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PRICING UNDER DISTRESS

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Working Paper 32538
http://www.nber.org/papers/w32538

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2024, Revised September 2025

All results have been reviewed to ensure no confidential data are disclosed. The authors would like to thank Fernando Alvarez, Isaac Baley, Gadi Barlevy, Jesus Fernandez-Villaverde, Fabio Ghironi, Cosmin Ilut (discussant), Nils Gornemann, John Haltiwanger, Francesco Lippi, Luminita Stevens, and seminar participants at the the University of Maryland, the IMF´s Polak ARC, the Federal Reserve Banks of Atlanta, Chicago, Cleveland, Philadelphia, and St. Louis, the BSE Summer Forum, the SITE Conference, among others. We are also grateful to Andrew Castro, Sebastian Gallardo and Eugene Oue for excellent research assistance. All remaining errors are our own. The views expressed in this paper are those of the authors and do not represent those of the IMF, IMF Management, or its Executive Board, nor those of the Central Bank of Chile or its Board, nor those of the National Bureau of Economic Research.

Pricing Under Distress
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JEL No. E31

ABSTRACT

We isolate the anticipation effect of uncertainty on firms' price-setting behavior using a quasi-natural experiment: the 2019 Social Uprising in Chile. During the 31-day period following the outbreak of nationwide protests and riots, the frequency of supermarket price changes fell by about half, while the average size of adjustments rose by about half. Suppliers' prices remained stable, and local intensity of riots does not explain the variation, suggesting a forward-looking mechanism. A menu cost model with news about future idiosyncratic demand volatility replicates these dynamics. Anticipated uncertainty amplifies the short-run real effects of monetary policy, highlighting the importance of timing.

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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.

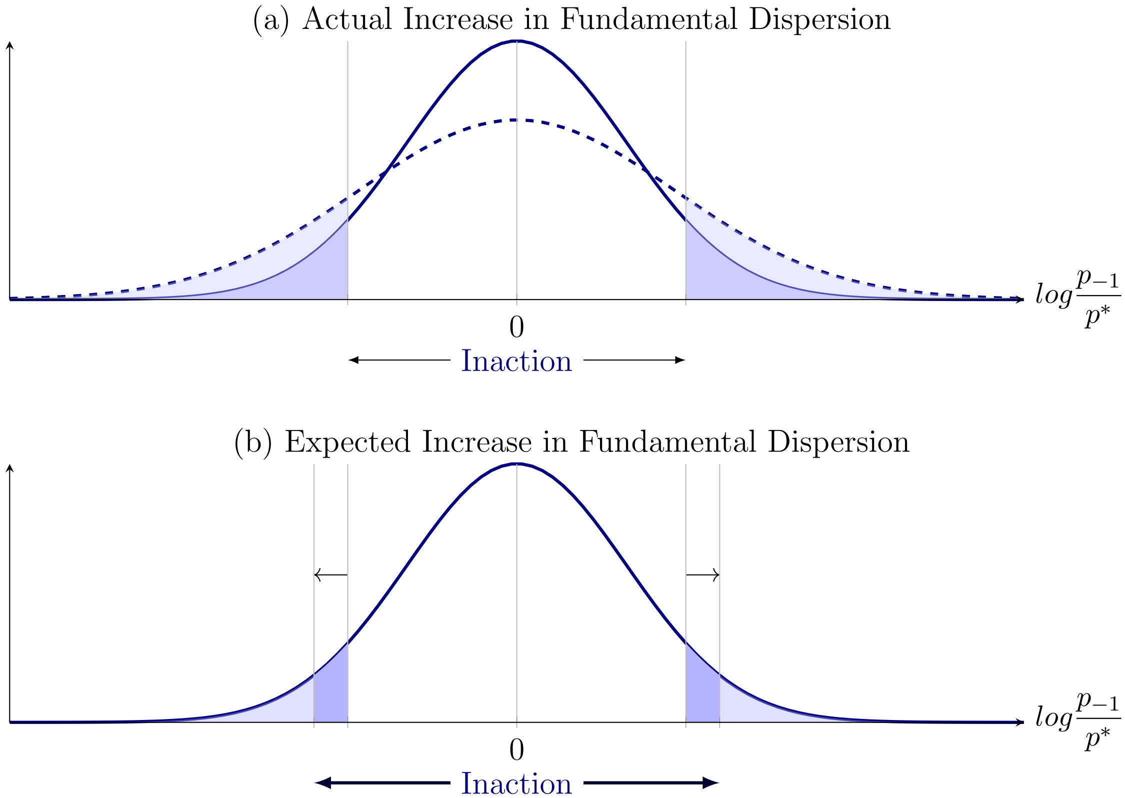
Uncertainty is typically modeled as time variation in the dispersion of a fundamental that shapes firms' decisions. In the menu-cost framework of Vavra (2014), for example, the dispersion of firm-level productivity shocks changes over time. An increase in this dispersion has two distinct effects: (i) 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] Much of the existing literature, including Bloom (2009), Bloom (2014), and Vavra (2014), effectively bundles the two together, which makes it difficult to know which mechanism dominates in practice.

To demonstrate how the realization and anticipation effects affect decisions we turn to a simple and tractable model introduced by Dixit (1991). In this model, a forward-looking decision maker faces a random variable x every period, which is iid over time, following a normal distribution with zero mean and standard deviation σ. The ideal value of this variable for the decision maker is zero and any departure from zero has the cost $f(x) = kx^2$. One can think of x as the log of a firm's lagged price relative to its optimal price in the absence of any pricing rigidities. This would show how far the firm would be from its ideal price if it kept its lagged price and not change it. If the firm wants to reset x to zero to eliminate this gap, then they have to pay a fixed cost g. Dixit (1991) shows that the dynamic problem of the firm has the feature that if $x \in [-h, h]$, the firm keeps it unchanged; otherwise it sets $x = 0$ and pays the fixed cost. He also provides a closed-form approximation for h. More details about the model are relegated to Appendix A.

The solid-blue distribution in both panels of Figure 1 shows the price-gap distribution under the baseline dispersion. Price changes that fall in the blue shaded areas in the two ends of the distribution are implemented and the white part in between shows the inaction region where no price changes occur. In Panel (a), we consider a one-time, unexpected increase in the dispersion of the fundamental distribution today with no changes in the future, and the dashed-blue line shows the new price-gap distribution. Because the inaction bands only

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

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



Notes: Panel (a) shows the effects of an increase in the price gap distribution, going from the less dispersed solid-blue distribution to the more dispersed dashed-blue distribution. All else are held equal, including expectations about future states. 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 as depicted by the shift in the grey vertical lines. 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: $k = 1$, $g = 0.3945$, $\sigma = 0.65$ for the solid-blue distribution and $\sigma = 0.936$ for the dashed-blue distribution. The solution in Appendix A shows that the inaction regions are $[-1, 1]$ and $[-1.2, 1.2]$.

depend on the (unchanged) fundamental distribution in the subsequent periods, the inaction bands do not change. The wider dashed-blue distribution has more mass in the tails relative to the blue distribution, therefore, there are more price changes (the light-blue shaded area is added to the dark-blue shaded area) and the average price change is higher. This is the realization effect caused by an increase in dispersion isolated from the anticipation effect.

In Panel (b) we show what happens if the dispersion is expected to increase permanently tomorrow, with no change in today's distribution. Because the distribution does not change today, the distribution of desired price changes is also unchanged. Consider a firm whose price was just outside the inaction bands before the change – it was willing to pay the fixed cost and change its price. After the news of an increase in future dispersion arrive, the firm takes into account that increased dispersion tomorrow may render its current price change suboptimal, leading it to pay another adjustment cost tomorrow to remedy this. As a result it chooses to postpone price adjustment until its state tomorrow is revealed. This behavior extends the inaction region today, leading to fewer price changes today, and larger price changes conditional on adjustment. This is the effect of anticipation isolated from the realization effect.

The simple model in Figure 1 shows that the realization and anticipation effects have sharply different implications. When dispersion rises today, the distribution of desired price changes widens and more firms adjust, leading to a higher frequency of price changes and larger adjustments on average. This is the realization effect. When dispersion is instead expected to rise in the future, today's distribution of desired prices is unchanged, and firms delay adjustment to avoid paying the cost again tomorrow. The anticipation effect therefore reduces the frequency of price changes while increasing their average size. These opposite comparative statics matter for both micro evidence and macroeconomic transmission: in the realized case studied by Vavra (2014), monetary policy becomes less effective, while in the anticipation case, firms' delay in adjustment implies that monetary policy can become more powerful on impact.

The distinction between realization and anticipation is especially relevant in environments where expectations about future institutions or policies shift before any concrete reform takes place. Elections, constitutional referenda such as Brexit, regime transitions, uncertanity about changes in trade policies, and episodes of mass protest can all raise the perceived dispersion of future outcomes while leaving contemporaneous fundamentals largely unchanged.[2] In these situations, firms may not know which products will be taxed, subsidized, or regulated, or even which goods will be popular with consumers. Polarization in many countries has made such forward-looking uncertainty more common, as businesses anticipate major institutional or policy shifts without knowing their precise form. These are precisely the conditions under which anticipation effects may dominate realization effects, making the distinction central for how we interpret micro evidence and assess the transmission of macroeconomic shocks.

This leads to the following natural question: can we find a clear example of a major event where the main effect of uncertainty was anticipation rather than realization? We argue that the 2019 Social Uprising (*"Estallido Social"* in Spanish) in Chile provides such an

[2]Episodes such as Brexit illustrate how political shocks can raise forward-looking uncertainty and alter firm behavior. For example, Graziano et al. (2021) document that Brexit-related trade policy uncertainty reduced UK–EU trade flows, while Hobijn et al. (2021) show that the Brexit referendum led to sizable changes in UK price adjustment dynamics.

episode. On October 18, 2019, localized demonstrations over a small subway fare increase unexpectedly escalated into a nationwide wave of protests. In the weeks that followed, the movement broadened into a call for deep social and institutional change, captured by the widespread slogan "Chile changed." In this sense, the Social Uprising fits the definition of a quasi-natural experiment: it was sudden and unexpected. Furthermore, from the perspective of firms, this may have heightened expectations of major political and institutional change, even as immediate operating costs and input fundamentals remained largely stable.

We study the price-setting behavior of supermarkets during this episode, drawing on a uniquely granular dataset built from electronic value-added tax invoices. These data allow us to observe daily prices for thousands of products across different stores and regions in Chile, and for a subset of items we can also observe the prices paid to suppliers, which lets us identify changes in costs. Two main empirical results emerge. First, the frequency of both price increases and decreases fell sharply during the Social Uprising, while the size of price changes, conditional on adjustment, rose substantially. Second, suppliers did not alter their pricing behavior, and the geographical intensity of violent incidents associated with the Uprising was uncorrelated with supermarkets' pricing response. Together, these findings indicate that concurrent supply or local demand shocks are unlikely to account for the observed behavior. Instead, the patterns are consistent with the anticipation mechanism described in our simple model, where firms delay adjustment in the face of an expected increase in future dispersion in demand conditions.

To interpret these findings and quantify the role of anticipation, we extend the menu-cost framework of Vavra (2014). We introduce idiosyncratic demand shocks and allow for variable markups through a Kimball (1995) aggregator. This modification ensures that shocks to demand dispersion affect pricing decisions. We calibrate the model using our matched price and cost data, which allows us to discipline the idiosyncratic shock processes directly with micro evidence. Quantitatively we find that this anticipation channel can explain 31% of the decrease in frequency and 52% of the increase in the size of price changes observed in the data.

While the Social Uprising may have had other effects that complemented the anticipation channel (such as a decline in current demand or higher realized uncertainty), we find that the only alternative mechanism consistent with the observed pricing dynamics is a contemporaneous and temporary increase in menu costs. The critical distinction between these two mechanisms is that a one-time temporary pure menu cost shock would not alter reset prices, whereas the anticipation of greater future demand dispersion would. We test this difference using markup dynamics during the Social Uprising and find that markups rose in this period. This pattern rules out menu costs as the sole driver of supermarkets' pricing behavior.

We therefore conclude that while a temporary rise in menu costs may have accompanied the anticipation effect, only news about future idiosyncratic demand volatility can jointly explain all three facts: the drop in frequency, the increase in size, and the rise in markups.[3]

Turning to the effectiveness of monetary policy, our model shows that when the central bank stimulates the economy in periods where future demand dispersion is expected to increase, monetary policy is about 24% more effective on impact relative to an intervention without such expectations. Thus, this class of uncertainty amplifies the short-run potency of policy. If there is also an increase in menu costs in addition to the arrival of news, then monetary policy becomes 62% more effective on impact. By contrast, if policy is implemented only after the news has arrived and the dispersion increase has been realized, it is virtually ineffective. This is consistent with Vavra (2014), who shows that monetary policy is less effective when idiosyncratic TFP dispersion rises contemporaneously. Taken together, our results highlight that the timing of monetary interventions relative to large aggregate events is critical: policy is most effective when firms anticipate future volatility but have not yet observed it, and least effective once that volatility is realized.

Beyond the Chilean case, our analysis points to a broader lesson. In many contemporary environments, from Brexit to highly polarized elections, firms face uncertainty that is primarily about the future rather than the present. Anticipation of structural or policy changes can alter expectations about which goods will be demanded, which sectors will be regulated, or which products will be viable, even before any change is enacted. Recognizing when such anticipation effects dominate realization effects is essential for interpreting micro evidence on pricing, for evaluating macroeconomic transmission, and for understanding when monetary policy becomes more or less effective.

