Pricing under Distress*

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Abstract

When uncertainty increases it creates two confounding effects: a realization effect and an anticipation effect. These two effects may have opposing results on current behavior. By using a quasi natural experiment focusing on the pricing behavior of supermarkets during the 2019 riots in Chile we identify the consequences of the anticipation effect: during the 31-day period following the riots supermarkets reduce the frequency of price changes by about 50% and conditional on a price change, the absolute magnitude of price changes is about 50% larger. We attribute these changes to the arrival of news about a future increase in idiosyncratic demand dispersion. We develop a quantitative menu cost model and calibrate it using Chilean product-level data. Only news about future demand dispersion can deliver simultaneously less frequent and conditionally larger price changes. The effectiveness of monetary policy interventions crucially depends on the timing of the intervention relative to the arrival of the news and whether or not the change materializes. In particular, while the realization of uncertainty decreases the effectiveness of monetary policy, monetary policy is more effective when the news about future volatility arrives.

Keywords: Menu costs, uncertainty, demand shocks, variable markups, riots, sticky prices.

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1 Introduction

The pricing decision of firms is central in macroeconomics, in particular because the degree of price flexibility determines the real effects of monetary policy. The more frequently firms adjust their prices, the less effective monetary policy will be 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. An increase in this dispersion has two distinct effects: the distribution is more disperse today and it is expected to remain more dispersed tomorrow. We can label these as the realization and the anticipation of the uncertainty, respectively. It is reasonable to expect that these two effects have different implications for behavior. For example upon receiving the information that a hurricane may have a landfall nearby in the next few days, residents may board up their houses or buy essential groceries. When and if a landfall actually occurs, they stay home until the storm passes. It is important to realize that the former activities are done regardless of whether or not the landfall actually occurs.

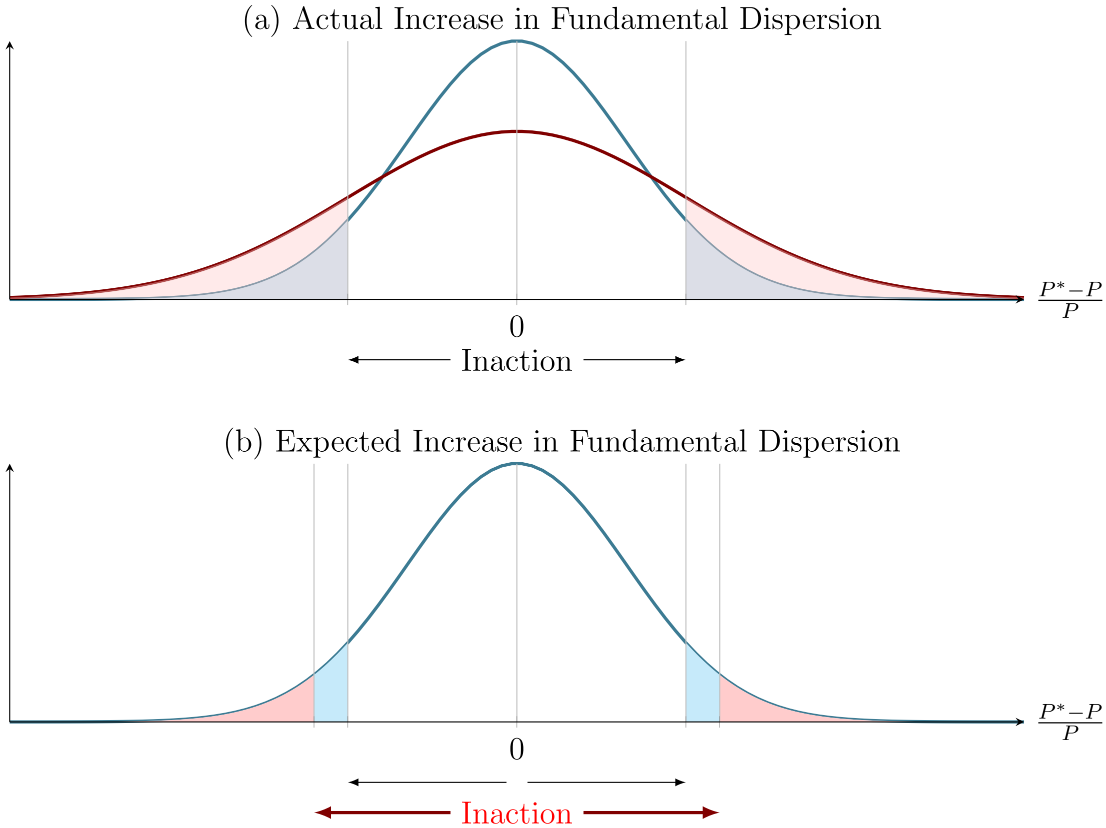
To understand the fundamental difference between expected and realized dispersion let's consider a stylized menu cost model where the firms draw an idiosyncratic variable from a fundamental distribution whose dispersion changes over time. In any given period the firm, facing a fixed cost of adjustment, chooses to keep its current price unchanged when P^*, its desired price change is not too far from P, its previous price. The blue distribution in both panels of Figure 1 shows the percentage 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 red line shows the new distribution of desired price changes. Because the inaction bands only depend on the (unchanged) future fundamental distribution in the future, the inaction limits do not change. The wider red distribution has more mass in the tails relative to the blue distribution, therefore, there are more price changes (the red shaded area is added to the blue shaded area) and the average price change is higher. This is the effect of a pure change in dispersion isolated from the anticipation effect.

