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PRICING UNDER DISTRESS

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Pricing Under Distress
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ABSTRACT

Uncertainty triggers two confounding effects: a realization and an anticipation effect. By using the 2019 riots in Chile as a quasi-natural experiment, we show that the pricing behavior of supermarkets is consistent with a pure anticipation effect: during the 31-day period following the start of the Riots, supermarkets reduce the frequency of price changes and, conditional on a price change, the absolute magnitude of price changes increase. A quantitative menu cost model with news about a future increase in idiosyncratic demand dispersion can deliver these pricing dynamics. The effectiveness of monetary policy crucially depends on the timing of the intervention.

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1 Introduction

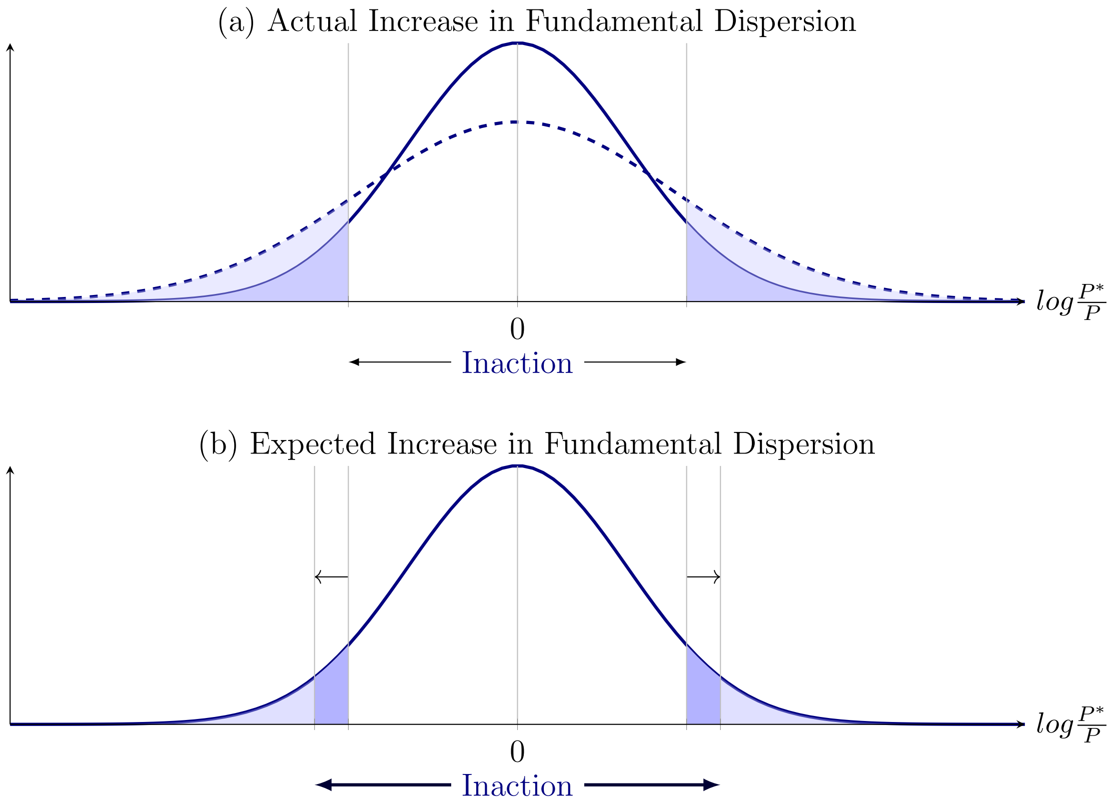
The pricing decision of firms is central in macroeconomics. The frequency and the extent to which firms adjust their prices help determine the effectiveness of monetary policy in affecting real outcomes. Price setting is necessarily a forward-looking activity as firms anticipate that the price they set today will have to remain unchanged for some time. This forward-looking behavior makes expectations, and in general uncertainty about the future a key ingredient of the firms' price setting problem.

Typically, uncertainty is modeled by introducing time variation in the dispersion of a distribution of a fundamental that affects firm's decisions. For example in the menu-cost model of Vavra (2014), the dispersion of the distribution from which firm-level productivity is drawn changes over time. An increase in this dispersion has two distinct effects: (i) the distribution is more disperse today and (ii) it is expected to remain more dispersed tomorrow. We label these the *realization* and the *anticipation* effects of uncertainty, respectively.[1] It is well understood that these two effects have different and likely opposite implications for firms' behavior.

To demonstrate how the realization and anticipation effects may 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 lagged-price of a firm relative to the aggregate price level which changes because of changes in aggregate conditions and ideally the firm wants its current price to match the aggregate price level. If the firm wants to reset x to zero to do so, then they have to pay a fixed cost g. Dixit (1991) shows that the dynamic problem of the firm has the feature that if $x \in [-h, h]$ then the firm keeps it unchanged and otherwise sets $x = 0$ and

[1] In his seminal paper Bloom (2009) uses uncertainty and volatility effects to refer to these channels, respectively.

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 $[-1.2, 1.2]$.

pays the fixed cost, and derives a closed-form formula for an 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 log difference between P^* and P 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 increase in the dispersion of the fundamental distribution today with no changes in the future, and the dashed-blue line shows the new distribution of desired price changes. Because the inaction bands only 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, leading to less price changes and larger price changes changes conditional on a change. This is the effect of anticipation isolated from the realization effect.

The simple model in Figure 1 demonstrates that anticipation and realization effects of a change in uncertainty may have distinctly different and in this case opposite effects on the distribution of price changes. The realization effect increases the frequency and size of price changes and the anticipation effect reduces the frequency of price changes while increasing the average price change. Especially the effect on frequency of price changes suggests that the exact nature of change in uncertainty needs to be understood to identify its effect on effectiveness of monetary policy. In Vavra (2014)'s analysis of the effect of uncertainty shocks on the effectiveness of monetary policy, the uncertainty shock triggered both effects – firm-level dispersion goes up today and is anticipated to remain high for a while. Because the realization effect dominates, he concludes that monetary policy is less effective in the presence of uncertainty shocks.

This leads to the following natural question: can we find an example of a major event where the main effect of the change in uncertainty was anticipation and not realization? In the first part of the paper we show that the Chilean Riots in 2019 indeed provide a good example. On October 18, 2019, major riots unexpectedly erupted all across Chile when earlier localized peaceful protests of a small fare increase near the subway stations turned violent. During the course of the next month major protests and looting of public property and private businesses, including supermarkets followed. We demonstrate that this episode fits the definition of a quasi-natural-experiment, as it was sudden, unexpected and short lived. We study the price-setting behavior of supermarkets during this episode as compared to the preceding years. A uniquely granular dataset built from electronic invoices for the value-added tax allows us to do so. We are able to observe daily prices of thousands of products across different locations in Chile. For a subset of these products we also observe the prices the suppliers' charge the supermarket, allowing us to identify changes in the supermarkets' costs. Thus the unique data and the unexpected nature of the Riots, make them a perfect laboratory to study the effects of large unexpected events on firms' pricing decisions.

We find that the Chilean riots are associated with about a 40% (60%) decrease in the frequency of positive (negative) price changes and that, conditional on a price change the absolute size was about 20% larger. These effects are robust to a battery of fixed effects and product-supermarket level dynamic controls. Moreover, we show that suppliers did not change their pricing behavior in pricing the goods they sell to the supermarkets. These results mean that a change in concurrent supply factors is unlikely to be a possible explanation of the results we document. We also show that the geographical intensity of the riots is uncorrelated with their effects, suggesting that concurrent demand disturbances are unlikely contributers to our results. Recalling the results from the simple model in Figure 1, the results we find are in fact consistent with the situation depicted in panel (b), where future dispersion is expected to change with no major changes today.

To establish that we can indeed justify the empirical results with an expected increase in future idiosyncratic demand dispersion we turn to a quantitative menu-cost model. Because Vavra (2014) studies the effect of uncertainty shocks in monetary policy effectiveness in this set of models, we build on his framework to make our point. He shows that when monetary policy is implemented in periods of increased uncertainty, which will persist for some time, then it is less effective relative to normal times. Crucially, we use the model to also discuss how the anticipation channel influences the effectiveness of monetary policy and how the timing of policy relative to the arrival of the news has implications for it.[2] In order to do so, we introduce idiosyncratic demand shocks, and for these shocks to affect prices, we allow for variable markups using a Kimball (1995) aggregator, instead of the more standard CES aggregator. We leverage the granularity of our data by calibrating the model using pricing and cost data at the product level for Chile. Observing the prices paid by supermarkets for their products allows us to make our model consistent with moments that other studies cannot target. In the model we implement a one-time unexpected arrival of news about the dispersion of the idiosyncratic demand distribution, which may in fact happen with some probability. When this news arrive, the firms in the model exactly do what we find in the empirical results: they reduce the frequency at which they change their prices and conditional on a price change they implement bigger changes. Quantitatively we find that this anticipation channel can explain 25% of the decrease in frequency and 40% of the increase in the size of price changes observed in the data.

[2] In the context of many popular pricing models, a decline in the frequency of price changes, a result that we find in the data, would imply that the effectiveness of monetary policy increases. Focusing on a particular model allows us to quantify the effect of the anticipation effect of uncertainty and also discuss how results change when the realization effect is absent.

Turning to the key question of effectiveness of monetary policy, when the central bank stimulates the economy in periods where future demand dispersion is expected to increase, monetary policy is about 20% more effective on impact relative to an intervention without such expectation about future demand dispersion. Thus, this class of uncertainty increases the effectiveness of monetary policy. Alternatively, if monetary policy is implemented in the period after arrival of the news, and if the dispersion increase is realized, monetary policy has almost one quarter of the effect of the case when dispersion does not change. This is in line with the results of Vavra (2014), who shows that monetary policy is less effective if it is implemented in a period where idiosyncratic TFP dispersion of firms increase.Thus our results highlight the importance of the timing of monetary policy relative to large aggregate events.

Literature review.

Our paper contributes to three distinct literatures. First is the literature on uncertainty and firm-level decisions where uncertainty is modeled as time-varying volatility of either aggregate or idiosyncratic shocks. Fernández-Villaverde et al. (2011) and Fernández-Villaverde et al. (2015) study the effect of time-varying volatility of aggregate shocks (real interest rate for a small open economy and fiscal policy, respectively) and show that these uncertainty shocks can create business-cycle level fluctuations. Of the papers focusing on time-variation in the dispersion of idiosyncratic shocks, some of the early seminal papers in the literature such as Bloom (2009), Bloom (2014), abstract from the pricing decisions of firms. They demonstrate the importance of the wait-and-see behavior in investment or hiring in response to an anticipated increase in dispersion in the future.

A smaller but growing set of papers focus on the price-setting behavior of firms when they are faced with uncertainty. This set includes Vavra (2014), who show that in more uncertain times firms change their prices more frequently, decreasing the effectiveness of monetary policy.[3] In contrast, using models with information frictions and learning, Baley and Blanco (2019) and Ilut et al. (2020) conclude that higher firm-level uncertainty reduces the re-

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

sponsiveness of prices and hence amplifies the real effects of nominal shocks. These papers also provide a micro-foundation for price rigidities, where alternatives such as customers anger in Rotemberg (2002) or rational inattention (for a summary, Maćkowiak et al. (2023)) have also been proposed. Klepacz (2021) studies how the effects of the time-varying volatility of an aggregate shocks affects the pricing behavior of firms and thus the effectiveness of monetary policy. None of these papers distinguish between the anticipation and the realization effects, while our focus is squarely on the consequences of the anticipation effect. Although it is not the goal of our paper to provide a detailed comparison of these models' implications with ours, we show that a standard menu cost model augmented to allow for news shocks on demand cross-sectional volatility can generate more rigidity in times of uncertainty if the anticipation effect dominates, or if the realization effect is absent.

Berger et al. (2019) and Dew-Becker et al. (2017) take a more empirical approach in disentangling the anticipation and realization effects. They find that while an increase in current volatility (realization) has a negative effect on the economy, anticipation of an increase in the future does not have a significant effect. They relate this to the ability of investors to hedge against future shocks. Similarly, Drenik and Perez (2020) identify the realization channel of uncertainty by showing that price dispersion goes up after an increase in uncertainty about inflation. Finally, Kumar et al. (2023) show the effects of a change in the level uncertainty experienced by firms using information treatments in a firm-level survey, focusing on how some key decisions such as price setting, and investment and sales changes. Our quasi-natural experiment approach turns out to be especially useful in identifying the anticipation channel as distinct from the realization channel and contributes to the empirical side of the literature studying uncertainty.

The second literature we contribute to studies firm-level prices both empirically and also theoretically using a version of a menu cost model, often focusing on the non-neutrality or effectiveness of monetary policy. The vast majority of the empirical literature on pricing has used monthly (e.g. using Bureau of Labor Statistics Consumer Price Index Database) or weekly data

(Chicago Booth Dominick's Dataset or Nielsen Dataset) without direct information on the cost of products.[4] Our empirical work is at the daily frequency, which enable us to learn about firms' pricing decisions with more precision. Moreover, the richness of our data allows us to calibrate our model to capture cost dynamics and to match the empirical cost-pass-through to prices.