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 due to a wait-and-see behavior.[4] Fernández-Villaverde et al. (2011) studies real interest rate volatility fluctuations in emerging economies while Fernández-Villaverde et al. (2015) studies fiscal uncertainty, both in the absence of changes in the 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

[3] Our empirical results rule out a product-specific or supermarket-specific increase in menu costs. Interpreting such a change as a national shock capturing unmodeled frictions, we also consider an experiment in which an increase in menu costs is combined with the news shock, calibrated to match all three moments. This combined specification reproduces the observed decline in frequency, the increase in size, and the rise in markups, and it reinforces our conclusions about monetary policy effectiveness.

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

examining how uncertainty affects firms' pricing behavior in a setting where first-moment shocks are largely absent.

An empirical challenge in this literature is to disentangle the anticipation effect due to higher uncertainty of future events from the realization effect due to higher volatility of current shocks. Berger et al. (2019) and Dew-Becker et al. (2017) find negative economic effects of increases in the volatility of current shocks, and insignificant effects of expected increases in the volatility of future shocks. Other papers seeking to isolate the anticipation effect are Baker et al. (2016), Jurado et al. (2015) and Kumar et al. (2023). We provide a quasi-natural experiment that isolates the anticipation channel from the realization channel.

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 counter-cyclical idiosyncratic volatility, he shows that the realization effect typically dominates the anticipation effect in a menu cost model, leading to counter-cyclical monetary policy effectiveness.[6] Drenik and Perez (2020) also empirically relate uncertainty with price dispersion. Baley and Blanco (2019) show that higher firm-level uncertainty increases the frequency and size of price changes at the micro level, but cross-sectional heterogeneity in the degree of firm-level uncertainy 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 direct evidence of the effect of uncertainty on both timing and magnitude of price changes. Critically, we use product-level input costs in disciplining our model and also compute markups, which help provide a novel empirical test of the anticipation channel.[7]

From a different angle, Ilut et al. (2020) show that Knightian uncertainty can generate infrequent price adjustment behavior. Other alternative micro foundations for nominal price rigidity are customers anger (Rotemberg, 2005) or rational inattention (Maćkowiak et al., 2023). None of these papers distinguish between the anticipation and the realization channels, while our focus is squarely on the consequences of the anticipation channel.

There is also the 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

[5]Early work on menu cost models, which jointly model the extensive and intensive margins of price adjustments, are Barro (1972), Sheshinski and Weiss (1977), Caplin and Spulber (1987), Caballero and Engel (1993) and Dotsey et al. (1999) while more recent contributions are 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 most menu cost models is to set the marginal cost process to match the distribution of price changes. We instead discipline the process of marginal costs using merged product, retailer, location level data suppliers' prices which allows to isolate the effect of uncertainty on retailers' prices from their suppliers. 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.

(1995) preferences. Aruoba et al. (2025) shows that a simple menu cost model with demand shocks and Kimball (1995) preferences can solve the tension between price dynamics and firm-level shocks highlighted by Klenow and Willis (2016). Although our model has common features with Aruoba et al. (2025), both closely follow existing menu cost models, except for the introduction of Kimball (1995) preferences and idiosyncratic demand shocks. In turn, our approach departs from Aruoba et al. (2025) in three key ways. First, we introduce leptokurtic productivity shocks. Second, we incorporate elements from the news literature, generating, to the best of our knowledge, the first pure "wait-and-see" effect in the pricing literature. Third, our model is directly calibrated to micro-pricing facts we obtain from our data, including costs.

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. In many of these papers the shocks reflect realized disruptions, supply shortages, lockdowns, or logistical bottlenecks, which increase the volatility of shocks today. In case of COVID-19, it is conceivable that some first-moment shocks are also in play. By contrast, we show that the 2019 Chilean Social Uprising produced a second-moment shock to the perceived volatility of idiosyncratic demand, without contemporaneous changes. This distinction allows us to isolate the anticipatory component of pricing behavior using a quasi-experimental design. Broadly consistent with our empirical findings is Cavallo et al. (2014) which documents greater nominal price rigidity after large earthquakes in Chile and Japan.

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 quasi-natural experiment. 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.

[8] More broadly on the effect of rare disasters, Barro (1972) and Gabaix (2012) study them theoretically and some 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, Boehm et al. (2019) and Wieland (2019), who use the 2011 earthquake in Japan.

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 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, price, and quantity 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. Appendix B.1 provides further details about 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. We do not rely on quantities from Factura data in our analysis. Instead, we use these detailed transaction data to observe shelf prices directly. Prices recorded in the Factura data closely match those in the consumer-facing Boleta data for overlapping periods and products.[9]

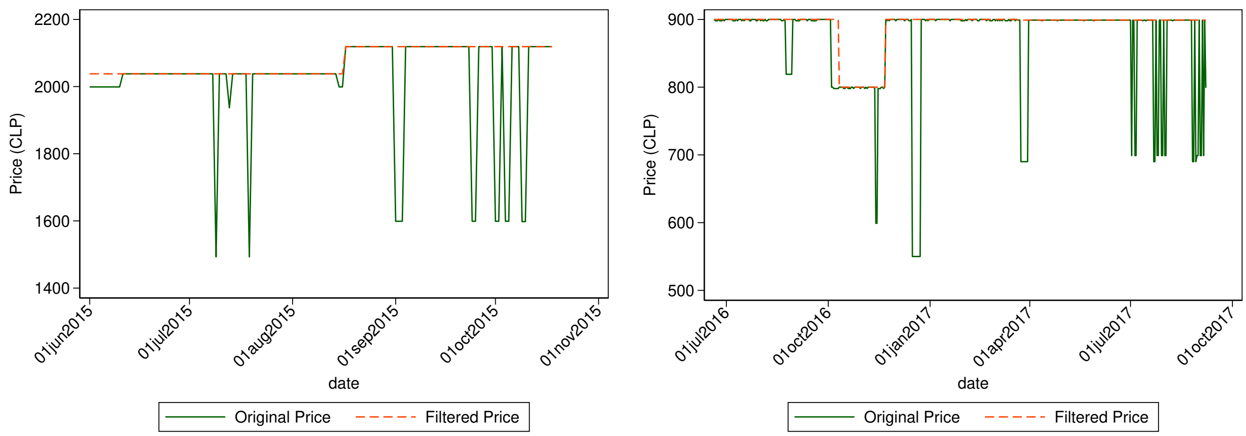
Our baseline sample consists of 33.7 million invoices. A product is defined as a unique triplet of a supermarket (seller's ID), a location, and a product description. We aggregate the transaction-level price data to daily frequency by taking the intra-day maximum price for each product triplet. This 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 short-lived sales. Figure 2 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 un-

[9] In Appendix C.1.1 we show that for the year 2023, a period outside the period we study, but one where both data are available, on average 60% 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 2: 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.

interrupted 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 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 final prices with information on the prices charged by suppliers. We do this by examining transactions in which supermarkets appear as buyers. Because the data lacks standardized product codes (such as UPCs), we apply a fuzzy matching algorithm based on textual product descriptions. 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. The resulting matched sample includes two 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, supermarket ID (buyer),

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
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		–	

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. The period of analysis spans January 1, 2015 through November 17, 2019.

and product description. Because the location of the supermarket is not recorded in these transactions, each supplier-supermarket pair corresponds to a single product ID. 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 2 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. Our dataset includes supermarkets across a broad range of regions and municipalities in Chile and it is geographically representative. 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 in the related literature.

3 Social Uprising as a Quasi-Natural Experiment

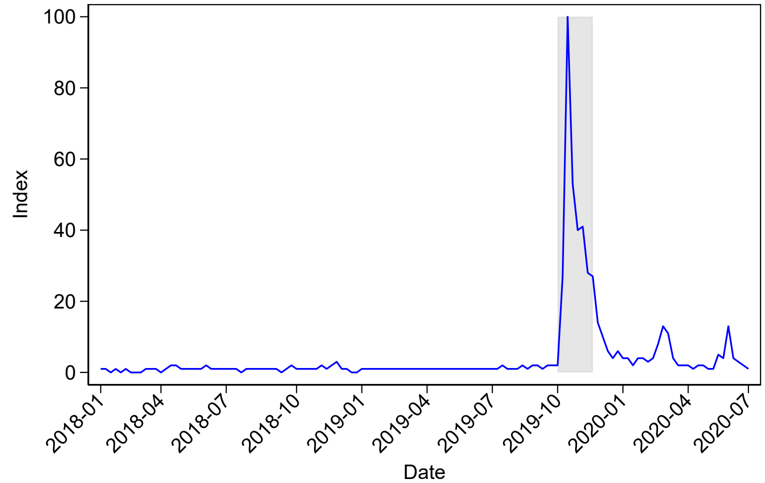
On October 6, 2019, Santiago's subway fare was raised by 4 percent, equivalent to about $0.05 USD. Students responded with peaceful demonstrations and some limited disruptions to the subway system. The situation changed drastically on October 18, when large disturbances erupted throughout the Santiago subway network. This 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 that the unrest was not only about the fare increase. Instead, it reflected a deeper and more widespread dissatisfaction in the 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 generated heightened expectations and increased uncertainty about Chile's future.[10]

From the perspective of this study, the Social Uprising had three defining characteristics. First, it was fully unexpected but relatively short-lived, making it particularly suitable as a quasi-natural experiment. Figure 3 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.

[10] 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: Google Trends for "Protestas" (Protests)



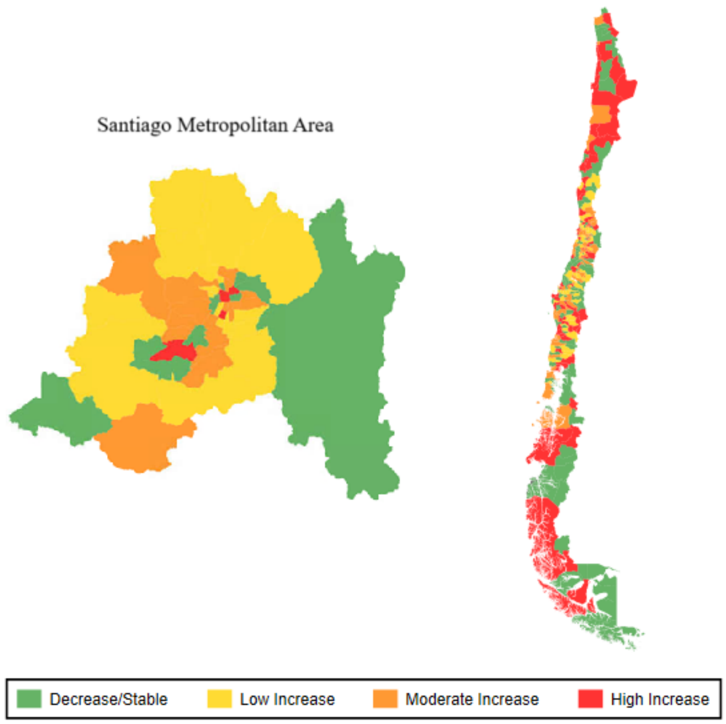
Notes: Figure shows a daily index of Google searches for "protestas" (protests) originating in Chile. The index is normalized so that the maximum value, on October 19, 2019, equals 100. The shaded area covers October 18 to November 17, 2019.

Second, the Social Uprising was widespread, but the intensity of its violent component, what we label as riot intensity, varied significantly across locations. Figure 4 displays a municipality-level map of riot intensity across Chile, with a close-up of the Santiago Metropolitan Area. 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. We exploit this heterogeneity in our empirical analysis.

Third, uncertainty rose sharply at the start of the Social Uprising. Figure 5 provides supporting evidence. The figure reports the standard deviation across individual forecasts in the Central Bank of Chile's Economic Expectations Survey for two questions: inflation expected by year-end, and the expected 12-month growth rate of the IMACEC index excluding mining. This survey is the central source used by the Bank to gauge market expectations and is based on input from a wide range of experts, including market participants and academics. Both measures of forecast dispersion increase substantially after October 18. 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 in line with the window we use for the Social Uprising.[11]

[11] As discussed by Bloom (2014), dispersion in professional forecasts is often used as a proxy for firm-level uncertainty. Extending the work by Baker et al. (2016), Ahir et al. (2022) builds a World Uncertainty Index (WUI) for a large set of countries using the frequency of the word "uncertainty" in the quarterly Economist

Figure 4: Geographical Distribution of Riot Intensity

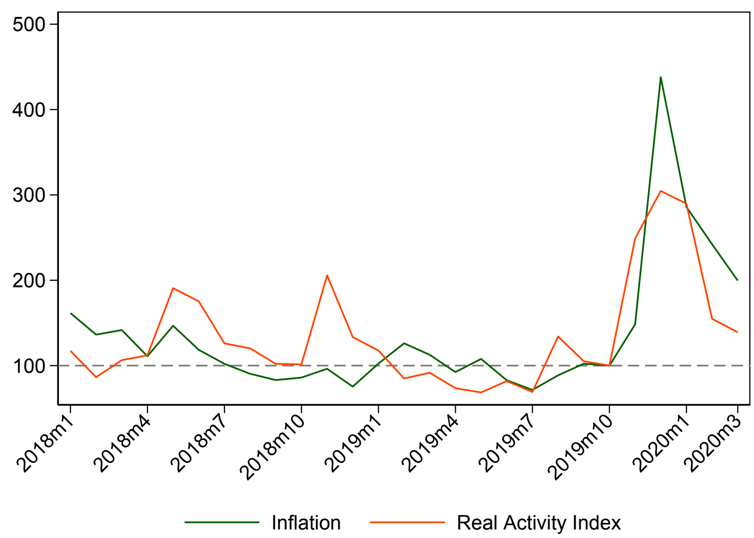


Notes: The map on the right shows riot intensity across all municipalities in Chile. The map on the left zooms into the Santiago Metropolitan Area. Riot intensity is measured as the change in the number of police reports for public disorder in October and November 2019, relative to the same period in 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.

