}[\log \nu]$	+	+	+
Increase in $\text{Var}[\log z]$	+	+	+
Increase in μ	0	0	+
Persistent increase in f	−	+	0
Permanent increase in f	−	+	0
News arriving Today ($t = 0$) **about Tomorrow** ($t = 1$)			
Increase in $\mathbb{E}[\log z]$	−	0	−
Increase in $\mathbb{E}[\log \nu]$	0	0	0
Increase in $\text{Var}[\log z]$	0	+	+
Increase in $\text{Var}[\log z]$ (No Leptokurtic)	−	+	+
Increase in μ	0	0	+
Decrease in f	−	+	0

Notes: "0" indicates statistically insignificant changes, "+" denotes a significant increase, and "−" a significant decrease.

five periods or permanently. We also examine forward-looking experiments with a news structure: increases in $\mathbb{E}[\log z]$, $\mathbb{E}[\log \nu]$, $\text{Var}[\log z]$, and μ, as well as a future decrease in f, which is the direction that induces firms to wait. The baseline news experiment involving future demand dispersion is discussed in the main text and is therefore not repeated as an alternative explanation here.

For changes in expected values, we introduce a temporary one-period intercept proportional to the steady-state standard deviation of the relevant shock. For changes in dispersion, we increase the standard deviation of the relevant innovation process. For contemporaneous changes at $t = 0$, the relevant moment increases by 50 percent; for menu costs, this corresponds to a 50 percent increase in f relative to its baseline value. For forward-looking news experiments, firms receive news at $t = 0$ about a one-period change at $t = 1$ that occurs with certainty; for menu-cost news, we instead report a 50 percent future decrease in f. Results are based on simulations with 100,000 firms. With such a large number of firms, simulation noise is minimal, so we use a significance threshold of 1 percent and label changes with higher p-values as "0".

Table A-18 summarizes the findings. The first row replicates the direction of the observed changes during the Social Uprising: a decline in frequency, an increase in size of price changes and an increase in markups. Each subsequent row reports the effect of a given shock relative to the baseline.

Five main results emerge. First, none of the contemporaneous changes, except for those that involve an increase in f, can generate significant responses in frequency and size with opposite signs.

Second, for current menu-cost increases, the persistence of the increase has little effect on the impact results. The main text considers a one-period increase in f that immediately reverts. Table A-18 reports robustness exercises with a persistent five-period increase and a permanent increase; both produce the same qualitative pattern as the one-period case: lower frequency, larger price changes conditional on adjustment, and no markup response. The economic force behind a menu-cost-driven decline in frequency is that adjusting today becomes expensive relative to postponing adjustment. This force is strongest when the increase is short-lived: firms can avoid paying the high menu cost today and, if needed, adjust later when the menu cost has returned to normal. When the increase is persistent or permanent, adjustment is costly today but is also expected to remain costly tomorrow, so postponing saves less on the menu cost. In the Bellman comparison between adjusting and not adjusting today, future menu costs enter the continuation values under both choices. They therefore affect the impact decision only through the different future states induced by today's decision. As a result, making the menu-cost increase longer-lived does not amplify the impact decline in adjustment frequency. In this exercise, a one-period increase in the menu cost leads to a 10 p.p. decline in frequency, while five-period and permanent increases lead to 7.19% and 7.17% declines, respectively. If anything, making the increase longer-lasting reduces, rather than amplifies, its impact effect.

Third, shocks to the variance of fundamentals increase both frequency and size since they make existing prices suboptimal.[A-6]

Fourth, among forward-looking experiments involving menu costs, the direction of the expected change matters. If firms expect menu costs to increase in the future, they have an incentive to adjust before adjustment becomes more costly, which works against the observed decline in current adjustment frequency. The relevant future-menu-cost experiment for generating wait-and-see behavior is therefore a future decrease in f: today's menu cost is high relative to the expected future cost, so firms have an incentive to wait. This experiment lowers current adjustment frequency and increases the size of price changes conditional on adjustment, but it does not generate the positive markup response observed in the data.

Fifth, turning to the remaining forward-looking experiments, news about future changes in the expected level of demand or productivity shifts the firm's optimal price path but does

[A-6] We also explored scenarios combining an anticipation shock with a small realization shock in $t = 0$. For example, a 10% contemporaneous increase in dispersion is enough to overturn the decline in frequency produced by our baseline news shock, consistent with the idea that realization effects counteract anticipation effects.