The theoretical study of monetary non-neutrality based on fixed costs to changing prices (menu cost models) can be traced back at least to Barro (1972) and Sheshinski and Weiss (1977) with Caplin and Spulber (1987), Caballero and Engel (1993) and Dotsey et al. (1999) as important early contributions. The availability of product-level data and the new developments in computational methods allowed the literature to build rich quantitative models and contrast them directly to the data. Nakamura and Steinsson (2010), Golosov and Lucas Jr (2007), Midrigan (2011) and Vavra (2014) are seminal papers in this literature. These quantitative menu cost models are able to generate sizable monetary non-neutralities, while capturing micro evidence on firm pricing behavior. They also show how one can link various pricing facts such as frequency of price changes to the effectiveness of monetary policy. Alvarez et al. (2016) shows this link theoretically using a sufficient statistic approach where frequency and kurtosis of price changes turn out to be key moments. Alvarez et al. (2023) provide empirical evidence from industry-level data that indeed these moments are crucial in shaping the effectiveness of monetary policy. We contribute to this literature by extending the baseline menu cost model to feature idiosyncratic demand shocks where, through a Kimball (1995) demand system, allowing firms to react differently to both demand and supply shocks.[5]

Our paper also contributes to the rich literature that considers the effects of rare events or disasters on the economy. In the context of event studies, Hobijn et al. (2006) study the introduction of the Euro, Gagnon (2009) studies high inflation in Mexico, and Alvarez et al. (2019) analyzes the hyper inflation

[4]The only previous work we know of that exploits this type of data to study supermarkets' pricing behavior is Eichenbaum et al. (2011), who use data from one supermarket, and they focus on the pass-through of costs to prices.

[5]Alvarez et al. (2022) prove further theoretical results when the demand system features strategic complementarities such as ours.

episode in Argentina. On the rare disasters, Barro (1972) and Gabaix (2012) study them theoretically and some empirical examples include Baskaya and Kalemli-Ozcan (2016) 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.

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

2 Data

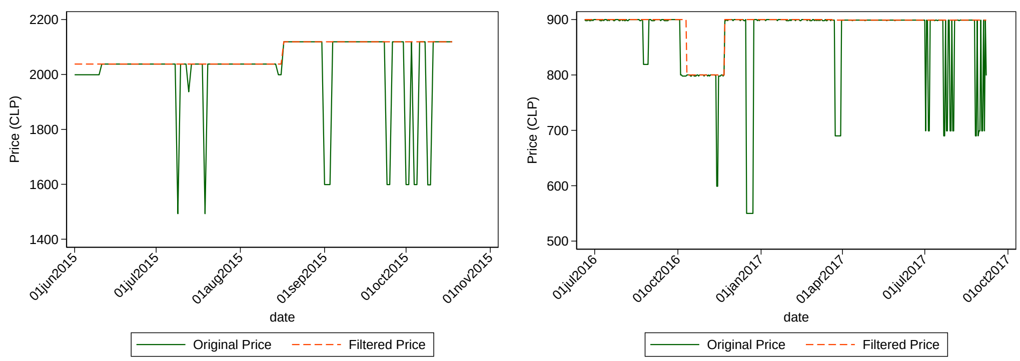
We use a business-to-business (B2B) transaction-level dataset built from electronic invoices ("Factura Electronica" in Spanish) collected by the Chilean Tax Authority (Servicio de Impuestos Internos) and provided anonymously to the Central Bank of Chile (CBC). The coverage and granularity of the information in this dataset are unique: they provide a record of the date, description of the product, buyer, seller, price and quantity for the universe of B2B transactions. We use this dataset focusing on the period from January 2015 to December 2019 where the latter is selected to avoid the contamination of the data from the Covid lockdown that was imposed in March 2020. Appendix B.1 provides details about the construction of the data.

Our goal in the empirical part of the paper is to show how the pricing behavior of firms in Chile was affected by the Riots. We focus on the transactions at supermarkets in our analysis. Supermarket prices have traditionally been the topic of study in the vast micro and macro literatures that look at how firms set their prices. What makes supermarkets an ideal setup is that they have well-defined prices for the goods they buy and sell. Apart from discounts (either valid for everyone, or for those with a coupon or a loyalty

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 uses the method in Kehoe and Midrigan (2015) to remove short-term price fluctuations.

card) supermarkets do not price discriminate. Therefore, when we look at the maximum price for a good within a day, one can be quite certain that this is the price listed on the shelf. Because our dataset is B2B, we study the prices of the goods purchased by firms in supermarkets. These transactions amount to an average of 13% of total sales reported by supermarkets in Chile. It is important to emphasize that we do not rely on the quantity sold, but use these transactions as a way of observing the prices at the supermarket.

A product is defined as a unique triplet of a supermarket (seller's id), location (branch code), and product description. Our baseline sample is comprised of 32.9 million transactions from a total of 11.4 million invoices. We aggregate the transaction-level price information to daily frequency by taking the intra-day maximum price for each product; the triplet as defined above. This filters out discounted purchases by some customers within the day. Next we apply the filter proposed by Kehoe and Midrigan (2015) to eliminate high-frequency variation (most importantly short-lived sales) in prices across days. Figure 2 shows the daily price (defined as the intra-day maximum) for two randomly selected goods along with the output of the filter in Kehoe and Midrigan

(2015). As expected, the filter successfully eliminates high-frequency changes that quickly revert to the mode. In addition to this, we impose a continuity filter that only keeps products sold at least 3 days per week, for at least 20 consecutive weeks. These filters result in our "baseline sample" with 7.2 million product-day observations with 25,108 products sold across 67 supermarkets at a total of 494 different locations, covering the period from January 2015 to December 2019.

The richness of the information in the electronic B2B invoice data allows us to complement the final prices in our baseline sample with price data from the suppliers of the supermarkets by looking at the transactions where the supermarkets are listed as buyers. Because the data does not contain standardized product descriptions (such as UPC codes), we use fuzzy matching techniques based on the product descriptions. A product in the matched subsample becomes the unique triplet from the baseline sample and a supplier's id that matches the supplier's product description with the description of the final sale. Since the matching is not perfect, this "matched sample" results in a smaller set of goods: 2.3 million observations of daily prices charged for 8,478 products by 37 supermarkets at a total of 349 different locations. This sample matches the supermarkets to 228 different suppliers. In addition to these two samples of supermarkets, in parts of our analysis where we focus on the suppliers' pricing decisions using the "suppliers sample", we use the prices that these 228 suppliers charge for the products they sell to the supermarkets in the matched sample. This sample is comprised of 1,448 products, where a product is defined as the unique triplet of a supplier (seller's id), a supermarket (buyer's id), and a product description.[6]

Table 1 presents descriptive statistics for the two supermarket samples, baseline and matched samples as well as the supplier sample. The upper panel includes the variables generally used in the literature to characterize price setting, starting with the share of product-day observations where a price

[6] On the matched sample, the 955 single product descriptions are sold to different locations-supermarkets generating 8478 product ids. Form the supplier perspective, only the supermarket id is reported (not the location) giving rise to 1448 product ids on this sample.

Table 1: Descriptive Statistics

	Baseline sample		Matched Sample		Suppliers Sample	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Price Setting						
Total Breaks	0.0125	0.1111	0.0136	0.1158	0.0104	0.1015
Positive Breaks	0.0069	0.0830	0.0071	0.0842	0.0064	0.0798
Negative Breaks	0.0056	0.0745	0.0065	0.0802	0.0040	0.0633
Size Positive	0.1019	0.1071	0.1052	0.1093	0.1095	0.1251
Size Negative	0.1102	0.1163	0.1100	0.1148	0.1352	0.1520
Sample Info						
No of Supermarkets	67		37		-	
No of Suppliers	-		228		228	
No of Supermarkets-locations	494		349		-	
No of Product ID	25,108		8,478		1,448	
No of Product Description	8,357		955		955	
No of Observations	7,246,966		2,324,403		386,676	

Notes: This table presents descriptive statistics for the three samples we use: all supermarkets (baseline sample), matched supermarkets and matched suppliers. The upper panel describes the main dependent variables for the empirical analysis and the lower one provides a general characterization of the observations in each sample.

change happens. This is then disaggregated by positive and negative breaks. We also report the average size and standard deviation of a price change. Size is measured using log differences. For instance, Product Y in Figure 2 shows one positive and one negative break. The negative break represents a price change of -0.1178 ($log(800) - log(900)$). In the Baseline sample, 1.25% of products change prices on an average day, with more price increases than decreases. The average positive change is 10.2%, while the average negative change is 11%. The other two samples show similar patterns. In Appendix B.2, we present some more descriptive statistics and compare the properties of the Chilean data with similar results from the literature.

3 The 2019 Riots in Chile

3.1 Riots as a Quasi-Natural Experiment

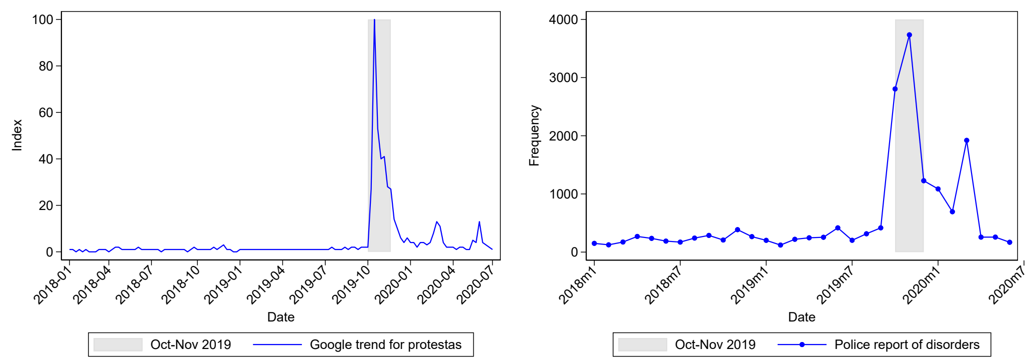
On October 6, 2019, Santiago's subway fare was raised by 4% (about $0.05 USD). Students reacted to this increase with peaceful demonstrations and some limited disruptions on the subway system. The situation radically changed on October 18, when massive and violent disruptions erupted in the entire Santiago subway system, carried out by individuals beyond the initial group of student protesters. Despite an early response by police, by the early morning of October 19, a considerable part of Santiago's metro system had been damaged. This marked the beginning of the most violent and intense episode of riots that the country has witnessed in its recent history. Every day for the next month, mobs across the country attacked, looted and burned down public property and private businesses. On November 15, about a month after the violent phase of the Riots began, a broad political agreement across several parties was reached on a course of action to change the constitution. To a large extent, this brought a stop to the violence.

While a detailed analysis of the Riots is beyond the scope of this paper, experts argue that the Riots were not simply about the increase in the subway fare, but it was the manifestation of something much bigger. Indeed, the Riots became a social movement across the country where different social leaders voiced their concerns about their sectors, such as education, health, pension system and wages. It went from student-led demonstrations to a nationwide call for a renewed social agreement under the slogan "Chile cambió" (Chile changed). To respond to these demands, the government, political, social, and business leaders agreed that structural changes were needed, creating high expectations and uncertainty for Chile's future.

From the perspective of our work, there are four distinctive characteristics of the Riots. First, the episode was fully unexpected yet relatively short-lived. This feature makes it particularly useful as a quasi-natural experiment. Panel (a) of Figure 3 plots a daily index for the number of Google searches for

Figure 3: Google trends for Protests and Police Reports of Public Disorders

(a) "protestas" (protests) (b) "desórdenes" (public disorders)



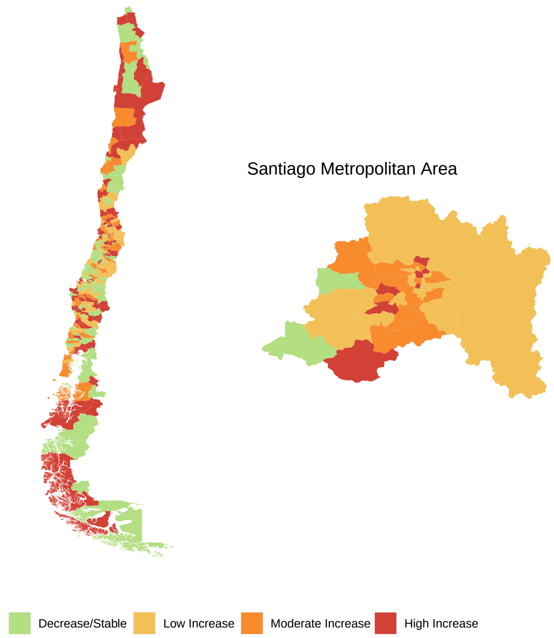
Notes: Panel (a) displays a daily index for the number of Google search for "protestas" (protests in Spanish) that originate in Chile, where the maximum daily searches in the whole sample, which happens to be on October 19, 2019, is normalized to 100. Panel (b) shows the number of monthly police reports of "desórdenes" (public disorders in Spanish). Shaded area shows the period between October 18, 2019 and November 17, 2019, inclusive.

"protestas" (protests in Spanish) that originate in Chile. This index increases 100-fold between October 17 and October 19, indicating a sudden increase. This episode was, nonetheless, relatively short-lived, and by November 17 the index falls to near pre-October 18 levels. We will consider this 31-day window, the shaded region in the Figure, as the most intense period of the Riots.