Before turning to our main empirical analysis, we illustrate the effect of the Social Uprising on pricing behavior using raw daily data from the baseline sample. Figure 6 presents the daily frequency and average size of price changes throughout 2019. Panel (a) shows the share of product prices that change each day, which is our measure of the average frequency of price changes. During the 31-day period following October 18, marked by the shaded area, there is a clear and abrupt decline in the frequency of price changes, falling below 0.6 percent compared to a pre-Social Uprising average of 1.1 percent. Panel (b) shows a simultaneous increase in the average absolute size of price changes, rising from 13.6 percent to 17.4 percent, a 28 percent increase. 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,

Intelligence Unit country reports. The WUI for Chile –available on FRED with code WUICHL–shows a similar pattern during this period. It averages 0.18 for the period 2010Q1-2019Q3 and jumps to 1.07 in 2019Q4, the quarter that includes the Social Uprising, which is a 6-fold increase.

Figure 5: Uncertainty as Proxied by Standard Deviation Across Forecasters



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.

or changes in product composition. In short, we observe a clear shift in pricing behavior along both the frequency and magnitude of adjustments during the Social Uprising period.[12]

4 Empirical Results

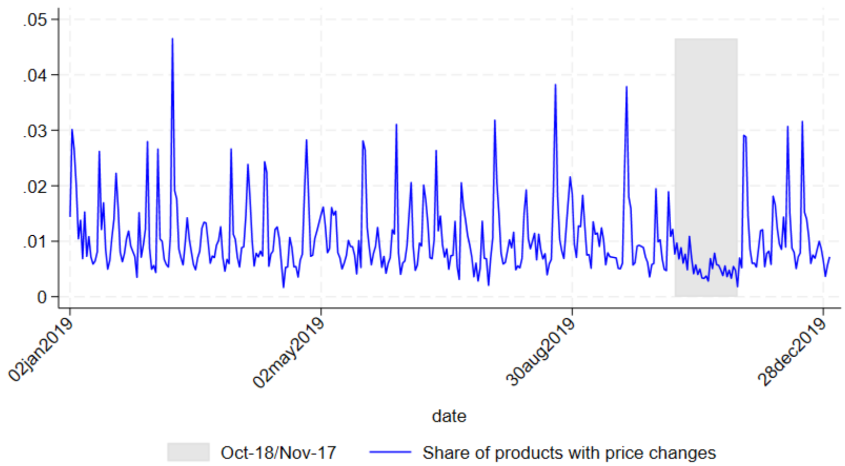
Having established that the Social Uprising satisfies the conditions of a quasi-natural experiment, we now assess its effect on the pricing behavior of supermarkets. We proceed in three steps. First, we analyze the baseline sample to examine how the frequency and size of price changes evolved during the Social Uprising period. The patterns observed in the raw data persist: the frequency of price changes declines, while the absolute size of price changes increases.

Second, we investigate whether these changes could be attributed to upstream price adjustments. To do so, we analyze the pricing behavior of suppliers to the supermarkets in our sample. We find no evidence that supplier pricing changed during the Social Uprising period.

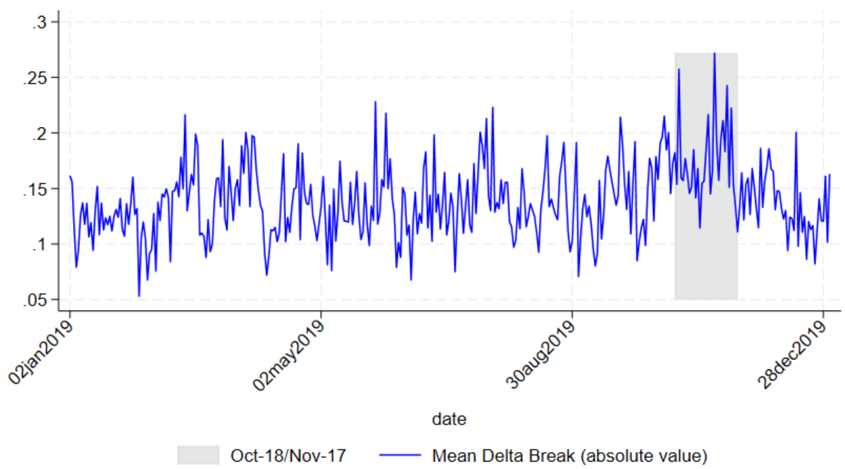
Third, we explore whether supermarkets in areas with more intense unrest responded

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

Figure 6: Frequency and Size of Price Changes in 2019



(a) Frequency of Price Changes



(b) Size of Price Changes

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. Both panels are based on the baseline sample. The shaded area covers the period from October 18 to November 17, 2019.

differently, exploiting the geographic variation in riot intensity shown in Figure 4. This allows us to test whether pricing behavior responded to localized disruptions—such as looting or transportation breakdowns—or to a national, forward-looking shift in expectations. We again find no evidence of heterogeneous responses by riot intensity.

We present these results in sequence, followed by a summary of robustness checks. We conclude the section by taking stock of what we have learned and setting up the model-based analysis in the next section.

4.1 Baseline Results for Supermarkets

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 supermarket chain X" constitutes a distinct product. Our main empirical specification is given by the equation

$$y_{it} = \text{Fixed Effects} + \beta D_t + \gamma_1 X_{1,it} + \gamma_2 X_{2,t} + \varepsilon^y_{it}, \tag{1}$$

where y_{it} is one of four dependent variables measured at the product-day level: a binary indicator for a price change (separately for positive and negative changes), or the absolute size of a price change (conditional on a change, again separated by sign). The variable D_t is a dummy equal to one during the 31-day Social Uprising period beginning on October 18, 2019. The vector $X_{1,it}$ includes time-varying product-level controls, and $X_{2,t}$ includes economic activity controls measured at the supermarket or national level. The coefficient of interest, β, captures the average change in pricing behavior during the Social Uprising. We include product fixed effects, which control for all time-invariant characteristics at this level, including location, retailer identity, and persistent product characteristics. As a result, our identification of β comes from changes in pricing behavior for the same product at the same store over time—comparing before and during the Social Uprising period.

The fixed effects in (1) include: product, 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 Monday price 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 two measures of economic activity: (i) total monthly retail sector sales, which controls for broad market trends, and (ii) total weekly purchases by each supermarket from its suppliers, capturing chain-level demand shifts. This second measure is constant across all product-store combinations within a supermarket. We cluster standard errors at the supermarket-location level to allow for location-specific serial correlation in pricing decisions.

Table 2 presents the regression results. Columns (1) and (2) show that the frequency of both positive and negative price changes declined significantly during the Social Uprising—by approximately 0.26 and 0.31 percentage points, respectively. These effects are economically meaningful, corresponding to reductions of more than 40 percent and 60 percent relative to

Table 2: Change in Pricing Behavior During the Social Uprising, Supermarkets (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

Notes: This table reports estimates of β from Equation (1), using the baseline sample. 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.

their pre-Social Uprising means of 0.65 and 0.53 percent, respectively.

Columns (3) and (4) present results for the size of price changes, conditional on adjustment. During the Social Uprising period, price changes became less frequent, but the average size of those that did occur increased. The mean positive price change rose by 3.38 percentage points and the mean negative change by 4.88 percentage points. These shifts represent increases of approximately 29 and 39 percent relative to their unconditional means.

The main takeaway is that during the Social Uprising period, supermarkets adjusted prices less often, but made larger adjustments when they did. Table A-7 in Appendix C.2.1 shows that the effects are symmetric across price increases and decreases. This symmetry suggests that the driver of the change in price dynamics has to equally impact the supermarkets' willingness to increase and decrease prices.

4.2 Effect of Supply Factors on Supermarkets

One possible explanation for the baseline results is that supermarkets may have simply passed through price changes implemented by their suppliers. To test this hypothesis, we turn to the suppliers sample, which includes firms that provide the goods sold by the supermarkets in our baseline sample. We estimate (1) using this sample, with price changes defined at the supplier–supermarket–product level.[13]

As shown in Table 3, we do not detect any statistically significant changes in the frequency or size of supplier price adjustments during the Social Uprising period. The point estimates

[13] One may wonder whether our baseline results hold in the matched sample. Table A-8 in Appendix C shows that this is indeed the case.

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

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0004	-0.0012	0.0098	-0.0105
	(0.0007)	(0.0008)	(0.0124)	(0.0196)
Observations	836,004	836,004	5,145	2,952
Adjusted R-squared	0.028	0.028	0.354	0.364
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.0067	0.0039	0.0941	0.1254

Notes: This table reports estimates of β from Equation (1), using the suppliers sample. The dependent variables mirror those in Table 2. The economic activity control corresponds to each supplier's total sales across all customers. Standard errors are clustered at the supplier–supermarket link level. *** p<0.01, ** p<0.05, * p<0.1.

are small, and in most cases the standard errors are similar to those in the supermarket sample. The only exception is Column (4), where the lower number of supplier-side price changes results in somewhat larger standard errors. These results suggest that the shifts observed in supermarket pricing behavior are unlikely to be driven by parallel upstream cost shocks.

While we cannot observe contract terms directly, one plausible explanation is that supermarkets and suppliers operate under long-term pricing agreements. These arrangements may be subject to periodic renegotiation but are unlikely to change rapidly in response to events such as the Social Uprising. Supplier prices represent the key marginal cost for supermarkets, and we do not find significant changes in these costs during the Social Uprising period.[14]

Taken together, the evidence from the supplier sample indicates that the supermarket-level pricing response is not mechanically driven by upstream price changes.

4.3 Local Intensity of Social Uprising: Is it About Now?

Having ruled out supplier pricing as the primary driver of the Social Uprising effects, we next ask whether local riot intensity helps explain the shift in supermarket pricing. If pricing behavior were driven by localized contemporaneous shocks, such as store damage, transport disruptions, or staffing shortages, we would expect the magnitude of the response to vary with riot intensity.

[14] For a given product in a supermarket, all other expenses such as labor, energy, and rent are fixed, so the marginal cost of selling an additional unit is simply the supplier price.

Table 4: Supermarket Analysis: Baseline Sample and Riot Intensity

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
Panel A: Continuous Riots Intensity Measure				
D	-0.0033***	-0.0032***	0.0281*	0.0464***
	(0.0005)	(0.0004)	(0.0154)	(0.0142)
D * intensity	2.79e-05	5.34e-06	0.0002	9.31e-05
	(1.76e-05)	(9.47e-06)	(0.0005)	(0.0004)
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
Panel B: Dummy Riots Intensity Measure				
D	-0.0026***	-0.0023***	0.0343**	0.0721***
	(0.0006)	(0.0005)	(0.0159)	(0.0265)
D * intensity	3.60e-05	-0.0009	-0.0005	-0.0272
	(0.0007)	(0.0006)	(0.0213)	(0.0286)
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

Notes: This table reports the estimated coefficients β and θ from Equation (2), using two alternative proxies for riot intensity. The continuous proxy is the change in public disorder reports in October–November 2019 relative to the same period in 2018, adjusted for population. The binary proxy equals one if this change is above the national median. Standard errors are clustered at the seller-location level. *** p<0.01, ** p<0.05, * p<0.1.

We exploit the geographic variation in riot intensity shown in Figure 4, grouping municipalities based on the severity of the unrest. We construct two proxies for riot intensity. The first is a continuous measure, defined as the change in police reports for public disorder in October and November 2019 relative to the same period in 2018, adjusted for population. This is the measure shown in Figure 4. The second is a binary indicator equal to one if the municipality experienced a disorder increase above the national median.

To estimate whether the pricing response varied by local riot intensity, we interact each proxy with the Social Uprising period dummy and estimate the regression

$$y_{it} = \text{Fixed Effects} + \beta D_t + \theta D_t \times \text{Intensity} + \gamma_1 X_{1,it} + \gamma_2 X_{2,t} + \varepsilon_{it}^{y}, \tag{2}$$

where the variable *Intensity* is either the continuous or binary measure. Note that the direct effect of *Intensity* is absorbed by the product fixed effect, since product is defined at the product–supermarket–location level.

Table 4 presents the results. Panel A reports estimates using the continuous proxy, and

Panel B uses the binary version. In both cases, the coefficient on the Social Uprising period dummy (β) remains significant and similar in magnitude to the estimates in Table 2.

The interaction terms (θ) are statistically insignificant across all specifications, and the point estimates are very small relative to the corresponding β and the unconditional mean of the dependent variables with one exception. This suggests that local riot intensity did not materially alter the pricing response. They are consistent with a nationally shared response—potentially reflecting an anticipatory shift in expectations rather than direct operational disruptions at the local level.

4.4 Robustness and Extensions

In addition to providing further descriptive statistics, Appendix C presents a series of robustness checks and extensions to our main empirical findings reported in Table 2. These tests serve two purposes: to evaluate whether the effects we estimate 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 6, the drop in price change frequency and the rise in average size are visually apparent in the raw daily data. To assess the role of our control variables, we re-estimate Equation (1) while progressively removing controls. Tables A-9, A-10, and A-11 show that the main results are robust: frequency effects remain similar, and size effects are even slightly stronger when controls are excluded. In particular, dropping all controls increases the estimated size effect to 4.6 percentage points for positive changes and 6.2 percentage points for negative changes.

Pooled direction of price changes. Our baseline regressions separate price increases and decreases. In Table A-12, we pool all price changes and find results consistent with the separate regressions: the frequency of price changes falls by 0.57 percentage points, and the average size increases by 3.8 percentage points. Figure A-1, which plots residuals from this pooled regression (excluding the Social Uprising dummy), visually confirms the shift during the Social Uprising period.