In Panel (b) we show what happens if tomorrow's dispersion is expected to increase with no change in today's distribution. Because the distribution does not change today, the distribution of desired price changes is also unchanged.[1] 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 changes conditional on a change. This is the effect of anticipation isolated from the realization effect.

In this paper our contribution to the understanding of how uncertainty affects the macroeconomy is twofold. First, using a novel dataset and a quasi-natural experiment, we demonstrate that there are episodes where the anticipation of uncertainty may occur without the concurrent realization of the increase in dispersion. Second, we build a quantitative model to investigate the firm-level, aggregate and policy implications of such episodes. The quan-

[1] Changes in expectation about states in the future affect the desired price today. This effectively alters the desired price gap distribution today but the effect is second-order.

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



Note: Panel (a) shows the effects of an increase in the price gap distribution, going from the less dispersed blue distribution to the more dispersed red distribution. All else are held equal, including expectations about future states. The grey vertical lines represent the inaction bands. The blue and red 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 regions as depicted by the grey vertical lines. The red shaded areas represent the mass of firms adjusting whereas the blue shaded areas represent the mass of firms that choose not to adjust after the shock to future dispersion.

titative literature on pricing has mainly focused on how firms change their prices over the business cycle (Nakamura and Steinsson, 2010; Midrigan, 2011; Vavra, 2014). Using both the empirical results and the quantitative model, we provide evidence that *news shocks* about second moments, shocks that are large and less frequent relative to traditional business cycle fluctuations, are indeed important.[2] Because monetary policy is one of the key policy

[2]Other strains of macroeconomics have studied rare disasters both, theoretically (Barro, 1972; Gabaix, 2012) and empirically; Baskaya and Kalemli-Ozcan (2016) use the 1999 earthquake in Turkey, Acemoglu et

instruments of a government in response to large and infrequent shocks, studying policy in this context becomes even more important.

A good example of the aforementioned large and infrequent shocks is social unrest. According to Hadzi-Vaskov et al. (2021) riots have increased by 244% during the last decade, triggering long-lasting macroeconomic effects. This form of social unrest has been increasing in both the developing countries (e.g. the Arab world and Latin America) and the developed countries (e.g. France and the U.S.). Further examples of these shocks can be found in natural disasters such as hurricanes or earthquakes. In this paper we use the Chilean riots of 2019 to study the effect of social unrest on the pricing dynamics of supermarkets. On October 18, 2019, major riots unexpectedly erupted all across Chile when peaceful protests of earlier increases in subway fares turned violent. During the course of the next 30 days major protests and looting of public property and private businesses, including supermarkets followed.