A second distinctive characteristic of this episode is that it was violent in nature. Panel (b) of Figure 3 plots the number of monthly police reports of "desórdenes" (public disorders in Spanish), an official definition that involves the destruction of private and/or public property, which includes supermarkets. There is a clear spike within the month that the riots took place with a ten-fold increase in the number of reported events.

A third salient characteristic of this episode is that the Riots were widespread in Chile, with various degrees of intensity across regions. This fact is documented in Figure 4 which contains the map of Chile split into its 346 municipalities, where the left panel shows the whole country and the right panel zooms into the Santiago Metropolitan Area. More intense colors denote lo-

Figure 4: Geographical Distribution of Intensity of Public Disorders During the Riots

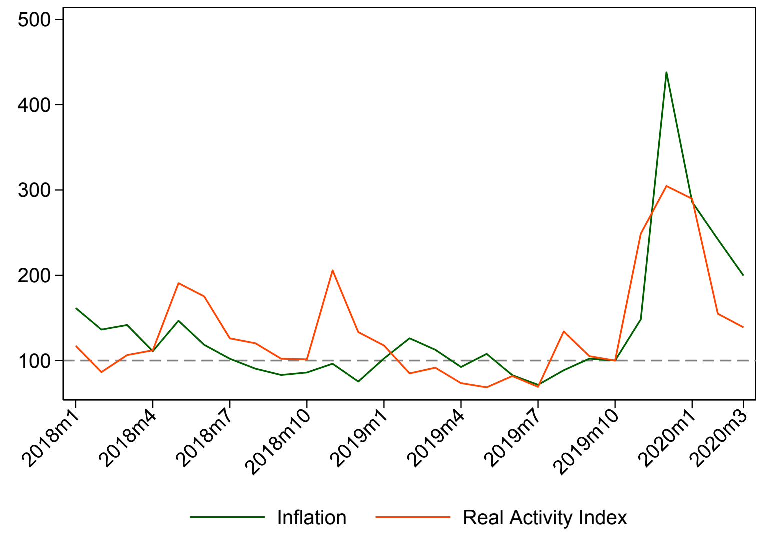


Notes: The map of Chile on the left displays the intensity of riots at the municipality (commune) level and on the right is a close-up of the Santiago Metropolitan Area. This measure is the change in the number of police reports for public disorders in October and November 2019 relative to October and November 2018, adjusted for population. Municipalities are classified in four categories: green for those in which crime remained equal or decreased, yellow for the bottom third of municipalities organized by growth in crime, orange, and red, for the middle and top third, respectively.

cations where the increase in the number of public disorders, a category that includes the massive manifestations associated with the riots, was larger. The figure shows a rich amount of heterogeneity in the intensity of the riots with no distinctive geographical pattern across regions, and also within Santiago Metropolitan Area. We exploit this heterogeneity in our analysis.

The fourth and final feature is that uncertainty increased following the Riots. Figure 5 provides evidence for this. In this figure we report the standard deviation across the participants in the "La Encuesta de Expectativas Económicas" (Economic Expectations Survey) conducted by the Central Bank of Chile for two key questions: Inflation expectations for December of the cur-

Figure 5: Uncertainty as Proxied by Standard Deviation Across Forecasters

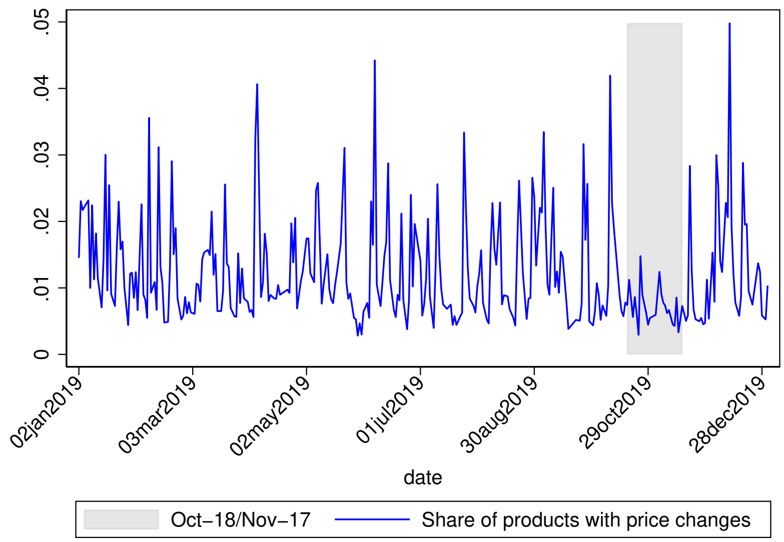


Notes: The figure shows the monthly standard deviation of two forecasts across roughly 50 forecasters from the "La Encuesta de Expectativas Económicas" (Economic Expectations Survey) conducted by the CBC: inflation expectations for December of the current year and expectations for the the 12-month change in the IMACEC index that excludes mining. The standard deviations are normalized at 100 right before the Riots.

rent year and expectations for the the 12-month change in the IMACEC index (monthly GDP) that excludes mining. This survey is the most widely used source for inflation expectations measures by the CBC in its policy making process. Its longest historical coverage relative to other surveys as well as the variety of experts consulted from market participants to academics, makes it a suitable proxy for inflation expectations. In the figure, the standard deviations are normalized at 100 right before the Riots. The figure shows that in the first two months following the riots, the standard deviation of forecasts increase three-fold for real activity and almost five-fold for inflation, both of which are unprecedented levels. In the months that follow – the figure stops in March 2020 to avoid the period of the Covid lockdowns in Chile – uncertainty gradually falls.

Before turning to our main empirical analysis, we show the effect of the Riots on the pricing behavior of supermarkets using just the raw data from the baseline sample. Figure 6 presents the daily frequency of price changes, the

Figure 6: Frequency of Price Changes in 2019



Notes: The figure shows the daily frequency of price changes throughout the year 2019. The solid line indicates the share of prices that change among the analyzed products. Shaded area shows the period between October 18, 2019 and November 17, 2019, inclusive.

share of prices that change among the products analyzed, focusing on the year 2019. The figure shows a regular pattern before the Riots, as price changes seem to be concentrated on some particular days, showing as big spikes in the frequency of price changes. During the Riots, however, these spikes disappear and the frequency falls to under 1%, from an average of 1.25% in our baseline sample. The gray shaded area shows the same 31-day period following October 18 as we highlighted in Figure 3. After this period, frequency of price changes seem to return to its pre-Riots pattern. Note that, given the length of our continuity filter (products sold in a particular location at least three times a week for 20 consecutive weeks) this pattern cannot be explained by the closure of looted supermarkets which would be unable to sell their products. This is a clear change in the pricing pattern of products that were sold before, during, and after the Riots. In the next section we turn to exploring more formally how the price-setting behavior of supermarkets changed during the Riots.

4 Empirical Results

Having established that the Riots fit the of a quasi-natural experiment, we turn to identifying the effect of the Riots on the pricing behavior of supermarkets. We do so in three steps. First, we look at our baseline sample and analyze the frequency of price changes and the size of changes. Second, we look at the pricing behavior of the suppliers of supermarkets to investigate if any changes we find for the supermarkets stem from the changes in the pricing behavior of the suppliers. Third, we use the measure of intensity of Riots in Figure 4 to determine if supermarkets in regions with more intense riots change their pricing behavior in a different way than others.

4.1 Baseline Results for Supermarkets

Throughout this section, we use the following empirical model

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

where y_{it} is one of four possible dependent variables of interest reflecting the frequency and size of price changes differentiated by sign, D_t is a dummy that takes the value of 1 for the 31 days starting on October 18, 2019, X_{1it} is a vector of time-varying product-level controls, and X_{2t} denotes a set of economic activity controls.[7] The model includes the following fixed effects: product, day of the week, week of the month, month of the year, and non-mandatory holidays. This exhaustive set of fixed effects captures the time-invariant patterns in pricing; for example, a product changing prices every Monday, or every second week of the month or a specific month of every year. The vector $X_{1i,t}$ includes a third-order polynomial of the number of days since the last price change was observed, and the number of price changes of the product in the last 30 days. These controls are meant to capture any product-specific

[7] When studying the frequency of price changes, the dependent variable takes the value of 1 if a change of the particular sign occurs, and 0 otherwise. For size regressions, the dependent variable reflects the absolute value of the log-difference of the price change, conditional on the occurrence of a price change of the particular sign.

Table 2: Change in Pricing Behavior During the Riots - Supermarkets (Baseline Sample)

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.00300***	-0.00332***	0.0173***	0.0256***
	(0.000456)	(0.000383)	(0.00530)	(0.00714)
Observations	7,203,155	7,203,155	43,475	34,088
Adjusted R-squared	0.002	0.002	0.381	0.439
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00695	0.00560	0.102	0.110

Notes: Clustered standard errors at location-seller level in parentheses. *, ** and *** represent statistical significance at 10%, 5% and 1% levels, respectively.

time-varying pricing dynamics. Meanwhile, the vector X_{2t} incorporates two measures of economic activity. First, we control for the retail sector's monthly total sales to capture sector-wide changes in this business. Second, we build a weekly measure of all purchases made by each supermarket from all of its suppliers (this is common for every location-product within a supermarket). This second control removes aggregate dynamics at the supermarket level – for example a supermarket may be expanding its business and purchasing inventory from its suppliers. The coefficient of interest β captures the change in the pricing behavior of supermarkets at the product-location level during the Riots. Note that since we include a product fixed effect, the identification of β comes from the change in pricing of products that are sold both before and during the Riots. We cluster standard errors at the seller-location level allowing for a location-specific pricing behavior. Throughout the paper, we estimate (1) using four different dependent variables: two of these are dummy variables that indicate the occurrence of a price change (a "break"), one for positive and one for negative ones; the other two measure the magnitude of price changes ("size"), conditional on a change, again for positive and negative ones separately using log differences.

Table 2 presents the results of the OLS estimation of (1) for our baseline sample. Columns (1) and (2) show that the frequency of positive and negative price changes fell during the Riots, both by about 0.3 percentage points. The fall in frequency is economically significant when compared to the unconditional frequency of daily price changes that are 0.7% and 0.6%, respectively. These numbers put the decline during the Riots at more than 40% of the unconditional mean for positive changes and more than 60% for negative changes. Columns (3) and (4) use the size of a price change conditional on a change occurring as the dependent variable. During the Riots, although price changes were less frequent, realized price changes were significantly larger in absolute terms. The results show an increase of 1.73 percentage points in the size of positive price changes and an increase of 2.56 percentage points in the size of negative price changes during the Riots. Once again, these are also economically significant changes, compared to the unconditional means of price changes, these absolute increases represent 17% and 23%, respectively. Appendix C shows that these results are robust to using unfiltered prices and allowing for differential response for large and small supermarkets. Thus, the main empirical result is that during the Riots, supermarkets implemented less price changes than usual and conditional on changing prices the absolute size of changes were larger than usual, with no clear asymmetry between price increases and decreases. This result mitigates the concern that supermarkets might not be willing to increase prices in this period given that the Riots originated by protesting a price increase.

4.2 Effect of Supply Factors on Supermarkets

A possible explanation of our baseline results is that perhaps the supermarkets are simply passing through the price changes that their suppliers are implementing. To test this explanation, we turn to the suppliers sample – the sample of firms that provide some of the goods that supermarkets in our baseline sample sell – and estimate (1). Table 3 shows that, unlike the supermarkets, there has been no change in the pricing behavior of the suppliers – none of the coefficients are significant. Therefore, there is no evidence that the change in the behavior of supermarkets during the Riots is simply a reflection of their suppliers' pricing decisions. While it is not possible to know for sure

Table 3: Change in Pricing Behavior During the Riots - Suppliers Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	0.000575	-0.000527	0.000926	-0.0159
	(0.00102)	(0.000999)	(0.0234)	(0.0350)
Observations	386,676	386,676	2,183	1,322
Adjusted R-squared	0.009	0.013	0.335	0.340
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00641	0.00402	0.110	0.135

Notes: The economic activity control corresponds in this case to the total sales of each supplier to all of its costumers. Clustered standard errors at supplier-supermarket link level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

with our data, one explanation for this result could be the long-term nature of contracts between supermarkets and their suppliers where prices (and perhaps other non-price terms) are negotiated in advance and it is not possible to alter these terms in short notice. The source of this result is not central for our analysis – one way or another during this period the supermarkets did not experience a change in the prices they pay to their suppliers. We further explore the supply factor using the Matched Sample, where we can study supermarkets' price settings directly controlling for the cost of the goods sold. Table 17, in Appendix C, shows that including the cost of recent re-stocking at the product level does not change our baseline estimates. Thus, changes in pricing behavior are likely due to changes related to demand factors form the supermarket perspective.