Filtering. One concern is that our application of the Kehoe and Midrigan (2015) filter may understate true pricing activity if supermarkets responded to the Social Uprising with short-lived price changes (e.g., promotions or rapid reversals). To evaluate this, Table A-13 presents results using unfiltered (raw) prices. We find that the estimated decline in frequency and the increase in size is somewhat smaller relative to the unconditional means of the respective variables, which are in turn larger without the filter. Nevertheless they are still highly significant. These results suggest that our filtering approach is, if anything, conservative. Another robustness check we considered was using a balanced panel of products that pass our continuity restriction for every week in the period September 23, 2019 to November 17, 2019. Table A-14 shows the results for 6,973 products that satisfy this criterion. The decline in frequency for these products is about 30% smaller than the baseline results, though still highly significant and the change in size of prices very similar.

Fixed effects and supermarket-wide pricing. Our baseline specification includes product-level fixed effects (defined at the product–store–chain level). One might worry, however, that if supermarket chains coordinate pricing across stores, as documented by DellaVigna and Gentzkow (2019), these fixed effects could miss higher-level policies. Table A-15 replaces product fixed effects with chain-level fixed effects. The results remain robust, and the estimated size effects are slightly larger. In Table A-16, we also interact the Social Uprising dummy with an indicator for supermarket size (based on monthly sales at supermarket-location level) and find no evidence of differential effects between large and small chains.

Geographic aggregation. In Section 4.3, we analyze riot intensity at the municipality level. To address the concern raised above, that supermarkets may choose price policies centrally, we repeat the same analysis using supermarket-level exposure to unrest, defined as a weighted average of riot intensity across municipalities where the supermarket operates. Table A-17 presents these results, which largely replicate those in Table 4: local intensity is not significantly associated with differences in pricing behavior, reinforcing the view that the pricing response reflects a nationally shared shift in expectations.

Additional controls. Finally, we augment our baseline regressions with several new control variables. Table A-18 adds the daily CLP/USD exchange rate; Table A-19 includes each supermarket's monthly wage bill; and Table A-20 adds the most recent price change by the product's supplier (in the matched sample). Across all three specifications, the coefficients on the Social Uprising dummy remains stable and statistically significant. These findings suggest that the estimated effects are not confounded by exchange rate pass-through, labor cost pressures, or contemporaneous changes in restocking costs—echoing the supplier-side results in Table 3.

Taken together, these robustness checks reinforce the conclusion that the observed drop in frequency and rise in size of price changes during the Social Uprising are not an artifact of control variables, fixed effects structure, filtering, or compositional changes in the data.

4.5 Summary of Empirical Results

Our results show that 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. The frequency of price changes declined by between 40 and 60 percent, while the size of price changes, conditional on an adjustment, increased by between 29 and 39 percent compared to the pre-Social Uprising period. Due to the continuity requirement we used in constructing our data, these results are identified by products that are sold both during and before the Social Uprising and are not influenced by store closures during the Social Uprising.

In contrast, the firms that supply goods to supermarkets show no change in their pricing behavior. We enhanced these results by directly controlling for other costs of supermarkets and the results are very similar to the baseline results. These findings suggest that the shift in supermarket behavior was not driven by cost pass-through from suppliers, or other supply-side concerns, but instead by factors on the demand side.

Moreover, we find no relationship between the local intensity of riots and the change in pricing behavior. This implies that the changes were not driven by direct operational disruptions but by concerns shared by all supermarkets. In other words, it seems like the supermarkets were not reacting to what they see in front of their door, but to what they see on the news. The changes in pricing behavior we identified are also symmetric across price increases and decreases, indicating that they could not be driven by concerns about drawing criticism for increasing prices during the Social Uprising, an event which was triggered by a price *increase*. Taken together with the sharp rise in uncertainty documented at the start of the Social Uprising—as measured by forecast disagreement in the Central Bank of Chile's survey—these findings point to an anticipatory mechanism.

We interpret these results as consistent with a scenario in which firms anticipated greater dispersion in future demand but did not yet observe it. While other channels may also have played a role, our findings support the plausibility of a forward-looking pricing response to anticipated uncertainty.

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 demonstrate that *news* about a possible increase in the dispersion of future idiosyncratic demand—i.e., an anticipation effect—can generate the empirical results we documented during the Chilean Social Uprising, and that alternative explanations by themselves cannot. Second, we investigate how the arrival and timing of such news influence the effectiveness of monetary policy.

Our model is a standard menu cost model with two additional and necessary ingredients. First, we include idiosyncratic demand shocks in addition to productivity shocks. In normal times, which we use to calibrate the model, these follow standard AR(1) processes with constant innovation variances. 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.[15] This step is essential: under CES, idiosyncratic demand shocks do not affect optimal prices, precluding any anticipation effect.

A final distinguishing feature of our approach is empirical: 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 match key pricing moments—such as cost pass-through and markup behavior—and to identify the model more precisely. Crucially, it also enables us to empirically distinguish between competing mechanisms: while both menu cost and news shocks can explain changes in frequency and size, only the news channel affects reset prices relative to cost, a difference we capture using markup dynamics in 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.[16]

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

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

where n^i is a variety-specific demand shifter that scales consumer preferences for good i. As in Aruoba et al. (2025), we allow n^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

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

[16]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.

al. (2021)

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

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

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

The solution to this problem yields a system of implicit demand functions for each variety, $y^i = y(p^i, n^i; P, Y, \lambda)$, where the unit cost index $P(\mathbf{p})$ and the Lagrange multiplier $\lambda(\mathbf{p})$ both depend on the full vector of prices.[17]

When $\psi = 0$, the aggregator collapses to the familiar CES case. In this limit, n^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 n^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) provides 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 produce 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 and 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)

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

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

Idiosyncratic demand n follows a standard AR(1) process

$$\log n = \rho_n \log n_{-1} + \sigma_n \epsilon^n, \quad \epsilon^n \sim \mathcal{N}(0,1). \tag{7}$$

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, multiplier for the final-good problem λ, and the implied demand function $y(p, n; P, Y, \lambda)$. In solving this problem, the firm faces a fixed cost f expressed in terms of labor units to change prices. Thus at the start of each period, the firm decides whether to re-optimize and pay f, or keep $p = p_{-1}$. 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 n on pricing operates through the Kimball aggregator discussed earlier: firms with higher n face less elastic demand and charge higher markups. Under CES, this channel would be absent—prices would depend only on cost. Under Kimball, both cost and demand fundamentals shape pricing, leading to incomplete pass-through and markup variation.[18] This variable-elasticity structure also implies strategic complementarities in price-setting. Deviating from the average price becomes more costly when demand is less elastic, steepening the profit function near the optimal price. 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 (n, 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.

[18]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 (n, 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	Vavra (2014)
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 Quantitative Results

We now bring the model to the data in two steps. First, we calibrate the model using Chilean microdata that includes both retail and supplier prices, allowing us to directly discipline both cost-side and pricing behavior. Second, we use the calibrated model to explore how anticipated volatility shocks—such as those triggered by the Chilean Social Uprising—affect firms' pricing decisions and the transmission of monetary policy. The next subsection details our calibration strategy.

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 pricing moments, and instead discipline the stochastic processes using direct information on both prices and costs. This approach constitutes a contribution to the quantitative menu cost literature. Consistent with standard practice, we set the model frequency to monthly. 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 3.7% 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 retailer 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

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_n	Demand AR(1) persistence	0.76	Fraction up	0.53	0.53
σ_n	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.

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 $(\omega, \psi, \rho_n, \sigma_n, f)$ 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 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 vs. 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 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_n, σ_n) are jointly chosen to match the average size of price changes (11%) and the fraction of increases (53%). With $(\rho_n, \sigma_n) = (0.76, 0.088)$, the model hits both targets precisely.

6.2 Social Uprising as a News Shock

We now use the model to evaluate the impact of an uncertainty shock similar to the one we argue occurred during the Chilean Social Uprising. Our baseline experiment introduces an unanticipated, one-time news shock about a potential increase in the dispersion of future idiosyncratic demand. Specifically, at time $t = 0$, firms are told that with probability $\mathcal{P}$, the standard deviation of demand innovations in the next period ($t = 1$) will increase by a factor of D. Regardless of whether this increase materializes, the shock is known to be transitory: from $t = 2$ onward, the innovation standard deviation returns to its baseline value σ_n with certainty.

Formally, idiosyncratic demand in $t = 1$ evolves as

$$\log(n_1) = \rho_n \cdot \log(n_0) + v \cdot \sigma_n \cdot \epsilon_1^n, \text{ where } v = \begin{cases} D & \text{with prob. } \mathcal{P}, \\ 1 & \text{with prob. } 1 - \mathcal{P}, \end{cases} \tag{9}$$

and from $t = 2$ onward, the process reverts to the baseline AR(1) form in equation (7).

Although the shock affects the economy only through beliefs in $t = 0$, it 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.

Using the monthly version of our data, we find that during the Social Uprising: (i) the frequency of price changes fell by 13.5 percentage points, and (ii) the average (absolute) size of price changes rose by 2.1 percentage points—both highly significant.[19] To conduct a quantitatively meaningful experiment, we must choose values for $(D, \mathcal{P})$. Our calibration approach is guided by external evidence, not by directly targeting of the pricing moments we seek to explain. While no direct firm-level survey of uncertainty exists for the Social Uprising period, Figure 5 shows that professional forecasters' uncertainty measures rose by a factor of 3 to 5, suggesting a substantial shift in expectations.[20]

We set $D = 4$, the midpoint of the observed uncertainty increase, and $\mathcal{P} = 0.75$. At these values, the model predicts a 4.2 percentage point decline in the frequency of price changes

[19]The monthly data aggregates prices by keeping the observation from the first Friday of each month, or the nearest weekday if that Friday is a holiday.

[20] Although the available uncertainty measures reflect forecast disagreement about aggregate variables (such as inflation and GDP), existing evidence suggests that firm-level uncertainty comoves strongly with such macro-level dispersion. Ropele et al. (2024) show that firms with greater disagreement about aggregate inflation also report higher uncertainty about their own pricing and demand conditions. This supports our modeling assumption that increased macro forecast dispersion can be interpreted as a rise in perceived idiosyncratic volatility.

and a 1.1 percentage point increase in average size of price changes—capturing 31% and 52% of the empirical changes, respectively.[21] The mechanism follows the logic of the simple model in the Introduction: when firms expect greater future volatility in their demand, the range of likely optimal prices widens. As a result, they become more cautious about adjusting prices today, leading to a larger inaction region. In other words, heightened uncertainty makes firms more likely to wait and see.

Appendix E.1 explores a range of $(D, \mathcal{P})$ combinations and yields three insights. First, all combinations considered produce qualitative patterns consistent with the data. Second, the results depend primarily on the product $\mathcal{P} \cdot D$: different $(D, \mathcal{P})$ pairs with the same product yield similar outcomes. Third, the effect on the frequency of price changes levels off with increasing $\mathcal{P} \cdot D$—the maximum decline the model can generate through this news channel alone is approximately 6 percentage points.

6.3 Alternative Explanations

In the previous section, we showed that the anticipation effect triggered by a news shock to future idiosyncratic demand volatility can explain 30–50% of the pricing behavior observed during the Social Uprising. In this section, we consider alternative explanations with two objectives. First, we assess whether any of these mechanisms could by themselves account for the empirical results and thus potentially overturn our interpretation. Second, we evaluate whether any might serve as a complementary channel, helping to explain the residual variance left by the news shock alone. We take up the latter in the next section and focus here on ruling out alternatives.

We treat the parameters $(\beta, \mu, \xi, \omega, \psi)$ as structural and fixed throughout. This leaves the menu cost f and the stochastic properties of idiosyncratic shocks as plausible channels through which the Social Uprising could affect pricing. We consider both contemporaneous changes at $t = 0$, as well as 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 they revert to their baseline value in the following period.

Specifically, we examine five contemporaneous experiments: increases in $\mathbb{E}[\log z]$, $\mathbb{E}[\log n]$, $\mathrm{Var}[\log n]$, $\mathrm{Var}[\log z]$, and f, and four forward-looking experiments with a news structure: increases in $\mathbb{E}[\log z]$, $\mathbb{E}[\log n]$, $\mathrm{Var}[\log z]$, and f. That is, we consider the possibility that the Social Uprising affected the mean or dispersion of productivity or demand shocks, or altered

[21] Model outcomes are computed as the difference in mean outcomes across two simulations of 100,000 firms each—with and without the news shock.

Table 7: Alternative Explanations

	Change in Frequency	Change in Size
Data	$-$	$+$
Change Today $(t = 0)$		
Increase in $\mathbb{E}[\log z]$	$+$	0
Increase in $\mathbb{E}[\log n]$	0	0
Increase in $\text{Var}[\log n]$	$+$	$+$
Increase in $\text{Var}[\log z]$	$+$	$+$
Increase in f	$-$	$+$
News arriving in $t = 0$ **about Tomorrow** $(t = 1)$		
Increase in $\mathbb{E}[\log z]$	0	0
Increase in $\mathbb{E}[\log n]$	0	0
Increase in $\text{Var}[\log z]$	0	0
Increase in f	$+$	$-$

Notes: See footnote 22 for simulation details."0" indicates statistically insignificant changes, "+" denotes a significant increase, and "−" a significant decrease.

the fixed cost of price adjustment.[22]

Table 7 summarizes the findings. The first row replicates the direction of the observed changes during the Social Uprising: a decline in frequency and an increase in size of price changes. Each subsequent row reports the effect of a given shock relative to the baseline.