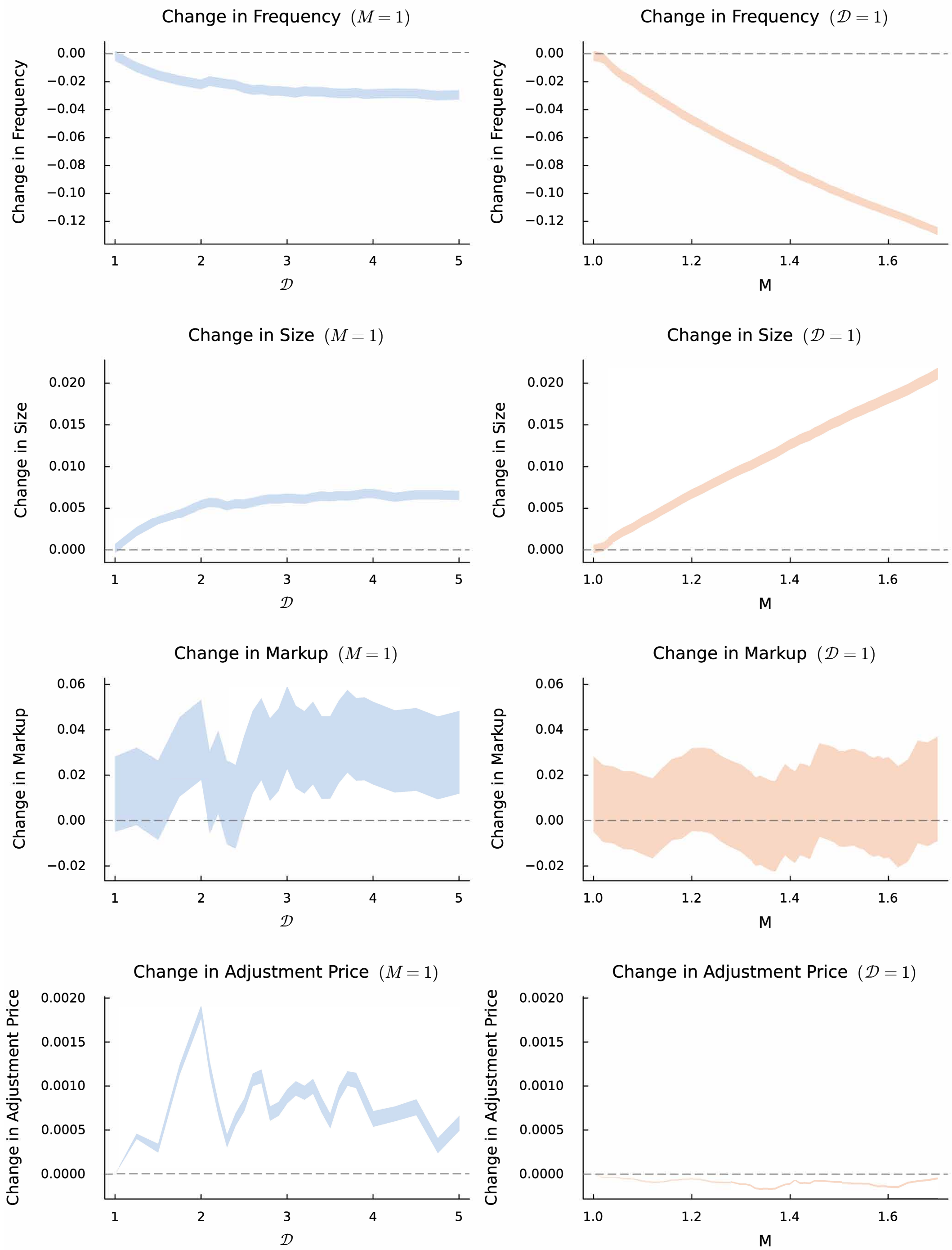
not introduce uncertainty about what that path will be. As a result, there is no "wait-and-see" value: firms either adjust today if the expected future gain justifies the menu cost, or they wait to adjust tomorrow. From our baseline results, we already know that an expected increase in $\text{Var}[\log \nu]$ tomorrow is able to match the patterns in the data. One may wonder if there is anything special about demand and whether an expected increase in $\text{Var}[\log z]$ tomorrow would also match the patterns. We first run this experiment with the leptokurtic process we have for z. This experiment does not deliver a meaningful wait-and-see behavior. This is because, with the leptokurtic structure, TFP shocks affect firm states only when a new draw arrives, which occurs with probability $p_z = 0.19$. This limits the scope for anticipated TFP shocks to influence behavior. To confirm this, we considered a version where we removed the leptokurtic process for firm-level TFP and replaced it with a standard AR(1) for log(z) featuring $\rho_z = 0.873$ and $\sigma_z = 0.052$, which mimic the properties of the original leptokurtic process as closely as possible. This version can match the three facts. Thus, the news/anticipation mechanism is not specific to demand shocks, but applies more generally to idiosyncratic shocks that affect firms' desired prices.