4.3 Now versus the Future: Intensity of Riots

Having discarded supplier's pricing behavior as a source of the change in pricing behavior of supermarkets during the Riots, we analyze if concurrent changes related to the Riots are associated with the observed changes in pricing dynamics. To do this, we use the geographical variation in the intensity of the riots to see if supermarkets in regions with a higher intensity changed their pricing behavior more compared to supermarkets in regions that are not

Table 4: Supermarket Analysis: Baseline Sample and Riot's Intensity

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.00319***	-0.00342***	0.0148***	0.0184**
	(0.000637)	(0.000501)	(0.00487)	(0.00815)
D * Intensity	0.000418	0.000206	0.00598	0.0190
	(0.000919)	(0.000562)	(0.0118)	(0.0155)
Observations	7,202,970	7,202,970	43,475	34,088
Adjusted R-squared	0.002	0.002	0.381	0.439
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
mean of Dependent Variable	0.00695	0.00560	0.102	0.110

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

experiencing the Riots as intensely. If supermarkets in regions with very intense riots experienced things such as workers, customers or suppliers being unable to reach the store, or damage to the store, then they may alter their pricing behavior accordingly. If this is the case, we expect the change in the pricing behavior of supermarkets to vary with riot intensity.[8]

Our approach uses the geographical variation depicted in Figure 4. In particular, we group municipalities according to the severity of the riots and build a dummy that indicates if the municipality saw an increase in the number of riot-related incidents above the median. We then interact this dummy with the Riots dummy. Note that the intensity dummy itself is absorbed by the product-location fixed effect. Specifically, we estimate

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

The results are reported in Table 4. The interaction term comes out insignificant in all regressions, indicating that the severity of the Riots did not affect how the supermarkets changed their pricing behavior during the Riots. We

[8]Similarly, if Riots diverted labor force of managerial attention from price adjustments into security or other tasks, this effect should be more pronounced in regions where Riots were more intense.

interpret this as evidence that the supermarkets' concern about what might happen in *the future* as opposed to what is currently happening is likely to drive the change in pricing dynamics documented in this section.

4.4 Summary of Empirical Results

Our results show that during the 31-day period that followed the October 18, 2019 riots, supermarkets in Chile changed the way they price their products. They reduced the frequency of price changes by about half and conditional on a price change the size of price changes increased by roughly 20% relative to the pre-Riots period. The firms that supply the products to the supermarkets, on the other hand, show no change in their pricing behavior. This result suggests that the source of the supermarkets' change in behavior is likely to be demand-based, rather than supply. We also show the intensity of the Riots in the immediate area around the supermarket does not affect the change in its pricing behavior. This result suggests, in turn, that the supermarkets are perhaps reacting to something that they expect to happen in the future, rather than happening now. Finally, recall that we presented evidence that uncertainty, measured by the disagreement among professional forecasts has increased drastically in the months that followed the Riots.[9] Putting all these together, a plausible explanation of the change in the pricing behavior is that the supermarkets anticipated that their demand would be more dispersed in the near future, but not currently. Naturally one can come up with a number of other plausible conjectures about the exact channel and there likely are multiple ones that simultaneously were at work. Nevertheless, the results so far help with our goal of arguing that receiving news about a possible future increase in uncertainty is empirically a realistic scenario. In the sections that follow we show that such a change can explain the empirical results using a quantitative model and investigate its policy implications.

[9] As discussed by Bloom (2014), dispersion among professional forecasters macroeconomic outcomes is often used as an indicator of firm-level uncertainty. More complex measures in the spirit of Baker et al. (2016) give a similar pattern as the Riots dominated the news.

5 Quantitative Model

In the rest of the paper we turn to a quantitative model to accomplish two tasks. First, we use the model to demonstrate that an expected increase (or news about an increase) in the dispersion of future demand can generate the empirical results we documented. Second, we investigate how the arrival and the timing of such news may impact the effectiveness of monetary policy.

Our model is based on the menu-cost model in Vavra (2014) in part because we want to contrast our policy effectiveness results with his. The key change is that we augment the model to include an idiosyncratic demand shock. In normal times, which is what we use to calibrate the model, this follows a standard AR(1) process with a constant innovation variance. We model the Riots as an instance where the firms receive news about a possible increase in the dispersion of the innovation that will be realized in the next period. In another important and necessary deviation from the baseline menu-cost model, we replace the standard constant elasticity of substitution (CES) aggregator with that of Kimball (1995).[10] This is necessary because with CES aggregation, idiosyncratic demand shocks will have no influence on the desired prices of firms.[11]

5.1 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.

[10]Non-CES aggregation such as Kimball are commonly used in international finance and international trade where constant markups and/or complete pass-through of costs are at odds with the data. See Gopinath and Itskhoki (2010) and Amiti et al. (2019) for recent examples.

[11]Of the features Vavra (2014) includes in his model, we take out Calvo plus (the situation where with some probability the firm gets a free price change) as it is not essential for our story, though it helps match small price changes in the data. We also drop all aggregate shocks from the model since our analysis is about a one-off event that happens while the economy is at its steady state.

The household solves the problem

$$\max_{C_t, h_t, \mathbf{B_{t+1}}} \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log\left(C_t\right) - \xi h_t\right] \tag{3}$$

subject to the budget constraint

$$P_t C_t + \mathbf{Q_t} \cdot \mathbf{B_{t+1}} \leq B_t + W_t h_t + \Pi_t \tag{4}$$

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 intratemporal condition

$$\frac{W_t}{P_t} = \xi C_t, \tag{5}$$

and the household's stochastic discount factor

$$\Xi_{t,t+1} \equiv \beta \frac{C_t}{C_{t+1}}. \tag{6}$$

5.2 Final Good Producer

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

$$\int_0^1 G\left(\frac{n_t^i y_t^i}{Y_t}\right) di = 1 \tag{7}$$

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 $G(\cdot)$

$$G\left(\frac{n_t^i y_t^i}{Y_t}\right) = \frac{\omega}{1+\omega\psi}\left[(1+\psi)\frac{n_t^i y_t^i}{Y_t} - \psi\right]^{\frac{1+\omega\psi}{\omega(1+\psi)}} + 1 - \frac{\omega}{1+\omega\psi} \tag{8}$$

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.

Taking as given variety prices p_t^i, as well as P_t, n_t^i and aggregate demand Y_t, the final-good producer chooses y_t^i to maximize profits

$$\max_{y_t^i} \quad 1 - \int_0^1 \frac{p_t^i y_t^i}{P_t Y_t} di \quad \text{subject to} \int_0^1 G\left(\frac{n_t^i y_t^i}{Y_t}\right) di = 1 \tag{9}$$

which yields the optimality condition

$$\frac{n_t^i y_t^i}{Y_t} = \frac{1}{1+\psi}\left[\left(\frac{p_t^i}{\lambda_t n_t^i P_t}\right)^{\frac{\omega(1+\psi)}{1-\omega}} + \psi\right] \text{ for every } i \in [0,1] \tag{10}$$

where λ_t is the Lagrange multiplier on the constraint in (9). This multiplier can be obtained by substituting the optimal demand into (7) to yield

$$\lambda_t = \left[\int \left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1+\omega\psi}{1-\omega}} di\right]^{\frac{1-\omega}{1+\omega\psi}} \tag{11}$$

The solution to the problem of the final-goods producer is, then, (10), along with (11), which implicitly define the demand for each variety, y_t^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

$$P_t = \frac{1}{1+\psi}\left[\int \left(\frac{p_t^i}{n_t^i}\right)^{\frac{1+\omega\psi}{1-\omega}} di\right]^{\frac{1-\omega}{1+\omega\psi}} + \frac{\psi}{1+\psi}\int \frac{p_t^i}{n_t^i} di \tag{12}$$

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

$$y_t^i = \left(n_t^i\right)^{\frac{1}{\omega-1}} \left(\frac{p_t^i}{P_t}\right)^{\frac{\omega}{1-\omega}} Y_t \tag{13}$$

$$P_t = \left[\int \left(\frac{p_t^i}{n_t^i}\right)^{\frac{1}{1-\omega}} di\right]^{1-\omega} \tag{14}$$

along with $\lambda_t = 1$.

5.3 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

$$y_t^i = z_t^i h_t^i \tag{15}$$

Following Midrigan (2011) and Vavra (2014), we assume that idiosyncratic productivity z_t^i follows an autoregressive process, with innovations arriving according to a Poisson process

$$\log\left(z_t^i\right) = \begin{cases} \rho_z \log\left(z_{t-1}^i\right) + \sigma_z \epsilon_t^{z,i}; \quad \epsilon_t^{z,i} \sim N\left(0,1\right) & \text{with probability } p_z \\ \log\left(z_{t-1}^i\right) & \text{with probability } 1 - p_z \end{cases} \tag{16}$$

Idiosyncratic demand n_t^i, which was introduced in the final-good firm's problem in (9), follows an AR(1) process

$$\log\left(n_t^i\right) = \rho_n \log\left(n_{t-1}^i\right) + \sigma_n \epsilon_t^{n,i} \text{ with } \epsilon_t^{n,i} \sim N(0,1) \tag{17}$$

For now the dispersion of the innovation, σ_n is constant. In Section 6.2, we introduce a one-time news about the innovation dispersion for the next period.

We can split the intermediate-good producers into two independent problems. In the first problem, given prices and the demand of the final-good producer, the firm chooses the price it charges for the current period. In the second problem, given all these, 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 $h_t^i = y_t^i / z_t^i$. Using this condition, as well as the demand of the final-good producer, for a given price p_t^i the profits of the firm are given by

$$\pi = \left(\frac{p_t^i}{P_t} - \frac{W_t}{z_t^i P_t} \right) \cdot \frac{Y_t}{n_t^i} \frac{1}{1+\psi} \left[\left(\frac{p_t^i}{\lambda_t n_t^i P_t} \right)^{\frac{\omega(1+\psi)}{1-\omega}} + \psi \right] \tag{18}$$

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. 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 ($\{p_t^i\}$ and P_t) are normalized by total nominal expenditures $S_t \equiv P_t Y_t$. We assume that nominal aggregate expenditure grows deterministically at a fixed rate μ

$$\log(S_t) = \mu + \log(S_{t-1}) \tag{19}$$

At the beginning of the period t, a firm who inherited price p_{t-1}^i from the previous period and facing fixed cost of adjustment f_t^i, chooses whether or not to adjust by comparing the value of adjusting against not adjusting

$$V\left(\frac{p_{t-1}^i}{S_t}, n_t^i, z_t^i; \frac{P_t}{S_t}, \lambda_t\right) = \max\left\{ V_A\left(n_t^i, z_t^i; \frac{P_t}{S_t}, \lambda_t\right), V_N\left(\frac{p_{t-1}^i}{S_t}, n_t^i, z_t^i; \frac{P_t}{S_t}, \lambda_t\right) \right\} \tag{20}$$

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

$$\begin{aligned} V_N\left(\frac{p_{t-1}^i}{S_t}, n_t^i, z_t^i; \frac{P_t}{S_t}, \lambda_t\right) &= \pi\left(\frac{p_{t-1}^i}{S_t}, n_t^i, z_t^i, \frac{P_t}{S_t}, \lambda_t\right) \\ &+ \mathbb{E}_t\left[\Xi_{t,t+1} V\left(\frac{p_{t-1}^i}{S_t}\frac{1}{e^{\mu}}, n_{t+1}^i, z_{t+1}^i; \frac{P_{t+1}}{S_t}\frac{1}{e^{\mu}}, \lambda_{t+1}\right)\right] \end{aligned} \tag{21}$$

where $\Xi_{t,t+1}$ is the households' stochastic discount factor (6), and $\pi(\cdot)$ is a function that represents flow profits as a function of the price charged and other state variables following (18).

Should the firm decide to adjust its price, it earns profit at the new price p_t^i/S_t but pays the adjustment cost

$$V_A\left(n_t^i, z_t^i; \frac{P_t}{S_t}, \lambda_t\right) = -f\frac{W_t}{P_t}$$
$$+\max_{\frac{p_t^i}{S_t}}\left\{\pi\left(\frac{p_t^i}{S_t}, n_t^i, z_t^i, \frac{P_t}{S_t}, \lambda_t\right) + \mathbb{E}_t\left[\Xi_{t,t+1}V\left(\frac{p_t^i}{S_t}\frac{1}{e^{\mu}}, n_{t+1}^i, z_{t+1}^i; \frac{P_{t+1}}{S_t}\frac{1}{e^{\mu}}, \lambda_{t+1}\right)\right]\right\} \tag{22}$$

The intermediate producer's problem is very much standard except for the introduction of the Kimball aggregator instead of the more common CES aggregator. Under CES demand, the desired price in a frictionless environment ($f = 0$) is given by a constant markup over marginal cost and independent of idiosyncratic demand. This means changes in costs (given by productivity z) are fully passed through to prices and changes in demand only affect quantities but not prices. We introduce Kimball aggregator as a way to ensure that idiosyncratic demand shocks influence the pricing decision. Demand for intermediate varieties under the Kimball aggregator features non-constant price elasticity when $\psi < 0$ – in particular, the price elasticity of demand is increasing in the relative price ($\frac{p}{P}$) and decreasing in relative quantity ($\frac{ny}{Y}$). This leads to incomplete cost pass-through and non-zero demand pass-through to prices. In other words, the optimal prices set by firms respond less than one-to-one when idiosyncratic productivity changes and become a function of idiosyncratic demand. Another implication of variable elasticity under Kimball aggregation is that the profit function features a steeper slope when moving away from the frictionless optimal price, which induces strategic complementarity in price-setting as deviation from the average price is more costly. This will have implications for policy, which we turn to below.

5.4 Equilibrium

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

Definition 5.1. *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 (4) along with*

$$\frac{W}{P} = \xi C \tag{23}$$
$$\Xi = \beta \tag{24}$$

   yield C, Ξ and h.