Four main results emerge.First, none of the contemporaneous changes—except an increase in f—can generate significant responses in frequency and size with opposite signs. Second, shocks to the variance of fundamentals increase both frequency and size since they make existing prices suboptimal.[23]

Third, among forward-looking experiments, only a future increase in the menu cost generates significant effects. In principle, a future increase in demand or TFP dispersion could also trigger inaction via a wait-and-see effect. But in our model, TFP shocks affect firm states only when a new draw arrives, which occurs with probability $p_z = 0.23$. This limits the scope for anticipated TFP shocks to influence behavior. We verified that increasing p_z or

[22] For increases in the expected value, we consider a temporary, one-period introduction of an intercept vector proportional to the steady-state standard deviation of the relevant shock parameter. This is equivalent to a temporary, one-time change in the mean of the relevant shock parameter. For increases in the variance, we use a temporary, one-period increase in the standard deviation of the relevant innovation process. For contemporaneous changes at $t = 0$, the increase in the moment of the shock parameter is 50% (or by 50% of the baseline value for f). For forward-looking news experiments, we assume a one-period shock at $t = 1$ that occurs with certainty, with a 100% increase in moment of the shock parameter (or 50% for f). Results are based on simulations with 100,000 firms. We use a significance threshold of 0.1%; changes with higher p-values are labeled "0" (insignificant).

[23] 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 (with $D = 4$ and $\mathcal{P} = 0.75$), consistent with the idea that realization effects counteract anticipation effects.

ρ_z generates a stronger anticipation effect, but at the cost of violating calibration targets.[24]

Fourth, an increase in f today, or an anticipated decrease in f tomorrow, match the empirical pattern: frequency falls and size increases. If price changes become more costly today, but the cost goes back to normal tomorrow, firms are more likely to postpone adjustment, widening the inaction band. Similarly, if firms expect adjustment costs to fall tomorrow, with a reversal in the next period, they may delay costly changes until the cheaper future arrives. We find the latter explanation implausible in the context of the Social Uprising. Given the widespread social unrest, operational uncertainty, and potential for logistical disruptions, firms would have little reason to anticipate a spontaneous, temporary *decline* in adjustment frictions.

Before concluding, we revisit the plausibility of interpreting the observed changes in pricing behavior as the result of a sudden and temporary increase in the menu cost f. In Section 4.3, we showed that these changes were not correlated with the local intensity of the riots. If higher f reflected physical or logistical disruptions—such as staffing shortages, delivery delays, or local security concerns—we would expect firms in more affected municipalities to behave differently, which they do not. Moreover, we find no change in supplier pricing behavior over the same period, suggesting that upstream operational frictions are unlikely to explain the shift.

We find little support for the idea that firms avoided price changes for political or reputational reasons. If that were the case, we would expect an asymmetric response, fewer price increases but continued or even increased price cuts. Instead, the decline in adjustment frequency is symmetric.

While we cannot rule out a temporary rise in the effective cost of price adjustment, we interpret it more broadly: not as a literal increase in technical or logistical costs, but as a reduced-form representation of forces outside the model's structure. In periods of widespread uncertainty and social stress, firms may reallocate managerial attention toward more immediate operational concerns, such as staff safety, inventory control, or damage prevention, delaying routine decisions like pricing unless deviations become unusually large.[25] This raises the effective inaction threshold, even if the physical or financial cost of repricing remains unchanged. Taken together, these considerations suggest that a literal menu cost shock is unlikely to be the primary driver of the observed behavior. However, to give the model full

[24] News about future changes in the expected level of demand or productivity shifts the firm's optimal price path but does 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. In contrast, news about future dispersion increases uncertainty, which can expand the inaction region and reduce adjustment today.

[25] Although not focusing on uncertainty and specific tasks, Turen (2023) proposes a model with infrequent price adjustments and state-dependent allocation of firms' attention.

flexibility to match the data, we allow for a temporary increase in f as a complementary channel to the news shock. We interpret this as a catch-all mechanism: a reduced-form proxy for behavioral frictions, reoptimization costs, or other omitted mechanisms that make firms more reluctant to adjust prices during turbulent periods. In the next section, we formalize this interpretation by combining the news shock with a one-period increase in f and evaluating their joint explanatory power.

6.4 News versus Change in Menu Cost

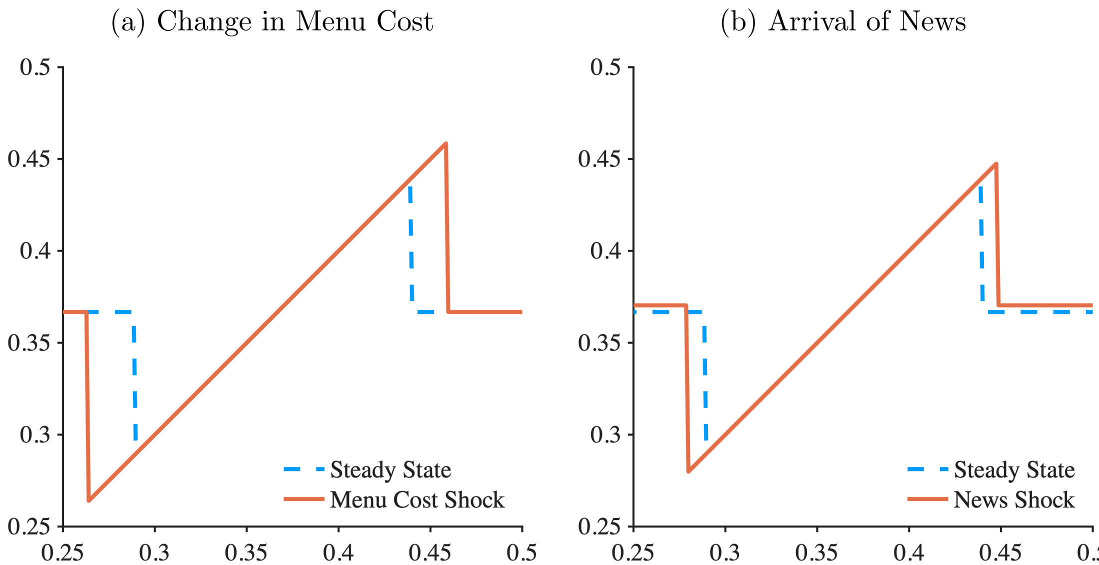
Given the analysis so far—and as previewed in the simple model in the Introduction—only two mechanisms emerge as viable candidates to explain the pricing behavior observed during the Social Uprising: (i) the arrival of news about future idiosyncratic demand volatility, and (ii) a contemporaneous, temporary increase in the fixed cost of adjusting prices. In Section 6.2, we showed that the former mechanism accounts for approximately 30% of the drop in the frequency of price changes and 50% of the increase in the size of changes. In this section, we evaluate the second mechanism. We begin by showing that although both mechanisms generate similar effects on frequency and size, they have sharply different implications for a third moment: the reset price. We then introduce empirical evidence on markups to evaluate which mechanism better fits the data. Finally, we show that combining both channels allows the model to match all three moments more closely.

To illustrate the distinction between the two mechanisms, Figure 7 compares firms' price-setting rules under a higher menu cost (panel a) and under a news shock (panel b), holding (n, 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 with no change tomorrow, makes price adjustment less likely today by widening the inaction region, but conditional on adjusting, firms choose the same reset price as in the baseline. 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, those firms that do adjust choose a different reset price, one 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.[26]

[26] (A.39) in Appendix D shows that the problem of a firm adjusting its price does not depend on f. Under a pure menu cost shock, reset prices and thus markups remain unchanged. Under a news shock, by contrast, the expected increase in dispersion tomorrow enters through the expectation term. Since the value function

Figure 7: Decision Rule Comparison: Menu Cost versus News



Notes: The plotted decision rule is the optimal price $p(p_{-1}, n, z)$ versus p_{-1}, with p and p_{-1} in logs. State variables are fixed at $n = 1.042$ and $z = 0.880$. Panel (a): increase in menu cost by 60%. Panel (b): arrival of news with $(D, \mathcal{P}) = (4, 0.75)$ as in Section 6.2.

This observation motivates the use of a third empirical moment, markup behavior, to distinguish the two channels. In our data, we observe both supermarket prices and supplier prices for the same products. As discussed in Section 6.1, we treat the supplier price as a proxy for marginal cost, allowing us to compute the log gross markup, $\mathcal{M} = \log(p) + \log(z)$, where z is proportional to the inverse of the supplier price. Since z is held fixed across our simulations, any changes in markups reflect changes in reset prices.

To test this implication, we estimate the effect of the Social Uprising on log gross markup at the product level, conditional on a price change occurring. This regression uses the same set of fixed effects in (6).[27]

Table 8 summarizes the empirical and model-implied changes in frequency, size, and markup. The news-only version accounts for roughly one-third of the drop in frequency and half of the increase in size, and predicts a 3.2 percentage point increase in markups—slightly higher than observed, but qualitatively consistent. A model without the news channel cannot replicate this markup effect, because menu cost shocks leave reset prices unchanged.

is nonlinear, Jensen's inequality implies that higher expected uncertainty affects 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.

[27]Running the markup regression conditional on a price change isolates the firm's reset price decision, holding marginal cost fixed. A significant increase in markup during the Social Uprising indicates that firms chose systematically different reset prices.

Table 8: Empirical vs. Model-Implied Changes During the Social Uprising

	Frequency	Size	Log Gross Markup
Data	-0.135^{***}	0.021^{**}	0.025^{***}
	(0.034)	(0.010)	(0.008)
News Only	-0.043^{***}	0.010^{***}	0.032^{**}
	(0.001)	(0.000)	(0.007)
News + Menu Cost	-0.135^{***}	0.028^{***}	0.027^{**}
	(0.001)	(0.000)	(0.010)

Notes: The first row reports regression estimates from the data using an indicator for the Social Uprising period, where columns 2 and 3 are conditional on price changes. The second and third rows report model-based regressions using simulated data for 100,000 firms. See Appendix E.1 for simulation details. *** p<0.01, ** p<0.05, * p<0.1.

The third row of Table 8 shows the results from combining the news shock with a modest temporary increase in the menu cost. The increase in f, calibrated at 54%, is chosen to close the gap on frequency and size while preserving the markup result. The combined model matches all three moments closely.

Taken together, these results suggest that the news channel is essential for understanding the firm-level response to the Social Uprising. While a menu cost shock can serve as a reduced-form proxy for additional frictions and help align the model with the data, it cannot explain the observed change in markups on its own. Only the anticipation of future volatility can rationalize the shift in reset prices relative to cost, as revealed by the markup evidence.

7 Policy Implications

Prior work, notably Vavra (2014), shows that 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 fact, we replicated this mechanism in Table 7, where a contemporaneous increase in dispersion leads to more frequent and larger price changes. In this section, we ask a complementary question: what happens to policy effectiveness when firms receive news today about an increase in dispersion that may occur tomorrow?

We operationalize monetary policy as a one-time, unanticipated shock to nominal aggregate expenditure in period $t = 0$.[28] Output response is measured as a fraction of the nominal

[28]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

Table 9: Output Response to MP Shock

	$t = 0$	$t = 1$	CIR
No News or Change in Menu Cost	0.459	0.234	0.884
News-Only (realized)	0.570	0.008	0.556
News-Only (not realized)	0.570	0.271	1.035
News (realized) + Menu Cost	0.743	0.016	0.764
News (not realized) + Menu Cost	0.743	0.318	1.307

Notes: Output is expressed as a fraction of the nominal expenditure shock. "Realized" means the news about higher dispersion is materialized in $t = 1$; "not realized" means it is not. The News-Only case uses $(D, \mathcal{P}) = (4, 0.75)$. The News + Menu Cost case adds a 54% increase in f, calibrated to match the observed decline in the frequency of price changes.

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 equal to $3 \times \mu$ (about 1.11%), mimicking a monetary expansion. From $t = 1$ 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 rigidity for the magnitude and duration of the effect, respectively.

Table 9 presents the results. The first row shows the baseline case with no news or menu cost shock—a textbook monetary expansion. The output response peaks at 0.46 and dissipates quickly, with a CIR of 0.88. These magnitudes are broadly consistent with prior estimates, though care is warranted in comparing across countries.[29]

The next two rows introduce a news shock in period $t = 0$, keeping monetary 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.

[29]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 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.

timing unchanged. Because the news induces caution, firms delay adjustment, increasing the initial effectiveness of the policy. The impact response rises to 0.57—a 24% increase. If the dispersion shock is not realized in $t = 1$, firms remain reluctant to adjust, and the CIR rises to 1.04. But if the shock is realized, 63% of firms adjust in $t = 1$ (versus the steady state of 26%), absorbing more of the nominal stimulus and reversing some of the initial output gains. As a result, output falls below baseline in later periods and the CIR drops to 0.56—lower than in the benchmark case without news. This reflects a temporary amplification followed by rapid neutralization and even slight reversal of the policy's real effects.

The final two rows repeat the exercise under the News + Menu Cost calibration from Section 6.4. Since this version fully matches the drop in frequency during the Social Uprising, it generates larger output responses across the board. The $t = 0$ response jumps to 0.74, and the CIR in the non-realized case exceeds 1.3. These magnitudes reflect the combined force of heightened perceived volatility and increased inaction, and reinforce the broader point from the News-Only calibration: even modest changes in expectations about future dispersion can significantly amplify the short-run effectiveness of monetary policy.

Appendix E.2 explores a related experiment in which 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 aligns with the result in Vavra (2014): realized dispersion increases price flexibility and neutralizes the real effects of policy. But if the news is not realized, the intervention retains strong effects—mirroring the findings in the contemporaneous case.

Two lessons 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 possibly reversing the initial gains in real activity. If not, rigidity persists and output gains are larger.

In sum, the anticipation of higher future volatility increases the short-run potency of monetary policy by inducing a temporary slowdown in price adjustment. But the durability of those effects hinges on what happens next. The timing of policy interventions relative to news shocks matters for their effectiveness. Interventions delivered while uncertainty is anticipated but not yet realized tend to have larger short-run real effects than those implemented once volatility materializes.