E.2 Influence of $\mathcal{D}$ and $\mathcal{M}$ on Moments

In the main text, we argued that a change in the *current* menu cost can generate large changes in adjustment frequency, whereas the effect of news is bounded. To demonstrate this, in Figure A-4 we plot how changes in $\mathcal{D}$ with $\mathcal{M} = 1$ (left column; assumed $\mathcal{P} = 0.5$) and changes in $\mathcal{M}$ with $\mathcal{D} = 1$ (right column) influence some key moments. The shaded bands show 99% bands. The first two rows show how frequency and size of price changes (conditional on a change) vary as the strength of each channel is increased. The right column shows a near-linear relationship between $\mathcal{M}$ and both frequency and size. Recall that the steady state frequency is 26% and hence the frequency plot is bounded by -0.26, which is considerably far given the range of values for $\mathcal{M}$ we consider. In contrast, the left panels show that by about $\mathcal{D} = 3$ a plateau is reached in both the change in frequency and size: frequency can decline by at most about 2.9 p.p., and size can increase by about 0.7 p.p. It is important to note that if we were to increase $\mathcal{P}$ these shaded areas shift upward roughly in a parallel fashion – for example with $\mathcal{P} = 1$, the limits are 5.5 p.p. and 1.4 p.p., which would be the largest values we can obtain from the news experiment.

To explain this upper bound, we revisit the mechanism through which the news shock operates. When firms anticipate greater dispersion tomorrow, they postpone adjustment today in order to avoid paying the menu cost again in the near future. This is a forward-looking, wait-and-see logic. To isolate the maximum possible strength of this force, we run a thought experiment where the cost of changing prices tomorrow is set to zero. In this

Figure A-4: Parameter Influence on Moments



Notes: The figure reports how the model moments respond to the strength of each channel. The left column varies the news parameter $\mathcal{D}$ holding $\mathcal{M} = 1$ and $\mathcal{P} = 0.5$. The right column varies the menu-cost parameter $\mathcal{M}$ holding $\mathcal{D} = 1$. Shaded bands are 99 percent simulation bands. The first three rows report the change in frequency, size conditional on adjustment, and markups conditional on adjustment. The last row reports the reset-price response after controlling for firm states.

environment, firms know they can reoptimize for free in the next period, so their pricing decision today becomes a one-shot, static problem. The only reason to pay today's menu cost is if the current price is already so misaligned that the gain from correcting it, even for a single period, exceeds the cost of adjustment. In this experiment, we find that the decline in the frequency of price changes reaches at most 6 percentage points, relative to the steady state. We interpret this as a theoretical upper bound on what the news channel alone can achieve, and it is close to the limit we report above. The key difference for a menu-cost shock is that a menu cost shock today can always be made large enough to eliminate adjustment entirely, while the news shock cannot overturn the decisions of firms whose prices are already far from optimal.

The third row of Figure A-4 shows how each channel affects markups conditional on adjustment. The news channel generates a positive markup response throughout the range of $\mathcal{D}$ values, while the menu-cost channel does not generate a systematic markup response. This distinction is somewhat obscured in the raw markup moment because markups depend on firm states. In the model, the log markup is log price minus log marginal cost. With linear technology and a common wage, marginal cost is proportional to $1/z$, so the log markup equals $\log p + \log z$ up to an aggregate wage term. Comparing changes for the same firm therefore controls for productivity, but the raw markup moment still pools firms with different demand states ν. Under Kimball demand, markups vary with ν, so selection into adjustment can introduce variation in the average markup response.

To isolate the reset-price component directly, the last row of Figure A-4 controls for both z and ν and reports how reset prices respond to each channel for comparable firms.[A-7] This exercise shows that news about future demand dispersion raises reset prices, while a menu-cost shock does not generate a systematic reset-price response. This is the reset-price logic behind the markup moment used in the main text: menu costs mainly affect which firms adjust, whereas news also changes the price chosen conditional on adjustment.

[A-7] Mechanically, the last row reports the coefficient on the Social Uprising indicator in a regression with log price as the dependent variable and controls for z and ν. The third row reports the corresponding coefficient using the log markup as the dependent variable without controlling for ν.