2. *Final-good producer problem yields $y^i(\cdot)$ following (10). Zero-profit condition (12) yields P/S and λ follows from (11).*

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 (20), (21), (22) as well as the optimization problem on the right hand side of (22). The sum of their profits yields Π.*

4. *Market clearing and consistency*

$$h = \int h(\cdot)G(\cdot)di \tag{25}$$
$$C = Y \tag{26}$$
$$\frac{S}{P} = Y \tag{27}$$

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

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	0.23	Prob. supplier price change
ρ_z	Idio. TFP Process	0.30	Supplier price dynamics
σ_z	Idio. TFP Process	0.14	Supplier price dynamics
ξ	Labor disutility	1.0	Normalization

Notes: This table presents the value of externally calibrated parameters in the model.

The solution algorithm is deferred to Appendix D.2.1.

6 Quantitative Results

We now turn to exploring the quantitative implications of our model. When calibrating the model we exploit the availability of micro data for Chile and use moments we obtain from this data. This strategy is a contribution to the quantitative menu cost literature that typically targets pricing moments to calibrate the properties of the stochastic processes. Once the model is calibrated we introduce the Riots to the model as news shocks about future demand dispersion and explore its implications.

6.1 Calibration

Consistent with other quantitative menu cost model, we set the model frequency to monthly. We calibrate a set of parameters shown in Table 5 externally. The discount rate β is set to 0.997, which amounts to a 3.5% real rate, and the labor disutility parameter ξ is normalized to unity. The growth rate of nominal expenditure μ is 0.37%, which is the difference between the growth rate of nominal GDP and the growth rate of real GDP in Chile between 1996 and 2021. We take advantage of the supermarket-supplier matched dataset to discipline the firm idiosyncratic productivity process. To do this, we assume that the marginal cost of a supermarket consists only of the per-unit price paid to the supplier. Specifically, we treat the inverse of the supplier price of a good sold by the supermarket as the TFP of the firm. As such, the probability of receiving a productivity shock p_z is set to 0.24 to match the monthly probability of a supplier price change in the data. To calibrate the productivity process conditional on a price change, we take the monthly panel of supplier price series and drop periods in which there are no price changes. With the trimmed series, we estimate a panel AR(1) including supplier fixed effects using the Arellano and Bond (1991) estimator with the log of the inverse of the supplier prices as the dependent variable. We then set ρ_z to the estimated coefficient on the lagged term and σ_z to the standard deviation of the regression residuals.

The remainder of model parameters $(\omega, \psi, \rho_n, \sigma_n, f)$ are jointly chosen to minimize the distance between a set of empirical moments and the corresponding model moments. The set of empirical moments that we use in the internal calibration includes the average markup, pass-through of cost to price, the fraction of price changes that are positive, the average size of price changes, and the monthly frequency of a price change.

Table 6 reports the calibrated parameter values alongside the calibration moment most directly related to each parameter. Comparison of the data and model moments show that the model is able to match the moments well. The parameters (ω, ψ) govern the curvature of the demand function of firms and hence are related to the average markup as well as the cost pass-through to price. The average markup of 33% in the model is close to the average markup in the supplier-supermarket matched sample which we compute to be 34%.[12] The supplier-supermarket matched data also allows us to estimate the pass-through of costs to prices. After trimming the observations where we do not observe a change in the supermarket price, we estimate the following

[12] Although we are able to match supermarket products to suppliers, we do not observe the units of the transactions in all cases. For example, a supermarket could purchase a 12-pack of beer for \$12 and then sell each beer for \$2. In this case, the standard markup measure $\log(2) - \log(12)$ would be inaccurate. Therefore, we keep only products for which the observed supermarket price is greater than the observed supplier price when computing the average markup.

Table 6: Internal Calibration

Parameter	Description	Value	Moment	Model	Data
ω	Kimball elasticity	1.285	Avg. Markup	0.33	0.34
ψ	Kimball super-elasticity	–1.98	Cost Pass-through	0.29	0.29
ρ_n	Idio. Demand AR(1)	0.79	Fraction up	0.52	0.52
σ_n	Idio. Demand AR(1)	0.090	Size	0.120	0.117
f	Menu Cost	0.046	Frequency	0.30	0.30

Notes: This table presents the value of the internally calibrated parameters along with the model's performance with targeted moments compared to the data.

regression

$$\Delta \log \left(p_t^i\right) = \beta \cdot \Delta \log \left(c_t^i\right) + \text{Firm FE}_i + \epsilon_t^i, \tag{28}$$

where c_t^i denote the matched supplier price for product i. The pass-through regression yields a value of $\beta = 0.29$, which is in line with short and medium run estimates of price-cost pass-through in the literature.[13] The use of Kimball aggregation and deviation from CES ($\psi < 0$) generates incomplete pass-through of 0.29 in the model as in the data.

Trivially, the menu cost f is related to the frequency of price changes – if the menu cost is large, then firms will be adjusting their prices less often. In the Chilean data, the monthly frequency of a price change is 0.30. Finally, the parameters that govern the idiosyncratic demand process, (ρ_n, σ_n) are calibrated jointly the average size of price adjustments and the fraction of price changes that are positive. With an AR(1) process with $(\rho_n, \sigma_n) = (0.79, 0.09)$ for idiosyncratic demand, the model is able to match the average size of adjustments of 11.7% and fraction of changes that are positive of 52%.

6.2 News Shock and the Riots

We now introduce an unanticipated, one-time news shock about the dispersion of shocks to idiosyncratic demand in the future. Specifically, the news shock informs firms that with probability $\mathcal{P}$, the innovation to their demand in the

[13] For example, Burstein and Gopinath (2014) run the same regression for exchange rate pass-through and obtain estimates in the range of 0.24–0.41.

next period will be drawn from a distribution that is D times as dispersed relative to the standard value of σ_n. Following this, in all subsequent periods, they are told that the dispersion of demand shock goes back to the baseline value of σ_n with certainty. Formally, following the arrival of the news in t, idiosyncratic demand in the next period is drawn from the following distribution.

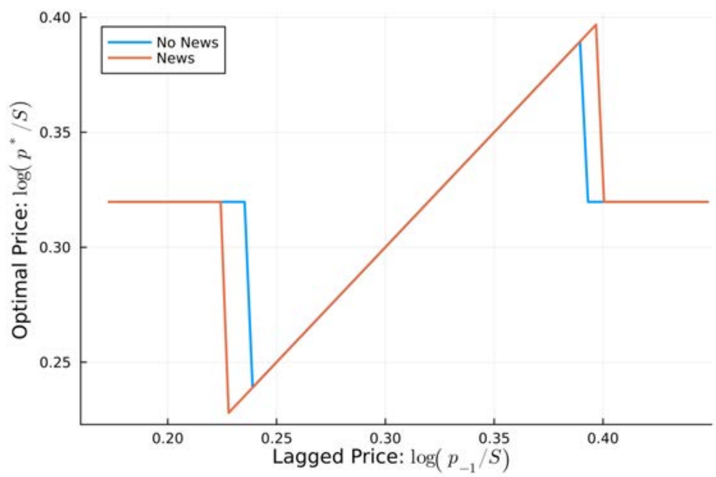
$$\begin{aligned} \log\left(n_{t+1}^i\right) &= \rho_n \cdot \log\left(n_t^i\right) + v_{t+1} \cdot \sigma_n \cdot \epsilon_{t+1}^{n,i} \\ v_{t+1} &= \begin{cases} D & \text{with prob. } \mathcal{P} \\ 1 & \text{with prob. } 1-\mathcal{P} \end{cases} \end{aligned}$$

As Figure 5 shows, following the Riots, measures of uncertainty increased to unprecedented levels in Chile. This is our motivation for using this particular process to model the Riots where we think of the Riots as introducing a high level of uncertainty for future demand for each product in a supermarket.

Even though from period $t+2$ onward the dispersion of the demand innovations goes back to normal, the arrival of the news creates a deviation of the economy from the stationary distribution which takes some time to converge back. Thus a proper analysis of the news shock requires solving for the transitional path of an economy that is initially in the stationary equilibrium and receives the news shock at $t=1$. In particular, we do this for both possible realizations of the news shock, as demand shock volatility may or may not increase in period $t=2$. We use a shooting algorithm to solve for the transitional dynamics of the model in response to the news shock. More details on the solution algorithm is provided in Appendix (D.2.2).

When price adjustments are costly, firms weigh the benefits of optimizing against the menu cost. As a result, firms only adjust their prices when the deviation from the desired price is sufficiently large. In the presence of higher uncertainty, that is when future realizations of idiosyncratic states become more dispersed, the firms' inaction region becomes wider as firms optimally choose to postpone price adjustments. This is the "wait-and-see" effect in Bloom (2009) and we refer to as the anticipation effect. If firms adjust today, the new price is more likely to become obsolete immediately in the next period.

Figure 7: Pricing Decision Rule With and Without News



Notes: This figure uses the firm pricing decision rule to show how news of future demand dispersion widen the inaction band on today's pricing decisions.

Should that happen, firms either pay the menu cost again or suffer from lower profits due to sub-optimal pricing. As a result, firms choose to not pay the menu cost today and wait until the uncertainty is resolved.

Figure 7 plots a representative slice of the pricing decision for a firm conditional on whether there is a news shock, with the lagged price (the price that will be in effect if the firm does not change its price) $\log(p^i_{t-1}/S_t)$ on the horizontal axis and the optimal price $\log(p^{i*}_t/S_t)$ on the vertical axis. The rest of the state variables are fixed at $\log(n) = 0.033$ and $\log(z) = 0$, where the former is about 0.2 standard deviations. The blue line shows the decision rule in the stationary equilibrium without a news shock and the orange line shows the decision rule after the arrival of the news shock. In response to the news shock, there is a widening of the inaction region which is represented by the 45-degree portion of the policy function – the firm does not adjust its price as doing so is costly and the deviation from the desired price is small enough. However, when the deviation from the desired price is sufficiently large, the firm changes its price to the desired level shown by the flat parts of the decision rule near the two edges. This leads to a second feature to highlight

Table 7: Monthly Regression of Frequency and Size on Riot Dummy

	Frequency	Size
Data	–0.112***	0.02***
	(0.0241)	(0.00603)

Notes: This table uses the Baseline monthly sample to calculate the decrease in the monthly frequency of price changes and the increase in the absolute size of a price change conditional on a price change taking place. The unconditional averages of these are 30 p.p and 11.8 p.p, respectively.

which is that the price changes that do take place are on average larger.[14] The widening of the inaction region rationalizes the empirical findings that price adjustment frequency decreases and the average size of price changes increases during the riot. A wider inaction region makes price changes less likely to occur as firms require a larger deviation from the optimal price to implement an adjustment. As a result, the size of a price change conditional on there being an adjustment is larger.

Before we can have a quantitatively meaningful exercise, we need some values for the parameters D and $\mathcal{P}$. Unfortunately, we do not have a direct way of setting these parameters. To get an idea of how the values of these parameters affect things, we solve the model with different combinations of $(D, \mathcal{P})$ and record the effect of the news shock on frequency of price changes and size of price changes, conditional on a change at the time of impact. We want to compare these to their data counterparts, which are the key results we report in Table 2. However these results were obtained from a daily sample while our model is monthly. Thus Table 7 recomputes these results for a sample where the daily data is aggregated to months.[15] We find that during the Riots the frequency of price changes at a monthly frequency fall by 11.2

[14]For other slices of decision rules at different values of $log(n)$ and $log(z)$, we see upward or downward shifts of the decision rules with news. This means that whether or not price changes get larger conditional on adjustment is a quantitative issue. We show below that they in fact do.

[15]The monthly aggregation of the daily data was done by keeping the prices observed on the first Friday of each month. If it was a holiday, we kept the weekday observation closest to that Friday.

p.p. and the size of price changes conditional on a change goes up by 2 p.p., both of which are still highly significant.

In order to assess the quantitative implication of a news shock to idiosyncratic demand volatility, we solve the model with different combinations of $(D, \mathcal{P})$ and report the effect of the news shock on frequency and size at the time of impact in Table 8.[16] We consider an increase in dispersion that is two to four times the unconditional value with a probability of being realized between 50% to 100%. In all configurations, the model is able to generate a reduction in price adjustment frequency, ranging from 0.8 p.p. to 3.9 p.p.. Correspondingly, the size of price adjustment in response to the news shock is always positive, with the effect ranging from 0.3 p.p. to 0.8 p.p.. Since there is no well-disciplined way of picking $(D, \mathcal{P})$, for the results that follow we use $D = 3$ and $\mathcal{P} = 0.75$, meaning that the firms are told the dispersion of the innovation to their idiosyncratic demand process is going to be three times as large as normal times with 75% probability. Given the extreme nature of the Riots, we think these are reasonable numbers, though changing them to some of the other values shown in Table 7 does not change the results in a meaningful way. Compared to the monthly empirical regression in Table 7, these values imply that news of uncertainty can explain 25% of the decrease in frequency and 40% of the increase in size observed during the month of the Chilean Riots.