8 Conclusion

Periods of heightened uncertainty often generate large changes in firm behavior, but distinguishing between the effects of realized volatility and anticipated volatility is empirically difficult. In this paper, we exploit a unique quasi-natural experiment, the October 2019 Social Uprising in Chile, and a high-frequency dataset of supermarket prices and costs to isolate the anticipation channel. We show that in the one-month period following the start of the Social Uprising, the frequency of price changes fell by 40–60 percent, while the average size of those changes increased by 40–50 percent. Importantly, these shifts occurred only on the supermarket (retail) side of the price chain; suppliers did not alter their pricing behavior. Moreover, we find no relationship between a store's pricing response and the local intensity of riots. Together, these facts point to an anticipatory adjustment in retailer behavior, motivated not by direct operational disruptions but by perceived changes in the economic environment and future consumer demand.

The broader context supports this interpretation. What began as localized protests quickly evolved into a nationwide Social Uprising, widely seen as a political and institutional rupture that raised the prospect of constitutional reform, redistribution, and a restructuring of economic policy. While difficult to measure directly, these developments plausibly increased firms' uncertainty about future demand conditions, even as contemporaneous costs and fundamentals remained relatively stable.

To formalize this idea, we embed anticipated volatility into an otherwise standard menu cost framework, allowing for news about future increases in the dispersion of idiosyncratic demand shocks. To ensure that such shocks affect pricing behavior, we adopt the Kimball (1995) aggregator, which allows demand shocks to influence pricing decisions. In this framework, the arrival of news about higher future dispersion induces firms to wait, expanding the inaction region and reducing the frequency of price changes. Calibrated to our Chilean data, the model explains roughly 31 percent of the observed decline in frequency and 52 percent of the increase in the size of price changes. Because the model abstracts from realized disruptions, these effects isolate the role of anticipation.

We also consider alternative explanations. Among several possibilities, only a contemporaneous increase in menu costs generates patterns consistent with the data. A pure menu cost shock cannot be the sole driver, since it would not affect reset prices or markups, yet we do observe a rise in markups during the Social Uprising. However, an increase in menu costs can complement the news channel, serving as a reduced-form proxy for behavioral frictions that make firms more reluctant to adjust. When we combine the news shock with a temporary rise in menu costs, the model reproduces all three moments—frequency, size, and markups—providing a unified explanation for the evidence.

Prior work, such as Vavra (2014), shows that contemporaneous volatility makes prices more flexible and reduces the real effects of monetary policy. By contrast, anticipated volatility has the opposite effect. In our model, news about higher future dispersion amplifies the immediate impact of monetary policy by about 24 percent relative to the baseline. When combined with a temporary increase in menu costs, the amplification is even stronger, reaching about 62 percent. These results underscore the importance of timing. Policy interventions are most effective when uncertainty is high but unrealized, and least effective once volatility has materialized.

Overall, our results underscore the need to distinguish between anticipation and realization when studying uncertainty. Policymakers responding to large-scale events, whether political, financial, or social, should consider not only current volatility in fundamentals, but also how firms perceive and internalize future risks. Beyond the Chilean case, the lesson is broader. In many contemporary environments—from Brexit to highly polarized elections—firms face uncertainty that is primarily about the future rather than the present. Anticipation of structural or policy changes can alter expectations about which goods will be demanded, which sectors will be regulated, or which products will remain viable, even before any reform takes place. Recognizing when such anticipation effects dominate realization effects is essential for interpreting micro evidence, assessing macroeconomic transmission, and understanding when monetary policy is more or less effective.

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Online Appendix to "Pricing Under Distress" Not for Publication

A Simple Model

This section summarizes the key results of the quadratic menu cost model in Dixit (1991). A firm faces a cost function $f(x) = kx^2$ where $k > 0$ and x is their log-price. Every instant they observe a log-price x that follows $dx = \sigma dz$ where z is the standard Wiener process. The firm's ideal log-price is $x = 0$ but it takes a fixed cost of $g > 0$ to implement this whenever the x they draw is different from zero.

The firm solves the problem

$$V(x) = \min E\left\{\int_0^\infty kx_t^2 e^{-\rho t} + \sum_i ge^{-\rho t_i}|x_0 = x\right\} \tag{A.1}$$

where t_i denotes the instants where x_t is shifted by exercising the control. The solution to this problem is $\{x_1, x_2, x_3\}$ with $x_1 < x_2 < x_3$, $x_2 = 0$ and $x_1 = -x_3 = h$ such that as long as $x_t \in [x_1, x_3]$ no control is exercised and if x_t is outside this range $x_t = 0$ is set paying the cost g. For small enough menu cost g, we can find the boundaries of the inaction region as

$$h = \left(\frac{6\sigma^2 g}{k}\right)^{1/4} \tag{A.2}$$

In the first exercise shown in panel (a) of Figure 1, initially the log-price is drawn from a distribution with dispersion σ, which is the blue distribution. Suddenly in the current instant the firm faces draws from a distribution from a more dispersed distribution, understanding that in the next instant log-prices will 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.

In the second exercise, which is shown in panel (b) of Figure 1, the firm is now told that while today's distribution is still the one with the original σ, from the next instant onward, the dispersion will increase permanently. This shifts the inaction bands outwards given the expression in (A.2) while the distribution they face in the current instant remains the same blue distribution.

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 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 Interntos"). 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 is 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 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.[30] 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 of the products stints for which this continuity restriction is verified, 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

[30] 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-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.

Table A-2: 10 more 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	Champinon	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".

less or equal than 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 matching rate of about 14% (i.e $1,920$ products from the $13,682$ in the baseline sample). We preferred a stricter criteria that lead 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 product 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 ("champinion"). Likewise, in the matched sample, fruits, vegetables, rice, salt, bread and oil enter as the most traded products too. Therefore, the

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, where f denotes the median frequency. Duration is always reported in months.

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 (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 to where 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.[31] Columns 2 and 3 show the results using the daily and monthly versions of our baseline data, respectively.[32]

[31]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.

[32]The frequency of price changes differs from the 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 Baseline Sample, respectively. 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 Additional Empirical Results

Appendix C presents additional empirical analysis that was not present in the main text due to space constraints. It is divided into three subsections. The first one presents additional descriptive statistics from the dataset. The second presents robustness analysis on our baseline results when simplifying the main specification by dropping some of the covariates used. The third presents additional robustness analysis by adding covariates to the baseline specification as well as considering deviations from it.

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

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.

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 to 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 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-squares are virtually unity, 0.97 and 0.98, 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.

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	0.0012	0.006
Panel B: Price Changes		
B.1: Raw data		
p1/p99	-0.525/0.525	-0.674/0.674
p5/p95	-0.281/0.283	-0.436/0.413
p10/p90	-0.182/0.188	-0.283/0.302
p25/p75	-0.064/0.081	-0.095/0.118
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

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 without the Social Uprising dummy. 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. (1), excluding the Social Uprising dummy.

C.1.2 Frequency and Size Distribution of Price Changes

Table A-6 complements the set of descriptive statistics on the frequency and size of prices changes (Figures 6 and A-1) by providing –both before and during the Social Uprising– the share of prices that changed in the baseline sample (Panel A), and the distribution of price changes (Panel B) via the various percentiles of the distribution. For the latter, raw price changes and residuals are used.

The main message from this table is in line with the baseline results and from Figure 1. The frequency of price changes greatly reduces during the Social Uprising, while the distribution of the size in price changes displays fatter tails.

C.2 Robustness: Alternative Specifications

This subsection starts by testing the symmmetry of the baseline results with respect to price increases and decreases followed by repeating the baseline results using the matched sample in Table A-8. Next it undertakes a series of robustness tests by dropping some of the covariates from the baseline estimation. Table A-9 presents results excluding the third-order polynomial of the number of days since the last price change. Table A-10 presents results when all controls are removed except for the fixed effects. Table A-11 documents what happens when one further removes all fixed effects. Lastly, Table A-12 presents results when one runs the baseline estimation but does not distinguish the sign of the price breaks. The main findings of our baseline specification are largely robust to all of these modifications.

C.2.1 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:

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

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.[33] 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 $\beta_1 + \beta_2$ exactly correspond to the results in Table 2. Panel A of Table A-7 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-7, indicate that the estimated coefficients for positive and negative breaks are very similar to those reported in Table 2, 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.2.2 Baseline Results Using the Matched Sample

An important check to validate the representativeness of the matched sample is to verify whether the results from the baseline estimation in Table 2, that come from using the baseline sample, are recovered when using the smaller matched sample. This is corroborated in Table A-8.

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

Table A-7: 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.2.3 Baseline Estimation without Age of Price

Table A-9: Baseline Estimation Excluding Price Age: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0023***	-0.0028***	0.0336***	0.0490***
	(0.0003)	(0.0002)	(0.0128)	(0.0097)
Observations	13,845,147	13,845,147	79,576	63,588
Adjusted R-squared	0.002	0.002	0.423	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 the estimated coefficient β from the baseline specification described in Regression (1), excluding the third-order polynomial of days since the last price change. All other product-level controls and economic activity controls remain included, along with the full set of fixed effects. The baseline sample

Table A-8: Baseline Estimation: Matched Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0022***	-0.0046***	0.0314***	0.0236**
	(0.0007)	(0.0004)	(0.0105)	(0.0101)
Observations	1,980,403	1,980,403	11,584	10,235
Adjusted R-squared	0.002	0.003	0.344	0.395
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.0067	0.0060	0.1001	0.1056

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

C.2.4 Baseline Results Excluding All Controls

Table A-10: Baseline Estimation Excluding All Controls: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0023***	-0.0030***	0.0308**	0.0464***
	(0.0003)	(0.0002)	(0.0128)	(0.0097)
Observations	13,845,174	13,845,174	79,577	63,589
Adjusted R-squared	0.002	0.002	0.421	0.470
Controls	No	No	No	No
Economic Activity Controls	No	No	No	No
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.0065	0.0053	0.1150	0.1237

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 location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C.2.5 Baseline Estimation Excluding All Controls and Fixed Effects

Table A-11: Baseline Estimation Excluding All Controls and Fixed Effects: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0033***	-0.0029***	0.0458***	0.0616***
	(0.0003)	(0.0002)	(0.0119)	(0.0097)
Observations	13,853,006	13,853,006	89,357	72,763
Adjusted R-squared	0.000	0.000	0.001	0.001
Controls	No	No	No	No
Economic Activity Controls	No	No	No	No
FE	No	No	No	No
Mean of Dependent Variable	0.0065	0.0053	0.1153	0.1241

Note: This table reports the estimated coefficient β from Regression (1), excluding all product-level controls, economic activity controls, and entire set of fixed effects. The specification includes only the Social Uprising dummy as a regressor. The baseline sample is used. Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C.2.6 Baseline Estimation Combining Positive and Negative Price Changes

Table A-12: Baseline Estimation Combining Positive and Negative Price Changes: Baseline Sample

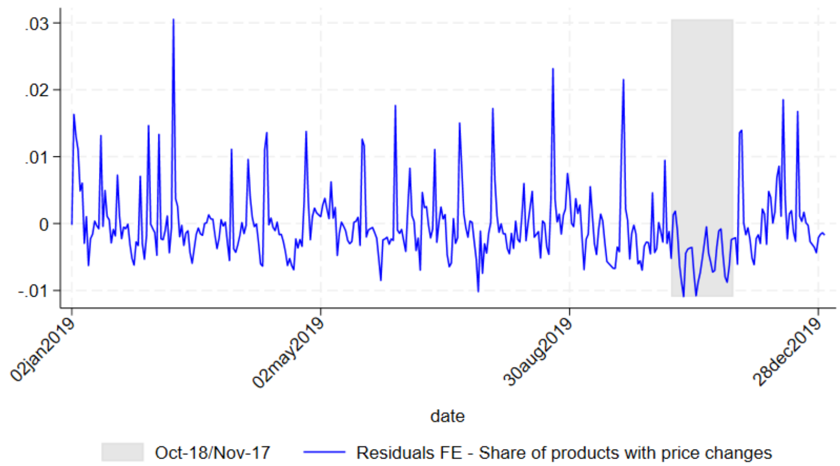
Variable	(1) Breaks	(2) Abs Size
D	-0.0057***	0.0379***
	(0.0005)	(0.0093)
Observations	13,845,147	155,471
Adjusted R-squared	0.005	0.484
Controls	Yes	Yes
Economic Activity Controls	Yes	Yes
FE	Yes	Yes
Mean of Dependent Variable	0.0117	0.1200

Note: This table reports the estimated coefficient β from Regression (1) when the dependent variable pools positive and negative price changes. For the specification on the size of price changes, the dependent variable is the absolute value of the change. Baseline sample is used. Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

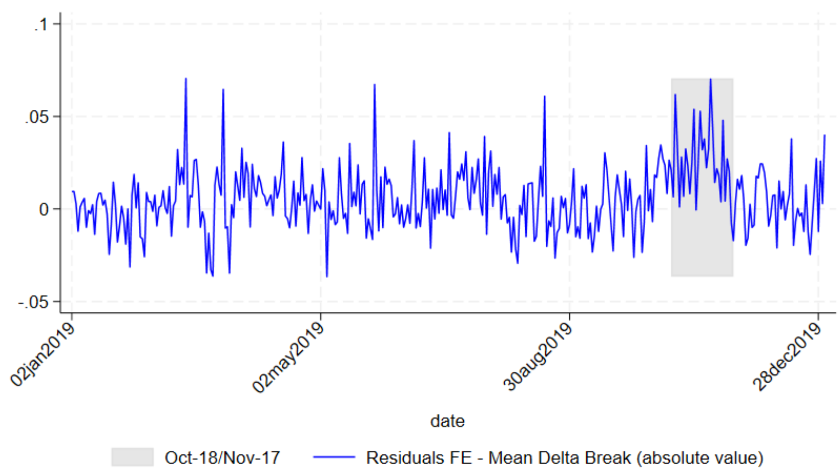
C.2.7 Residuals from Figure 6

Figure A-1 presents an alternative to Figure 6 on the frequency and size of price changes where average residuals from our baseline regression (1) are presented but excluding the

Figure A-1: Frequency and Size of Price Changes in 2019



(a) Frequency of Price Changes



(b) Size of Price Changes

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. In both panels, the residuals reflect variation net of fixed effects and controls. The solid lines depict the average, and the shaded area marks the Social Uprising period from October 18 to November 17, 2019 (inclusive).