It is important to keep in mind that the aforementioned results represent the effects of a news shock on impact. Upon arrival of the shock, firms expect future demand dispersion to increase but nothing fundamental has changed in the current period. This highlights the difference between our model and Vavra (2014) who examines the consequences of a simultaneous increase in idiosyncratic volatility and uncertainty about future realization. Our model is similar to Bloom (2009), as the news shock merely alters the expectation of future idiosyncratic volatility but is insulated from contemporaneous changes

[16] The model regression coefficient is obtained by comparing the mean frequency and size at the time of impact across two simulations of 10,000 firms – with and without the arrival of a news shock.

Table 8: Model Statistics: Firms' Reaction to the Arrival of News

(a) Frequency of Price Changes

D\P	0.5	0.75	1.0
2	–0.008	–0.019	–0.021
3	–0.010	–0.030	–0.038
4	–0.015	–0.032	–0.039

(b) Size of Price Changes

D\P	0.5	0.75	1.0
2	0.003	0.003	0.005
3	0.004	0.005	0.008
4	0.003	0.005	0.008

Notes: These tables use model simulated data under different configurations of D and P to show the decrease in monthly frequency and the increase on the absolute size of price changes implied by the calibrated model.

in idiosyncratic states. This is crucial for the implications on pricing behavior as an actual increase in idiosyncratic dispersion leads to more dispersed deviations from the desired price and therefore generates pressure for firms to adjust in either direction, which works against the "wait-and-see" effect.

Our goal is to show that the arrival of news about the dispersion of idiosyncratic demand is a plausible explanation for the empirical results we obtained in Section 4 – the decline in frequency and increase in size of price changes. As we discussed in the Introduction, there can be other changes that the Riots triggered which may deliver similar results. In fact, given that the model can deliver about a quarter to a third of the changes we observe, there is surely room for other explanations. For example, in the context of our model, one can consider a one-time increase in the menu cost f to reflect the idea that due to the Riots the opportunity cost of changing prices have increased. This may happen because supermarkets' limited human resources are better used elsewhere. Such a one-time increase in f will in fact deliver the right empirical results. The simple model of Dixit (1991) we presented in the Introduction delivers this result as well. Thus, an increase in the menu cost could complement our news based channel and close the gap between model and data.[17]

[17]Having said this, our empirical results show that the intensity of the Riots does not affect the change in the pricing behavior of supermarkets. Because one would expect that in areas with more intense riots the increase in f should be larger, it is unlikely that the menu cost change is the exclusive driver of our results. Nevertheless, a combining a contemporaneous increase in f with the arrival of the news can certainly increase the effects of

Another possible explanation is the decline in aggregate demand during the Riots. However, as (7) shows, what matters for an individual firm is their *relative* demand or market share ny/Y and as such a change in total demand would not lead to any change in pricing behavior by the firms in our model.

Finally, one can consider introducing the news about the dispersion of idiosyncratic TFP, instead of demand. For the general goal of our paper, where we want to show that making a distinction between the anticipation and realization effect of uncertainty, which shock we use does not really matter. Our result with news about TFP (available upon request) show that the qualitatively the effect is there but it is not nearly as strong as the results with demand. This is because TFP shocks in our model change from one period to the next only with $p_z = 0.23$, which is the only time that the news shock matters. In our experiments, when we increased p_z and ρ_z, then a quantitatively meaningful "wait-and-see" effect is generated, but of course at the expense of matching the calibration targets.

7 Policy Implications

So far, we have shown that a news shock about future idiosyncratic demand volatility leads to a decline in price adjustment frequency, and consequently a reduction in aggregate price flexibility. This has important implications for the transmission of nominal shocks to the real economy. If prices are perfectly flexible, that is they adjust costlessly every period, a nominal shock has no real effects because prices will adjust and completely absorb the shock. However, when prices are rigid, nominal shocks can have real effects as firms do not respond immediately to the shock.[18]

In this section, we explore the consequences of a news shock on monetary

our mechanism.

[18] Alvarez et al. (2016) show that in a textbook menu cost model that features CES aggregation, the real effect of monetary policy is inversely linked to the frequency of price changes. The sufficient statistic they derive does not apply here because of Kimball aggregation but recent work by Alvarez et al. (2022) show analytically that adding strategic complementarities amplify the real effects of monetary shocks holding frequency constant.

policy transmission. First, we show that the arrival of news about an increase in idiosyncratic demand dispersion in the future renders individual prices less flexible through a "wait-and-see" effect, which in turn raises the real transmission of a nominal policy shock. Second, we show that the overall potency of monetary policy crucially depends on the actual realization of idiosyncratic volatility. When the news shock is materialized, actual idiosyncratic dispersion shoots up and more firms find the need to adjust their prices and by larger amounts. As prices become more flexible, the real effects of policy are neutralized to a greater extent.

Recall that nominal expenditure in the model is given by $S_t = P_t C_t$ and so far we assumed that it grows at a deterministic rate μ, such that $\log(S_{t+1}) = \log(S_t) + \mu$. In what follows, we consider a one-time unanticipated shock to S of size $3 \times \mu$, which is a 1.11% increase to nominal expenditure in a month. This mimics a monetary policy expansion where the central bank increases the money supply once and for all. After this intervention S_t continues to follow its deterministic law of motion. The intervention gets the economy out of its stationary distribution initially and it eventually converges back to it. We use a shooting algorithm to characterize this transition path whose details are explained in Appendix (D.2.3). We report two statistics from each policy exercise. First is the peak response of output to the shock, which happens in the same period as the shock, as the model lacks any feature to delay the response. A useful way to report this is as a fraction of the nominal increase in S_t. Since $S = PC$, and $Y = C$, if all of the increase in S is reflected in aggregated price P (because prices are fully flexible), then C will not change. If on the other extreme prices cannot change at all, then P will be unchanged and all of the increase in S will be reflected in C. In the former case the impact response will be 0% and in the latter case it will be 100%. The second statistics, called Cumulative Impulse Response (CIR), cumulates the response of output over the duration of the non-zero response of output. In a monthly model like ours it will be the sum of all non-zero responses divided by 12. While the former statistic measures the immediate impact of monetary policy, the latter one also takes into account the persistence of the response.

Table 9: Output Response to MP Shock

	$t = 1$	$t = 2$	CIR
No News (MP at $t = 1$)	0.44	0.04	0.10
News (realized, MP at $t = 1$)	0.52	0.02	0.11
News (not realized, MP at $t = 1$)	0.52	0.12	0.12
News (realized, MP at $t = 2$)	0.00	0.09	0.02
News (not realized, MP at $t = 2$)	0.00	0.34	0.10

Notes: Each impulse response shows the average difference between an economy receiving a nominal expenditure shock in period 1 or 2 and an economy not receiving the nominal shock. The table uses the benchmark specification where $(D, P) = (3, 0.75)$.

Table 9 reports the results from our policy exercises where we show the response of output as a fraction of the shock to S in periods $t = 1$ and $t = 2$ as well as the CIR. Appendix D.2.4 shows how these are computed. The first row reports the case where there is a monetary policy intervention in period $t = 1$ with no news about the future. This corresponds to the "textbook" exercise conducted in the literature regularly. The economy has a fairly short-lived response to the shock with an impact response of 44% which quickly dies out.[19]. The next two rows show what happens if the firms receive news in period $t = 1$ about an increase in demand dispersion in period $t = 2$, while a monetary intervention is still taking place in the same period. Referring to Table 8, we use $D = 3$ and $\mathcal{P} = 0.75$ for these results. Row 2 shows the case where in period $t = 2$ the increase in dispersion is realized, where Row 3 shows the case where it is not. Naturally the $t = 1$ response in both cases is the same, and at 0.52 it is 18% higher than the case with no news.

[19] One needs to be careful in comparing the absolute magnitudes in this table with those that can be found in the literature due to differences in calibration, as most of the literature uses data from the U.S., where firm pricing behaviors differ from in Chile. In this regard, Alvarez et al. (2016) shows that the real effect of monetary shocks is proportional to the ratio of kurtosis to the frequency of price changes. In the U.S., the monthly frequency of price adjustments is about 0.11 and the kurtosis of price changes is 6.4 as reported by Vavra (2014). In our Chilean data, the frequency of price adjustment is almost three times as large at 0.30, with a smaller kurtosis of price changes of 5.6. Using the sufficient statistics approach of Alvarez et al. (2016) as a guide, everything else equal, the CIR in Chile should be approximately 29% that of the U.S.

Because news shock causes some firms to wait to change their prices, firms' responses to the change in nominal expenditure is slower. The real effect of the nominal expenditure shock in the following period rests crucially on the realization of the news shock. If the news does not realize, then the long-run response shown by CIR is about 20% larger. If the news do realize more firms change their prices in $t = 2$ and this cuts in to the overall effect of the policy. The increase in idiosyncratic demand dispersion leads to a surge in price adjustments by firms. When firms adjust, they adjust to both the nominal shock as well as individual demand shocks, thereby neutralizing a larger portion of the nominal shock. Two important lessons can be drawn from this first set of experiments. First, monetary interventions are more effective in times of heightened uncertainty about future idiosyncratic states as a result of the "wait-and-see" effect. Second, the overall effectiveness of a monetary intervention depends crucially on the realized path of volatility. If the news shock is never materialized and volatility does not end up increasing, monetary policy remains effective after the initial shock. On the other hand, the real effect of a monetary expansion is quickly attenuated if the news shock is materialized.

The last two rows of Table 9 show how the economy would react to an unexpected monetary policy shock in $t = 2$ while there is news about increased demand dispersion in period $t = 2$ that arrives in $t = 1$. Row 4 shows the case where in $t = 2$ demand dispersion in fact increases versus row 5 where it does not. Results in row 4 closely mimic the one in Vavra (2014) who studies a simultaneous increase in firm-level TFP dispersion and a monetary expansion. The effect of monetary policy (in period $t = 2$) is greatly reduced – the impact response at 0.09 and CIR at 0.02 are about 20% of their counterparts in row 1. In fact, when the increase in demand dispersion is realized, the desired prices of many firms lie outside of the inaction region. Thus, while the firms are adjusting their prices due to their larger idiosyncratic shocks, they also take the opportunity to account for the increase in S. The key result in Vavra (2014), monetary policy loses its effectiveness in periods where firm-level dispersion increases, holds in our model as well. Finally row 5 shows that if the monetary policy is implemented one period after the arrival of news but the news does not materialize, then the effectiveness of monetary policy is restored – the impact response is 25% smaller than that in row 1 because some of the firms that held off their price adjustment after the arrival of the news in $t = 1$ decide to change their prices in $t = 2$ and this extra adjustment reduces the effectiveness of monetary policy. When we look at the CIR, however, row 5 and row 1 show the same overall response.

In sum, we show that anticipation of higher future idiosyncratic dispersion reduces aggregate price flexibility and makes monetary intervention highly effective. However, in periods where increased volatility is realized, the real effect of monetary policy is greatly attenuated. The policy implication is that timing of monetary intervention is crucial when responding to a news shock about future idiosyncratic dispersion. If intervention is conducted concurrently with the news shock, policy is more effective, whereas if intervention is untimely, potency is tied to the realization of actual volatility.

8 Conclusion

Most analyses of uncertainty study two effects jointly: the realization (the world is more volatile today) and anticipation (it will likely be volatile tomorrow). In this paper we provide an empirical approach that allows us to isolate the effects of the anticipation channel. To do so we use a unique daily dataset of supermarket prices in Chile where we observe prices and costs of a large number of products over time. The Riots of October-November 2019 in Chile, which sparked unexpectedly rapidly and spread throughout the country, provide a quasi-natural experiment for this purpose. We find that in the one-month period following the first riots, supermarkets reduced the frequency of price adjustment by about 50%, while increasing the size of price changes that do take place by around 20%. Our results further show that while the supermarkets implemented these changes, the suppliers of the goods they sell did not change the way they price their products. We also show that the intensity of the Riots in the immediate area around the supermarket does not influence how much the supermarket deviates from their original pricing strategy. These results point to a demand-based explanation to the way the supermarkets change their pricing strategy, and one that relates to the expectation about the future. We formalize this in an otherwise standard menu cost model extended with anticipated increases in the dispersion of idiosyncratic demand. In order for these demand shocks to have an effect on pricing behavior, we replace the standard CES aggregator with the Kimball (1995) aggregator. Using the model, we are able to explain 25% of the decrease in the frequency of price changes and 40% of the increase in the size of price changes, isolating the anticipation effect from the realization effect.

Our work provides novel and important insights when assessing the effectiveness of monetary policy in times of increased uncertainty. Specifically, we find that real outcomes are *more* responsive to nominal disturbances such as monetary policy shocks in times of rising uncertainty, when the anticipation effect dominates (or the realization effect is nonexistent). Because firms hold off price adjustments, nominal shocks have larger real effects as prices do not respond as quickly. Interestingly, and consistent with Vavra (2014)'s analysis of idiosyncratic productivity dispersion, when higher demand dispersion is *eventually* realized, prices become more flexible and thus, monetary policy loses its effectiveness. Using our quantitative model as a laboratory, we show that the effectiveness of a policy intervention crucially depends on how much and when the news about future events get realized – before the volatility is realized, policy is more effective than usual but, when the news materialize and the dispersion increases, then policy becomes less effective. It is thus crucial for policymakers to identify the nature of the uncertainty shock and its effect on firms' price setting behavior when calibrating their monetary policy response in uncertain times.

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Online Appendix – 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

$$V(x) = \min E \left\{ \int_0^\infty kx_t^2 e^{-\rho t} + \sum_i g e^{-\rho t_i} | x_0 = x \right\} \tag{29}$$

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

$$h = \left(\frac{6\sigma^2 g}{k} \right)^{1/4} \tag{30}$$

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 (30) while the distribution they face in the current instant remains the same blue distribution.

B Pricing data

B.1 Construction of datasets

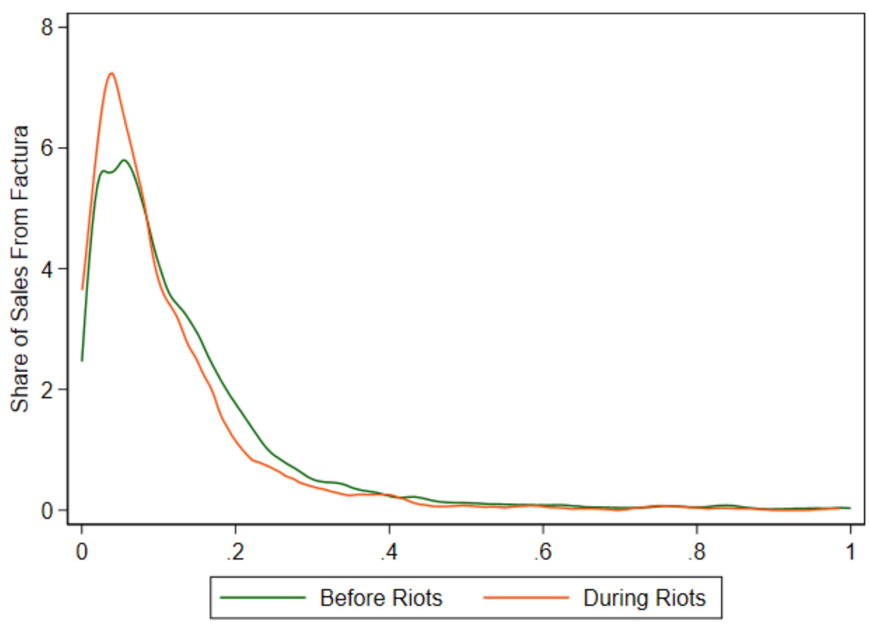
This appendix describes the pricing data used in this paper and how the datasets used for the empirical analysis in the main text were constructed. Our core data source is the register of the universe of business-to-business transactions reported by Chilean firms in the electronic VAT invoices ("Factura Electronica") to the Chilean Tax Authority ("Servicio de Impuestos Interntos"). This electronic reporting became mandatory on January 1st, 2014. 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, and a description, quantity sold, and price paid for each product in the invoice. 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, a VAT invoice or a regular ticket ("boleta electrónica") will be issued respectively. All invoice transactions are recorded in the dataset we study. Sales to final consumers are not observable at the same granular level before 2021. Only daily sales aggregates at the firm level were available, which we used later 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 buyer (from the suppliers' perspective) were classified under the main economic activity "retail traded in non-specialized stores". Then, we focused on firms that report annual sales higher than 4 million U.S. dollars. Given that the economic activity classification was not restrictive enough to exclude nonsupermarket retailers, such as warehouses or departmental stores, we required these firms to also have among the list of their sold products bread ("pan") and milk ("leche").

Based on the firms that fulfill the requirement described above, we constructed the two main datasets used for the empirical analysis, the baseline sample and the matched sample. The raw data accounts for 13% of supermarkets' total sales and 100% of their purchases. Figure 8 shows the distribution of this ratio for 26 supermarkets in the final sample, where total sales and business-to-business transactions are simultaneously available on a daily basis. The distribution does not change drastically during the riots.

Figure 8: Share of Sales from Factura over total sales



Since our unit of analysis is composed of products sold by supermarkets at specific locations, we encountered the challenge that even if firms report an identifier about branches, reporting the locations of the branches is not required by the Tax Authority. To address this issue, we determine a branch's geographical location as the most recurrent municipality reported by the buyers. We request that at least half of the buyers report the same municipality on a weekly basis, and it remains the same over time. Specifically, we used the following condition to validate a branch's location: (i) register sales on at least 50% of the days between their first and last observation in the dataset; (ii) at least 80% of weeks with one invoice or more issued as seller party must have at least 50% of buyers registered in the same municipality; (iii) have 95% of weeks registering the same municipality as the most recurrent among its buyers; and (iv) a supermarket's valid branch code must have positive sales on at least 80 days in the dataset.

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. Next, we apply the procedure proposed by Kehoe and Midrigan (2015) to filter out systematic discount prices that may remain. 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.[20]

To construct the matched sample two parallel methods of fuzzy matching were used, cosine similarity and 1-gram distance. To validate a match, we required either of the following three alternative conditions were satisfied: cosine distance is less or equal than 0.03, 1-gram distance is less or equal than 3, or cosine distance is less or equal than 0.05 and 1-gram distance less or equal than 5. Table 10 shows one example of successful matching according to each matching criterion as well as two unsuccessfully matched products.

Table 11 shows a sample of the 10 most traded products in the final databases.

The most traded product in the baseline sample are two different brands of sugar, three types of bread ("hallulla", "marraqueta" and "pan hot dog"), two

[20] 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 fortnight over 10 or more consecutive fortnights. The remaining data treatments is the same for this sample.

Table 10: Examples of fuzzy matching of product descriptions

	Product Description From Supermarket	Product Description From Supplier	Cosine Distance	Q-gram Distance
Successful matches	Trutro Entero Pollo	Trutro Entero Pollo Granel	$\in (0.2, 0.3)$	≥ 3
	Hallula KG	Hallulla	> 0.03	$\in [2, 3]$
	Lechuga Escarola Bolsa Un	Lechuga Escarola Bolsa	$\in (0.03, 0.05]$	$\in (3, 5]$
Unsuccessful matches	Atun Lomito Agua	Consumo Agua Potable Punta	> 0.5	-
	Platano Granel	Papas Granel	-	$\in (5, 6])$

Table 11: 10 more traded products

#	baseline sample	Matched Sample
1	Azucar Granulada 1 KG	Azucar Granulada 1 KG
2	Hallulla KG	Limon Malla 1 KG
3	Sal de Mesa XXXXX 1 KG	Palta Hass Granel
4	Aceite Vegetal 900 CC	Harina Polvo 1 KG
5	Marraqueta KG	Tomate Primera KG
6	Aceite Vegetal B 900 CC	Zanahoria Bolsa 1 KG
7	Azucar Granulada XXXXX 1 KG	Pimenton Verde
8	Aceite Vegetal 900 CC	Azucar Granulada XXXXX 1 KG
9	Pan Hot Dog KG	Aceite Vegetal 5 LT
10	Sal Fina 1 Kg	Aceite Vegetal 900 CC

brands of salt, and two brands of cooking oil. In the matched sample, flour, fruits and vegetables enter as the most traded products ("limon", "palta", "zanahoria" and "pimenton"). Therefore, our sample contains everyday groceries that are important in the price basket of any country.

B.2 Comparing the Chilean pricing data

Table 12 benchmarks the Chilean pricing data to the US data by replicating Nakamura and Steinsson (2008) monthly statistics. For this exercise, we focus on the pre-Riots period by ending the sample on September 30, 2019. The monthly data we use here was constructed following the same steps described in the calibration section of the model. The frequency is calculated as the ratio between the number of price changes and the number of observed months for each product. We calculate the implied duration as follows, $d = -1/\log(1-f)$,

Table 12: Frequency of Price Change (Nakamura and Steinsson, 2008)

Statistic	N&S - Monthly Data		From Calibration Sample	From Baseline Sample	
	Processed food	Unprocessed food	Monthly Data	Monthly Data	Daily Data
Median Freq	25.9	37.3	30.5	29.4	1
Median Implied Duration	3.3	2.1	2.7	2.9	3.2
Mean Freq	25.5	39.5	29.7	30.5	1.2

Note: The column N&S corresponds to the Nakamura and Steinsson (2008) results for the groups of products "Processed food" and "Unprocessed food" when sales and substitutions are included in the calculations. Frequencies are reported in percent per unit of time, months or days accordingly. Duration is always reported in months.

where f is the median or mean frequency.[21] For comparison purposes, we also report statistics for the daily baseline sample.

The frequency and duration of price changes calculated with the monthly Chilean data are in line with the magnitude that Nakamura and Steinsson (2008) report for the US. We also observe a slightly higher duration of prices when calculated at the daily level. Moreover, the results show the probability of a price change in a month is around 30% while the daily probability is in the order of 1%.

In Table 13, we run a second exercise to compare the Chilean prices data to the US data replicating Eichenbaum et al. (2014). We calculate the fraction of price changes that are smaller in absolute value than 1, 2.5, and 5 percent. To do so, we consider two databases, one with no adjustments and another one in which only price changes bigger than $1CLP were considered.[22] Columns 2 and 3 show the results using the baseline daily sample and the monthly data used to calibrate the model, respectively.[23] Similarly to the first exercise, we found the Chilean data follows closely the behavior of US data. Nevertheless, the higher frequency and richness of our data, combined with the Chilean Riots, allow us to study how economic distress affects price setting behavior at higher frequencies, an impossible task with US data.

[21] Because our data lacks product classifications, we cannot use the weights by product category implemented by Nakamura and Steinsson (2008).

[22] The Chilean exchange rate typically fluctuates between 550 and 850 CLP per US dollar.

[23] The frequency of price changes differs from the table 12 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 13: Small Price Changes (Eichenbaum et al, 2014)

	Eichenbaum et al (2014)		Chilean Data - Daily		Chilean Data - Monthly	
Total number of prices	4,791,569		10,069,681		87,804	
Total number of price changes	1,047,547		101,761		30,143	
Frequency of Price changes	21.9		1.01		34.3	
	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	17,299	17.0	2,524	8.4
Remove price changes that are less than a penny	61,017	5.9	6,154	6.0	1,153	3.8
Price changes smaller than 2.5 percent in absolute value						
No adjustment	142,822	13.6	27,996	27.5	6,267	20.8
Remove price changes that are less than a penny	132,935	12.8	16,751	16.5	4,896	16.2
Price changes smaller than 5 percent in absolute value						
No adjustment	256,303	24.5	45,433	44.6	12,122	40,2
Remove price changes that are less than a penny	245,519	24.3	34,119	33.5	10,595	35.1

Note: Replication of Table 1 of Eichenbaum et al. (2014), unweighted price changes statistics.

C Additional Empirical Results

C.1 Unfiltered Prices

Table 14 replicates the baseline analysis with raw unfiltered prices. As seen in Figure 2, the raw price series contain noise and multiple small price changes that are quickly reversed. The frequency results retain their sign and significance, while the noise renders the size of changes insignificant. These results suggest that the frequency of temporary price changes was also reduced during the riots.

Table 14: Baseline Estimation with Unfiltered Prices: Baseline Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.00650***	-0.00814***	0.00188	0.00130
	(0.00148)	(0.00178)	(0.00215)	(0.00187)
Observations	6,558,686	6,558,686	700,104	685,751
Adjusted R-squared	0.099	0.100	0.414	0.432
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.107	0.105	0.107	0.108

Note: Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In this table, instead of the filtered prices, we use the actual prices. That is, the dependent variables of frequency and magnitude of price changes include the short-term fluctuations.

C.2 Size Heterogeneity

We explore if the effects of riots on price-setting behavior are driven by size heterogeneity among supermarkets. We conducted this analysis from two approaches. The first was based on the size of the supermarkets within the database. To do this, we interact the riots dummy in the baseline regression with an indicator variable equal to one if the number of products associated with a supermarket location is above the median in the sample and zero otherwise. The results are shown in Panel A of Table 15. The estimated coefficients of the interactive term are statistically insignificant for the frequency of adjustments in both directions and the size of positive changes. However, for the size of negative price changes, we find that large supermarkets decrease prices by less in response to the riots. Panel B shows the same exercise while defining a Big supermarket according to average monthly sales observed from September 2018 to September 2019. The results align with those of the first approach and confirm the robustness of the effects of the riots after explicitly incorporating supermarket size heterogeneity.

Table 15: Baseline Estimation with Supermarket Size Interaction: Unmatched Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
Panel A: according number of observations				
D	-0.00346***	-0.00287***	0.0243**	0.0420***
	(0.000429)	(0.000368)	(0.0104)	(0.00976)
D * Big Supermarkets	0.000922	-0.000908	-0.0112	-0.0331***
	(0.000901)	(0.000566)	(0.0119)	(0.0126)
Observations	7,203,155	7,203,155	43,475	34,088
Adjusted R-squared	0.002	0.002	0.381	0.439
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00695	0.00560	0.102	0.110
Panel B: according monthly mean of Total Sales (before the continuity filter)				
D	-0.00387***	-0.00325***	0.0240**	0.0482***
	(0.000444)	(0.000369)	(0.0112)	(0.0107)
D * Big Supermarkets	0.00183**	-0.000228	-0.00922	-0.0416***
	(0.000846)	(0.000543)	(0.0126)	(0.0128)
Observations	5,999,030	5,999,030	36,778	29,598
Adjusted R-squared	0.002	0.002	0.381	0.440
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00702	0.00579	0.101	0.109

Note: Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Panel A presents the results of including a dummy that indicates if the supermarket location has a number of products in the sample above the median and include an interaction between the riots dummy and this Big Supermarkets dummy. Panel B shows the results when supermarket size is defined by average monthly sales observed from September 2018 to September 2019.