Social Uprising dummy from the estimation. 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 6 is found.

Table A-13: Baseline Estimation with Unfiltered Prices: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0117***	-0.0155***	0.0263***	0.0251***
	(0.0021)	(0.0024)	(0.0032)	(0.0033)
Observations	13,845,147	13,845,147	1,509,904	1,489,549
Adjusted R-squared	0.109	0.107	0.520	0.526
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.1092	0.1077	0.1423	0.1434

Note: In this table, instead of using the prices filtered with the method in Kehoe and Midrigan (2015), we use the raw prices. That is, the dependent variables of frequency and magnitude of price changes include the short-term fluctuations. The baseline sample is used. Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C.3 Additional robustness analysis and extensions

C.3.1 Unfiltered Prices

Table A-13 replicates the baseline analysis but with raw unfiltered prices, not applying the filtering used by Kehoe and Midrigan (2015). All results remain qualitatively robust. However, quantitatively, note that the increased noise in the unfiltered data (documented in Figure 2 with the raw price series containing noise and multiple short-lived price changes that are quickly reversed) makes the coefficients associated to the frequency and size smaller relative to the baseline results in Table 2, when compared to their (now larger) unconditional means.

C.3.2 Baseline results: Products with Continuous Availability Before and During the Social Uprising

Another robustness check we considered was using a balanced panel of products that pass our continuity filter restriction (see Appendix B.1) in every week between September 23 and November 11, 2019. Table A-14 shows the results for 6,973 products that satisfy this criterion. The decline in frequency for these products is about 30% smaller than the baseline results, though still highly significant, and the change in size of prices very similar.

Table A-14: Baseline results: Products with Continuous Availability Before and During the Social Uprising

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0018***	-0.0024***	0.0314**	0.0481***
	(0.0004)	(0.0002)	(0.0138)	(0.00981)
Observations	4,021,785	4,021,785	22,885	19,298
Adjusted R-squared	0.002	0.003	0.453	0.496
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.0060	0.0051	0.1176	0.1255

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 11, 2019. Clustered standard errors at location-seller level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.3.3 Baseline Results with a Supermarket Fixed Effect

Table A-15 reports results from the baseline specification when expanded to account for a fixed effect across the 183 supermarket chains. Our baseline results are robust to this control.

Table A-15: Results with a Supermarket Fixed Effect: Baseline Sample

Variable	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0027***	-0.0030***	0.0449***	0.0607***
	(0.0005)	(0.0005)	(0.0169)	(0.0154)
Observations	13,845,172	13,845,172	89,344	72,753
Adjusted R-squared	0.001	0.001	0.061	0.052
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	0.1153	0.1241

Note: The table reports baseline results when expanded to account for a supermarket fixed effect across the 183 stores in the baseline sample. We exclude the product fixed effect in these regressions. Clustered standard errors at supermarket level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.3.4 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

Table A-16: Results with Supermarket Location Size Interaction: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
Panel A: continuous size measure				
D	-0.0023***	-0.0026***	0.0178*	0.0454***
	(0.0003)	(0.0003)	(0.0098)	(0.0112)
D * Big Supermarket location	-2.54e-06	-4.08e-06**	0.0001	3.29e-05
	(2.49e-06)	(1.74e-06)	(0.0001)	(0.0001)
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
Panel B: dummy size measure				
D	-0.0024***	-0.0029***	0.0247*	0.0632***
	(0.0004)	(0.0003)	(0.0132)	(0.0167)
D * Big Supermarket location	-0.0002	-0.0003	0.0118	-0.0192
	(0.0005)	(0.0004)	(0.0206)	(0.0206)
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: The size of a supermarket's location is measured as its average monthly sales (in million CLP) during the pre-Social Uprising period. Panel A presents baseline results including an interaction between the Social Uprising dummy and the continuous size measure. In Panel B, "Big Supermarket location" is a dummy equal to one for locations above the 75th percentile in the size distribution. Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

two measures of size: a continuous variable based on average monthly sales during the pre-Social Uprising period, and a dummy indicating whether a location's average monthly sales is above the 75th percentile. In table A-16, we separately present the results of including an interaction of the Social Uprising dummy with each of these two measures. Across both measures, the baseline results from Table 2 remain robust. The interaction terms are generally insignificant, with only one exception (the interaction with the continuous size measure for the frequency of negative price changes, suggesting that the decline in the frequency of negative price adjustments was more pronounced among larger supermarket locations).

Table A-17: Riot's Intensity at the Supermarket Level: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
Panel A: continuous riots intensity measure				
D	-0.0041***	-0.0030***	0.0473***	0.0263
	(0.0008)	(0.0005)	(0.0131)	(0.0164)
D * intensity	6.34e-05*	-5.15e-06	-0.0005	0.0010
	(3.76e-05)	(1.69e-05)	(0.0006)	(0.0009)
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
Panel B: dummy riots intensity measure				
D	-0.0019***	-0.0021***	0.0353***	0.0289*
	(0.0005)	(0.0004)	(0.0122)	(0.0151)
D * intensity	-0.0009	-0.0012**	-0.0019	0.0262
	(0.0006)	(0.0005)	(0.0196)	(0.0192)
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

Notes: The table reports the estimated coefficients β and θ from Regression (2), corresponding to the Social Uprising dummy and its interaction with two proxies for riots intensity. Panel A presents the result for a continuous intensity measure constructed as a weighted sum of riots intensity levels across the municipalities where each supermarket operates, using as weights the share of total supermarket sales accounted for by each location. Panel B shows results from interacting the Social Uprising dummy with a dummy that is equal to one for supermarkets with intensity levels above the median. Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

C.3.5 Intensity of Riots at the Supermarket Level

Table A-17 reports a robustness analysis of the role of intensity in riots (Table 4 in the main text) when calculating an intensity measure that varies across supermarkets (not locations). In this case intensity is weighted by the relative share of the supermarket' sales in each municipality. As in our baseline results, the coefficients of the Social Uprising dummy continue to be significant and of similar magnitude to the baseline case in Table 2, and the coefficients associated with the interaction with the riots' intensity come out insignificant in all but two regressions. This continues to indicate that the severity of the riots did not affect how the supermarkets changed their pricing behavior during the Social Uprising.

C.3.6 Baseline Estimation with the Exchange Rate as a Control

Table A-18 presents our baseline specification augmented with the CLP to USD exchange rate. Baseline results are robust to this additional control.

Table A-18: Baseline Estimation with Exchange Rate Control: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0032***	-0.0034***	0.0328***	0.0454***
	(0.0003)	(0.0002)	(0.0125)	(0.00970)
Exchange Rate	0.0067***	0.0034***	0.0125	0.0380**
	(0.0007)	(0.0006)	(0.0155)	(0.0193)
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 presents the baseline results controlled by the log of the daily Chilean exchange rate to the USD. Clustered standard errors at location-seller level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C.3.7 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-19, 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.3.8 Cost of Re-stocking as a Control

Table A-20 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 to each supermarket. The new control shows the expected signs: when a supermarket's supplier increases (decreases) its prices for a product, supermarkets are less (more) likely to

Table A-19: Baseline Estimation with wage bill: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0025***	-0.0031***	0.0329**	0.0446***
	(0.0003)	(0.0002)	(0.0130)	(0.0096)
log Monthly Wage Bill	-0.0011**	-0.0002	0.0063	0.0351***
	(0.0005)	(0.0004)	(0.0070)	(0.0092)
Observations	13,811,108	13,811,108	79,483	63,513
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 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 location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A-20: Baseline Estimation Controlling by Cost of Re-stocking: Matched Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.0022***	-0.0047***	0.0314***	0.0236**
	(0.0007)	(0.0004)	(0.0104)	(0.0102)
Recent supplier's price change	0.0158***	-0.0112***	0.0660***	-0.1860***
	(0.0009)	(0.0012)	(0.0218)	(0.0230)
Observations	1,941,661	1,941,661	11,391	10,129
Adjusted R-squared	0.002	0.003	0.350	0.406
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.0067	0.0061	0.0998	0.1057

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 estimation is made on the matched sample. Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

decrease prices and, conditional on reducing them, they cut their prices by less (more). Most importantly, 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.

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

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

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

$$1 = P_t C_t \xi_t \tag{A.6}$$

$$\frac{W_t}{P_t} = \chi C_t, \tag{A.7}$$

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

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

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

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

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, n^i and aggregate demand Y, the final-good producer chooses y^i to maximize profits

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

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

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

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)

$$1 = \int \left\{ \frac{\omega_p}{1+\psi} \left[(1+\psi)\frac{n^i y^i}{Y} - \psi \right]^{\frac{1}{\omega_p}} + 1 - \frac{\omega_p}{1+\psi} \right\} di \tag{A.16}$$

$$1 = \int \left\{ \frac{\omega_p}{1+\psi} \left[\left(\frac{p^i}{\lambda n^i P} \right)^{\frac{\omega_p}{1-\omega_p}} \right]^{\frac{1}{\omega_p}} + 1 - \frac{\omega_p}{1+\psi} \right\} di \tag{A.17}$$

$$1 = \frac{\omega_p}{1+\psi} \cdot \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p^i}{n^i P} \right)^{\frac{1}{1-\omega_p}} di + \int 1 di - \int \frac{\omega_p}{1+\psi} di \tag{A.18}$$

$$\frac{\omega_p}{1+\psi} = \frac{\omega_p}{1+\psi} \cdot \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p^i}{n^i P} \right)^{\frac{1}{1-\omega_p}} di \tag{A.19}$$

$$1 = \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p^i}{n^i P} \right)^{\frac{1}{1-\omega_p}} di \tag{A.20}$$

$$\lambda^{\frac{1}{1-\omega_p}} = \int \left(\frac{p^i}{n^i P} \right)^{\frac{1}{1-\omega_p}} di \tag{A.21}$$

$$\lambda = \left[\int \left(\frac{p^i}{n^i P} \right)^{\frac{1}{1-\omega_p}} di \right]^{1-\omega_p}. \tag{A.22}$$

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

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

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

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

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

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

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

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

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

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

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 n^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

$$\begin{aligned}
\pi &= \left(\frac{p}{P} - \frac{W}{zP}\right)\frac{C}{n} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p}{\lambda n P}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right] && \text{(A.32)}\\
&= \left(\frac{p/S}{P/S} - \frac{\chi C}{z}\right)\frac{C}{n} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p/S}{\lambda n\,(P/S)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right] && \text{(A.33)}\\
&= \left(\frac{p/S}{P/S} - \frac{\chi S}{zP}\right) \cdot \frac{(P/S)^{-1}}{n} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p/S}{\lambda n\,(P/S)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right] && \text{(A.34)}\\
&= \left(\frac{p/S}{P/S} - \frac{\chi}{z\,(P/S)}\right) \cdot \frac{(P/S)^{-1}}{n} \cdot \frac{1}{1+\psi} \cdot \left[\left(\frac{p/S}{\lambda n\,(P/S)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi\right]. && \text{(A.35)}
\end{aligned}$$

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.[34] 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 who inherited price p_{-1} from the previous period and facing fixed cost of adjustment f, chooses whether or not to adjust by comparing the value of adjusting against not adjusting

$$V\left(\frac{p_{-1}}{S}, n, z; \frac{P}{S}, \lambda\right) = \max\left\{V_A\left(n, z; \frac{P}{S}, \lambda\right), V_N\left(\frac{p_{-1}}{S}, n, z; \frac{P}{S}, \lambda\right)\right\}. \tag{A.37}$$

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

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

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

Should the firm decide to adjust its price, it earns profit at the new price p/S but pays

[34] 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.

the adjustment cost

$$V_A\left(n,z;\frac{P}{S},\lambda\right) = -f\frac{W}{P} + \max_{\frac{p}{S}}\left\{\pi\left(\frac{p}{S},n,z,\frac{P}{S},\lambda\right)+\mathbb{E}\left[\Xi V\left(\frac{p}{S}\frac{1}{e^{\mu}},n',z';\frac{P'}{S}\frac{1}{e^{\mu}},\lambda'\right)\right]\right\}. \quad \text{(A.39)}$$

The intermediate producer's problem is very much 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 $V(\cdot)$, $V_A(\cdot)$ and $V_N(\cdot)$ 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 $G(\frac{p_i}{S},z^i,n^i)$ such that:*

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

$$\frac{W}{P} = \chi C, \quad \text{(A.40)}$$

$$\Xi = \beta \quad \text{(A.41)}$$

   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 $V(\cdot)$, $V_A(\cdot)$, $V_N(\cdot)$ 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*

$$h = \int h(\cdot)G(\cdot)di \tag{A.42}$$

$$C = Y \tag{A.43}$$

$$\frac{S}{P} = Y. \tag{A.44}$$

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 n, and firm price $\frac{p^i}{S}$. We use the Tauchen method to construct the z and n 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 $\frac{p}{S}^*\left(\frac{p_{-1}}{S}, z, n; \frac{\hat{P}}{S}, \hat{\lambda}\right)$.

4. Initialize a firm distribution $H_0\left(\frac{p_{-1}}{S}, z, n\right)$ over intermediate producers' idiosyncratic states. Using the law of motion of z and n, as well as the pricing decision rule $\frac{p}{S}^*$, iterate forward on the distribution until the mass of firms at each state $\left(\frac{p_{-1}}{S}, z, n\right)$ is stationary. This yields a stationary distribution $H^*\left(\frac{p_{-1}}{S}, z, n; \frac{\hat{P}}{S}, \hat{\lambda}\right)$.