C.3 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 riots 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 if our baseline estimates are robust to including wage rates as a control. In Table 16, we control for the monthly logarithm of Wage Bill calculated as the total sum

Table 16: Baseline Estimation with Labor variables of supermarkets as controls: Unmatched Sample

	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Negative Size
D	-0.00326***	-0.00365***	0.0130**	0.0233***
	(0.000467)	(0.000398)	(0.00609)	(0.00754)
log Monthly Wage Bill	-0.00203***	0.000109	0.0259***	0.0283**
	(0.000453)	(0.000524)	(0.00927)	(0.0118)
Observations	6,938,421	6,938,421	41,889	32,867
Adjusted R-squared	0.002	0.002	0.380	0.440
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00695	0.00560	0.102	0.110

Note: Clustered standard errors at location-seller level in parentheses. *** p<0.01, ** p<0.05, * p<0.1 This table shows the baseline results controlled by the monthly log of Wage Bill calculated as the total sum of taxable income across all the workers at the supermarket level in the current month. The wage information is reported by firms to the Unemployment Insurance registry (UI).

of taxable income across all the workers reported by firms to the Unemployment Insurance registry (UI) in the month under analysis. When labor costs are included, the direction and statistical significance of riots in the pricing pattern are maintained.

C.4 Matched Sample

Table 17 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. In fact, when a supermarket's supplier increases (decreases) its prices for a product, supermarkets are less (more) likely to decrease prices and, conditional on reducing them, they cut their prices by less (more). Note that the drop in frequency of price increases and decreases

Table 17: Supermarket Analysis: Matched Sample

Variables	(1) Positive Breaks	(2) Negative Breaks	(3) Size Positive	(4) Size Negative
D	-0.00433***	-0.00555***	0.0413***	0.00174
	(0.000810)	(0.000667)	(0.0132)	(0.0113)
Recent supplier's price change	0.0135***	-0.00907***	0.0508***	-0.157***
	(0.00137)	(0.00104)	(0.0109)	(0.0204)
Observations	2,209,634	2,209,634	13,999	12,416
Adjusted R-squared	0.003	0.003	0.344	0.468
Controls	Yes	Yes	Yes	Yes
Economic Activity Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00740	0.00668	0.105	0.110

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

during the riots remains for this sub-sample after controlling for recent changes in the cost of the goods sold. In terms of size, we find that price increases are significantly larger after the riots, while we lose significance for the size of price decreases, which likely comes from the fall in the number of observations as we are restricted to the matched sample of products.

D Model Appendix

D.1 Model Derivations

Household

The household solves

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t\left(logC_t-\chi h_t\right)\right] \tag{31}$$

subject to

$$P_tC_t+\ Q_t\cdot B_{t+1}\leq B_t+W_th_t+\Pi_t \tag{32}$$

The optimality conditions are

$$1 \quad = P_tC_t\lambda_t \tag{33}$$

$$\frac{W_t}{P_t} \quad = \chi C_t \tag{34}$$

Final Good Producer

Taking as given variety prices p_t^i, as well as P_t, n_t^i and aggregate demand Y_t, the final-good producer chooses y_t^i to maximize profits

$$\max_{y_t^i} \quad 1-\int\frac{p_t^iy_t^i}{P_tY_t}di \quad \text{subject to} \int G\left(\frac{n_t^iy_t^i}{Y_t}\right)di=1 \tag{35}$$

Taking the first-order condition with respect to y_t^i/Y_t yields the optimal demand schedule for each variety

$$\frac{p_t^i}{P_t} = \lambda n_t^i G'\left(\frac{n_t^i y_t^i}{Y_t}\right) \tag{36}$$

$$\frac{p_t^i}{P_t} = \lambda n_t^i \left[(1+\psi_p)\frac{n_t^i y_t^i}{Y_t} - \psi_p\right]^{\frac{1-\omega_p}{\omega_p}} \tag{37}$$

$$\left(\frac{p_t^i}{\lambda n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}} = (1+\psi_p)\frac{n_t^i y_t^i}{Y_t} - \psi_p \tag{38}$$

$$\frac{n_t^i y_t^i}{Y_t} = \frac{1}{1+\psi_p}\left(\left(\frac{p_t^i}{\lambda n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right) \tag{39}$$

Substituting the optimal demand schedule into the Kimball aggregator yields the expression for the Lagrange multiplier λ of the final producer's problem

$$1 = \int \left\{\frac{\omega_p}{1+\psi_p}\left[(1+\psi_p)\frac{n_t^i y_t^i}{Y_t} - \psi_p\right]^{\frac{1}{\omega_p}} + 1 - \frac{\omega_p}{1+\psi_p}\right\} di \tag{40}$$

$$1 = \int \left\{\frac{\omega_p}{1+\psi_p}\left[\left(\frac{p_t^i}{\lambda n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}}\right]^{\frac{1}{\omega_p}} + 1 - \frac{\omega_p}{1+\psi_p}\right\} di \tag{41}$$

$$1 = \frac{\omega_p}{1+\psi_p} \cdot \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1}{1-\omega_p}} di + \int 1 di - \int \frac{\omega_p}{1+\psi_p} di \tag{42}$$

$$\frac{\omega_p}{1+\psi_p} = \frac{\omega_p}{1+\psi_p} \cdot \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1}{1-\omega_p}} di \tag{43}$$

$$1 = \lambda^{\frac{1}{\omega_p - 1}} \cdot \int \left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1}{1-\omega_p}} di \tag{44}$$

$$\lambda^{\frac{1}{1-\omega_p}} = \int \left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1}{1-\omega_p}} di \tag{45}$$

$$\lambda = \left[\int \left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1}{1-\omega_p}} di\right]^{1-\omega_p} \tag{46}$$

The aggregate price index P_t can be derived from the zero profit condition

$$
\begin{aligned}
1 &= \int \frac{p_t^i y_t^i}{P_t Y_t} di && (47)\\
1 &= \int \frac{p_t^i}{P_t}\left[\frac{1}{n_t^i}\frac{1}{1+\psi_p}\left(\left(\frac{p_t^i}{\lambda n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right)\right] di && (48)\\
1 &= \int \frac{p_t^i}{P_t}\left[\frac{1}{n_t^i}\frac{1}{1+\psi_p}\left(\frac{p_t^i}{\lambda n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}} + \frac{1}{n_t^i}\frac{\psi_p}{1+\psi_p}\right] di && (49)\\
1 &= \lambda^{\frac{-\omega_p}{1-\omega_p}}\frac{1}{1+\psi_p}\int\left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1}{1-\omega_p}} di + \frac{\psi_p}{1+\psi_p}\int \frac{p_t^i}{n_t^i P_t} di && (50)\\
1 &= \frac{1}{1+\psi_p}\left[\int\left(\frac{p_t^i}{n_t^i P_t}\right)^{\frac{1}{1-\omega_p}} di\right]^{1-\omega_P} + \frac{\psi_p}{1+\psi_p}\int \frac{p_t^i}{n_t^i P_t} di && (51)\\
P_t &= \frac{1}{1+\psi_p}\left[\int\left(\frac{p_t^i}{n_t^i}\right)^{\frac{1}{1-\omega_p}} di\right]^{1-\omega_P} + \frac{\psi_p}{1+\psi_p}\int \frac{p_t^i}{n_t^i} di && (52)
\end{aligned}
$$

Intermediate Producers

Demand facing intermediate producer is

$$
y_t^i = \frac{Y_t}{n_t^i}\cdot\frac{1}{1+\psi_p}\cdot\left[\left(\frac{p_t^i}{\lambda_t n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right] \quad (53)
$$

The firm's profit function (gross of adjustment cost) is given by

$$
\begin{aligned}
\pi &= \left(\frac{p_t^i}{P_t} - \frac{W_t}{z_t^i P_t}\right)\frac{C_t}{n_t^i}\cdot\frac{1}{1+\psi_p}\cdot\left[\left(\frac{p_t^i}{\lambda_t n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right] && (54)\\
&= \left(\frac{p_t^i/S_t}{P_t/S_t} - \frac{\omega C_t}{z_t^i}\right)\frac{C_t}{n_t^i}\cdot\frac{1}{1+\psi_p}\cdot\left[\left(\frac{p_t^i/S_t}{\lambda_t n_t^i (P_t/S_t)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right] && (55)\\
&= \left(\frac{p_t^i/S_t}{P_t/S_t} - \frac{\omega S_t}{z_t^i P_t}\right)\cdot\frac{(P_t/S_t)^{-1}}{n_t^i}\cdot\frac{1}{1+\psi_p}\cdot\left[\left(\frac{p_t^i/S_t}{\lambda_t n_t^i (P_t/S_t)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right] && (56)\\
&= \left(\frac{p_t^i/S_t}{P_t/S_t} - \frac{\omega}{z_t^i (P_t/S_t)}\right)\cdot\frac{(P_t/S_t)^{-1}}{n_t^i}\cdot\frac{1}{1+\psi_p}\cdot\left[\left(\frac{p_t^i/S_t}{\lambda_t n_t^i (P_t/S_t)}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right] && (57)
\end{aligned}
$$

In the first equality, we replace Y_t with C_t 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 $S_t = P_t \cdot C_t$. We also normalize all nominal prices by S_t to remove S_t as a variable.

In the next section, we describe the solution method of the intermediate firms' problem as well as the solution algorithm of the whole model.

D.2 Solution Method and Algorithm

D.2.1 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 (11) and (12) 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.2.2 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 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 (20,21,22) 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 $\{\hat{V}_A(\cdot;t), \hat{V}_N(\cdot;t), \hat{V}(\cdot;t), \hat{\frac{p^*}{S}}(\cdot;t)\}_{t=2}^T$

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

7. In period $t = 1$, solve equations (20,21,22) 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 $\{\hat{V}_A(\cdot; 1), \hat{V}_N(\cdot; 1), \hat{V}(\cdot; 1), \hat{\frac{p^*}{S}}(\cdot; 1)\}$.[24]

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 $\hat{\frac{p^*}{S}}(\cdot; 1)$ 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 $\hat{H}(\cdot; t)$. 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 $\{\hat{\frac{\hat{P}_t}{S_t}}, \hat{\hat{\lambda}}_t\}_{t=1}^{T}$ period-by-period from equations (11) and (12) using implied sequence of firm distributions $\{\hat{H}(\cdot; t)\}_{t=1}^{T}$ for the case where the news shock is realized. Similarly, compute $\{\tilde{\frac{\tilde{P}}{S}}, \tilde{\tilde{\lambda}}_t\}_{t=1}^{T}$ for the case where the news shock is not realized.

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

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

D.2.3 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 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 $\{\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t\}_{t=1}^T$.

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 (20,21,22) 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 $t = T-1, ..., 1$, using the guesses $(\frac{\hat{P}_t}{S_t}, \hat{\lambda}_t)$ and $\hat{V}(\cdot; t+1)$ as the continuation value.

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

6. Assume that the economy is initially at the stationary equilibrium before the arrival of the monetary policy shock in period 1. 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 $\hat{\frac{p^*}{S}}(\cdot; 1)$ 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 $\hat{H}(\cdot; t)$. In particular, the shocks to n are more dispersed in period 2 when the news shock is realized.

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

7. 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 (11) and (12) using implied sequence of firm distributions $\{\hat{H}(\cdot; t)\}_{t=1}^{T}$.

8. Compute the absolute difference between the guessed sequences $\{\hat{\frac{P_t}{S_t}}, \hat{\lambda}_t\}_{t=1}^{T}$ and the implied sequences $\{\hat{\hat{\frac{P_t}{S_t}}}, \hat{\hat{\lambda}}_t\}_{t=1}^{T}\}$ 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.2.2) 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.2.2) 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 (20,21,22) 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 $\{\hat{\frac{\hat{P}_t}{S_t}}, \hat{\hat{\lambda}}_t\}_{t=1}^{T}$ period-by-period from equations (11) and (12) using implied sequence of firm distributions $\{\hat{H}(\cdot;t)\}_{t=1}^{T}$ for the case where the news shock is realized.

Similarly, compute $\{\frac{\tilde{\tilde{P}}}{S}, \tilde{\tilde{\lambda}}_t\}_{t=1}^{T}$ 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.2.4 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 changes reported in Table (8). The exact procedure is as follows. In our simulation, we use $N = 30,000$ and $B = 100$.

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 *riot* 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 $T = 15$. The solution algorithms can be found in Section (D.2.2) and Section (D.2.3).

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 at 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 at 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 at period $t = 1$ which is realized in $t = 2$ and a one-time nominal shock in period $t = 2$ and (ii) a transition with a one-time news shock at period $t = 1$ which is realized in $t = 2$ in the absence of nominal shocks.

Row 5: The output response is computed as the difference between (i) a transition with a one-time news shock at period $t = 1$ which is not realized and a one-time nominal shock in period $t = 2$ and (ii) a transition with a one-time news shock at period $t = 1$ which is not realized in the absence of nominal shocks.

In all rows, the cumulative impulse response is computed as the cumulative differences between two transitions over the first five periods divided by five.[25]

[25] Across all transitions, the aggregate price and output reverts to the steady state value after five periods. We compute the CIR using only the first five periods in order to eliminate noises at more distant horizons.