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 $t = 1$

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 $t = 1$.

1. Construct discrete grids for idiosyncratic productivity z, idiosyncratic demand n, 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 $T+1$ 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 $V_A^*(\cdot), V_N^*(\cdot), V^*(\cdot)$, 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, $\{\frac{\tilde{P}_t}{S_t}, \tilde{\lambda}_t\}_{t=1}^T$, is the guess for the case when the news shock is not realized. The second sequence, $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=1}^T$, is for when the news shock is realized.

5. Assume that in period $T+1$, the economy is at the stationary equilibrium with time-invariant value function $V^*(\cdot)$. For the case where the news shock is realized in $t=2$, solve backwards for the value functions at each period t:

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

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

   (c) Obtain $\{\hat{V}_A(\cdot;t), \hat{V}_N(\cdot;t), \hat{V}(\cdot;t), \frac{\hat{p}^*}{S}(\cdot;t)\}_{t=2}^T$

6. Repeat the step above for the case where the news shock is not realized to obtain $\{\tilde{V}_A(\cdot;t), \tilde{V}_N(\cdot;t), \tilde{V}(\cdot;t), \frac{p}{S}^*(\cdot;t)\}_{t=2}^T$

7. In period $t=1$, solve equations (A.37, A.38, A.39) using the guesses $(\frac{\hat{P}_1}{S_1}, \hat{\lambda}_1)$ and $V(\cdot) = \mathcal{P}\hat{V}(\cdot;2) + (1-\mathcal{P})\,\tilde{V}(\cdot;2)$ as the continuation value, yielding $\{\hat{V}_A(\cdot;1), \hat{V}_N(\cdot;1), \hat{V}(\cdot;1), \frac{\hat{p}}{S}^*(\cdot;1)\}$.[35]

8. Assume that the economy is initially at the stationary equilibrium before the arrival of the news shock in period 1. 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, n, S) and the pricing decision rule $\frac{\hat{p}}{S}^*(\cdot;1)$ to obtain the firm distribution in period 1 $\hat{H}(\cdot;1)$.

[35] Note that in $t=1$, the two cases (shock realizing and not realizing) coincide so that $\tilde{V} = \hat{V}$.

(b) For each $t = 2, ..., T$, iterate the lagged distribution $\hat{H}(\cdot; t-1)$ forward using the law of motion for (z, n, S) and the pricing decision $\hat{\frac{p}{S}}^*(\cdot; t-1)$ for $\hat{H}(\cdot; t)$. In particular, the shocks to n are more dispersed in period 2 when the news shock is realized.

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

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

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

11. Compute the absolute difference between the guessed sequences $\{\hat{\frac{P_t}{S_t}}, \hat{\lambda}_t\}_{t=1}^{T}$, $\{\tilde{\frac{P_t}{S_t}}, \tilde{\lambda}_t\}$ and the implied sequences $\{\hat{\hat{\frac{P_t}{S_t}}}, \hat{\hat{\lambda}}_t\}_{t=1}^{T}$, $\{\tilde{\tilde{\frac{P_t}{S_t}}}, \tilde{\tilde{\lambda}}_t\}$ 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.

D.5.3 Monetary Policy Shock

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 monetary policy shock in period $t = 1$.

1. Construct discrete grids for idiosyncratic productivity z, idiosyncratic demand n, 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 $T + 1$ 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 $V_A^*(\cdot), V_N^*(\cdot), V^*(\cdot)$, 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, labelled $\{\hat{\frac{P_t}{S_t}}, \hat{\lambda}_t\}_{t=1}^{T}$.

5. Assume that in period $T+1$, 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, solve equations (A.37, A.38, A.39) for $\hat{V}_A(\cdot;T), \hat{V}_N(\cdot;T), \hat{V}(\cdot;T)$ and the pricing decision rule $\hat{\frac{p}{S}}^*(\cdot;T)$ using the guesses $(\frac{\hat{P}_T}{S_T}, \hat{\lambda}_T)$ and $V^*(\cdot)$ as continuation value.

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

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

6. Assume that the economy is initially at the stationary equilibrium before the arrival of the monetary policy shock in period 1. 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, n, S) and the pricing decision rule $\hat{\frac{p}{S}}^*(\cdot;1)$ to obtain the firm distribution in period 1 $\hat{H}(\cdot;1)$.

   (b) For each $t = 2, ..., T$, iterate the lagged distribution $\hat{H}(\cdot;t-1)$ forward using the law of motion for (z, n, S) and the pricing decision $\hat{\frac{p}{S}}^*(\cdot;t-1)$ for $\hat{H}(\cdot;t)$.

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

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

8. Compute the absolute difference between the guessed sequences $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=1}^T$ and the implied sequences $\{\hat{\frac{\hat{P}_t}{S_t}}, \hat{\hat{\lambda}}_t\}_{t=1}^T\}$ 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 $t = 1$

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 $t = 1$.

News Shock at $t = 1$ and Monetary Policy Shock at $t = 2$

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 shock in period $t = 1$ and subsequently another unanticipated monetary policy shock in period $t = 2$.

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 $t = 1$. Save the firm distribution in $t = 1$ as $H_0(\cdot)$ as well as the equilibrium aggregate prices $(\frac{P_1}{S_1}, \lambda_1)$.

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

3. Assume that in period $T+1$, the economy is at the stationary equilibrium with time-invariant value function $V^*(\cdot)$. For the case where the news shock is realized in $t = 2$, solve backwards for the value functions at each period t:

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

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

   (c) Obtain $\{\hat{V}_A(\cdot; t), \hat{V}_N(\cdot; t), \hat{V}(\cdot; t), \hat{\frac{p}{S}}^*(\cdot; t)\}_{t=2}^{T}$

4. Repeat the step above for the case where the news shock is not realized to obtain $\{\tilde{V}_A(\cdot; t), \tilde{V}_N(\cdot; t), \tilde{V}(\cdot; t), \frac{p^*}{S}(\cdot; t)\}_{t=2}^{T}$

5. In period $t = 1$, the firm distribution over idiosyncratic states is given by $H_0(\cdot)$. Set $\hat{H}(\cdot; 1) = \tilde{H}(\cdot; 1) = H_0(\cdot)$ as a result. For the case where the news shock is realized, iterate the firm distribution forward at each period $t = 2, ..., T$ while incorporating the monetary policy shock in period $t = 2$:

   (a) Iterate the lagged distribution $\hat{H}(\cdot; t-1)$ forward using the law of motion for (z, n, S) and the pricing decision $\hat{\frac{p^*}{S}}(\cdot; t-1)$ for $\hat{H}(\cdot; t)$ to obtain $\{\hat{H}(\cdot; t)\}_{t=2}^{T}$.

6. Repeat the step above for the case where the news shock is not realized and obtain $\{\tilde{H}(\cdot; t)\}_{t=2}^{T}$

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

8. Compute the absolute difference between the guessed sequences $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=1}^{T}, \{\frac{\tilde{P}_t}{S_t}, \tilde{\lambda}_t\}$ and the implied sequences $\{\frac{\hat{\hat{P}}_t}{S_t}, \hat{\hat{\lambda}}_t\}_{t=1}^{T}, \{\frac{\tilde{\tilde{P}}_t}{S_t}, \tilde{\tilde{\lambda}}_t\}$ 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.

D.5.4 Construction of Impulse Responses

Model Responses of Pricing Moments

We use model simulated data to obtain the model response of frequency and average size of price to the arrival of news. The exact procedure is as follows. In our simulation, we use $N = 100,000$ and $B = 300$.

1. Simulate N firms in the stationary equilibrium for $B + 1$ periods. Call this sample A.

2. Simulate N firms starting from from the stationary equilibrium for $B + 1$ periods. In period $B + 1$, introduce the one-time news shock. Call this sample B.

3. In every period, for each firm in sample A and sample B, construct a dummy variable *adjust* that takes value of one if there is a price adjustment and zero otherwise. In addition, record the size of each price change in a variable size.

4. Combine the observations at period $B + 1$ from the two samples. Generate a dummy variable *news* that takes value of zero for observations in sample A and one for sample B.

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.

Output Responses to Nominal Expenditure Shocks

Table 9 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 $T = 20$. 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 $t = 1$ 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 $t = 1$ which is realized in period $t = 2$ and a one-time nominal shock in period $t = 1$ and (ii) a transition with a one-time news shock at period $t = 1$ which is realized in period $t = 2$ 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 $t = 1$ which is not realized, and a one-time nominal shock in period $t = 1$ and (ii) a transition with a one-time news shock at period $t = 1$ which is not realized in the absence of nominal shocks.

Row 4: The output response is computed as the difference between (i) a transition with a one-time news shock in period $t = 1$ which is realized in $t = 2$, a menu cost shock in period $t = 1$, and a one-time nominal shock in period $t = 1$ and (ii) a transition with a one-time news shock at period $t = 1$ which is realized in $t = 2$ and a menu cost shock in period $t = 1$ 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 in period $t = 1$ which is not realized in $t = 2$, a menu cost shock in period $t = 1$, and a one-time nominal shock in period $t = 1$ and (ii) a transition with a one-time news shock at period $t = 1$ which is not realized and a menu cost shock in period $t = 1$, 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 Effect of News on Frequency and Size: Alternative Calibrations

In the main text we used $D = 4$ and $\mathcal{P} = 0.75$ as our baseline calibration for the news process. In Table A-21 we show results for $D = \{3, 4, 5\}$ and $P = \{0.5, 0.75, 0.95\}$.

In the main text we argued that while a change in the *current* menu cost can lead to large changes in frequency, this is not the case for news and that it has an upper bound on how much it can reduce the frequency of price changes. To demonstrate this, in Figure A-2 we plot the change in frequency and size of price changes for different combinations of $(D, \mathcal{P})$. We plot these against the product $D \times \mathcal{P}$ because we find that it is this product and not the individual values that makes a material difference. We see that in the largest $D \times \mathcal{P}$ we consider, frequency falls by about 5.5 p.p. Moreover the scatter plot indicates

Table A-21: Parameter Influence on Moments: Frequency and Size

(a) Frequency

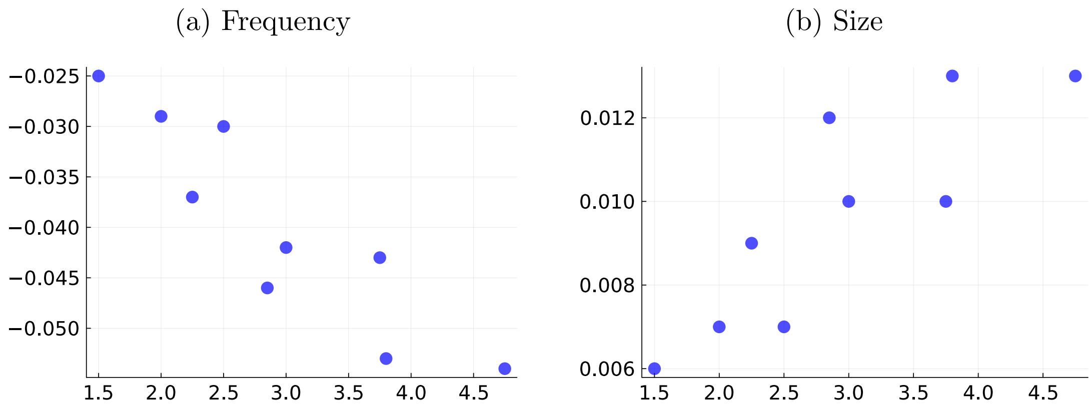
D \ $\mathcal{P}$	0.5	0.75	0.95
3	–0.025	–0.037	–0.046
4	–0.029	–0.043	–0.053
5	–0.030	–0.043	–0.054

(b) Size

D \ $\mathcal{P}$	0.5	0.75	0.95
3	0.006	0.009	0.012
4	0.007	0.010	0.013
5	0.007	0.010	0.013

Notes: The tables above show the change in frequency and size relative to the steady state, respectively, across combinations of $(D, \mathcal{P})$

Figure A-2: Parameter Influence on Moments: Frequency and Size



Notes: The plotted points are the change in frequency and size relative to the steady state, respectively, across combinations of $(D, \mathcal{P})$ represented as $D \times \mathcal{P}$.

that as $D \times \mathcal{P}$ increases, the additional decrease in frequency and the additional increase in size gets smaller, reaching a plateaus.

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 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 static 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

Table A-22: Output Response to MP Shock

	$t=0$	$t=1$	CIR
No News or Change in Menu Cost	0.000	0.459	0.884
News-Only (realized)	0.000	0.020	0.030
News-Only (not realized)	0.000	0.483	0.812
News + Menu Cost (realized)	0.000	0.020	0.030
News + Menu Cost (not realized)	0.000	0.424	0.727

Notes: Each impulse response shows the average difference between an economy receiving a nominal expenditure shock in period 2 and an economy not receiving the nominal shock. The first two columns show the response of output as a fraction of the shock in period $t = 1$ and $t = 2$, while the last column cumulates the total response. The table uses the benchmark specification where $(D, P) = (4, 0.75)$.

alone can achieve.

The key asymmetry 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. This is what allows the menu cost to act as a flexible catch all mechanism and pick up the residual slack left by the bounded effect of the news.

E.2 Policy

Table A-22 repeats the analysis in Table 9, changing the timing of the monetary policy shock. The shock now arrives in period $t = 1$, the period after the arrival of the news. The first row is identical to the first row of Table 9, shifted by one period. The second row show that if the news is realized in the same period as the monetary policy shock, the impact response goes from 0.459 to 0.020 and CIR goes from 0.884 to 0.030, indicating that monetary policy is essentially ineffective in stimulating real activity in this case. This aligns exactly with the result in Vavra (2014).