Turning to our empirical results, we use a uniquely granular transaction-level administrative dataset that contains price and quantity information for supermarkets. We aggregate these to obtain a daily dataset and combine with information that comes from suppliers of supermarkets. This allows us to understand price changes at the supermarket level, controlling for changes in replacement costs – essentially computing the markup of the supermarkets at the good level. 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. Moreover, the Chilean unrest was completely unexpected, with a clear beginning date and a well-defined normalization period. Thus the unique data and the unexpected nature of the social turmoil, make Chile a perfect laboratory to study the effects

al. (2018) use the Arab Spring in the early 2010s, Boehm et al. (2019) and Wieland (2019) use the 2011 earthquake in Japan.

of large unexpected events on firms' pricing decisions.

We find that the Chilean riots are associated with a 40% (60%) decrease in the frequency of negative (positive) price changes and that conditional on a price change the absolute size was 50% 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, nor did the supermarkets change the way they react to their costs. These results rule out supply factors as a possible explanation of the results we document. We also show that the geographical intensity of the riots is uncorrelated with their effects, which rules out possible concurrent demand disturbances. This leaves us with changes in expectations about future demand as a possible explanation.

To understand how we can justify the empirical evidence, we extend a state-of-the-art quantitative menu-cost model (Vavra, 2014) to study changes to expected demand. To do so, we include an idiosyncratic demand shock in the model. In order to allow for demand shocks to affect prices, we allow for variable markups using a Kimball (1995) aggregator. We also extend the stochastic structure to have time-varying dispersion of the idiosyncratic demand shock and allow for news about future realization of this dispersion in form of anticipated shocks (Barsky and Sims, 2011). We lever the granularity of our data to by calibrating the model using pricing and cost data at the product level. Observing the prices paid by supermarkets for their products allows us to make our model consistent with moments that other studies cannot target. For instance, we use product level data on the price paid by supermarkets to their suppliers to estimate the idiosyncratic TFP process of a supermarket. We also use product level cost-pass-through regressions to discipline the curvature in the Kimball (1995) aggregator.

In the model, news shocks to future dispersion of idiosyncratic demand have two distinct effects on the pricing policy of supermarkets. First, the increase in the expected dispersion of future idiosyncratic demand widen the inaction region of the pricing policy. This "wait-and-see" effect (Bloom, 2009) can explain the decrease in frequency and the increase in the conditional absolute size of price changes documented in the data. Second, because the cost of overpricing is relatively higher than the cost of under-pricing under Kimball (1995) aggregation, the expected increase in demand dispersion reduces the optimal reset price. The calibrated model shows that first effect dominates, thus replicating the non-targeted empirical regularities. This confirms that large and unexpected events like the riots can be thought of as events that increase the expected future dispersion of demand shocks without (necessarily) a current change in the level or the dispersion of demand. Furthermore, we document that a battery of alternative shocks cannot reconcile our empirical patterns, in particular, an unexpected increase in the cost of adjusting prices generates counterfactual price dynamics.

Our findings have important and novel policy implications. We show that in periods where firms expect an increase in future demand dispersion, price changes become less frequent. In contrast, when demand actually becomes more dispersed, the frequency of price changes increases. Because the effectiveness of policy depends on the degree on price flexibility, the timing of monetary policy in periods of distress becomes paramount. When the central bank stimulates the economy in periods where future demand dispersion is 70% more likely, the pass-through of the stimulus to real output is about 6 percentage points larger than when the expectation of future volatility is unchanged. When the dispersion of demand eventually increases (in line with the earlier news) then this increase triggers larger price adjustments by firms and similar to the findings of Vavra (2014), monetary policy becomes less effective than normal. Because these large events are episodes where policy makers may be especially eager to intervene, identifying a window in which policy effectiveness is high is an important contribution.

Literature review. 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 microdata and the new developments in computational methods allowed the literature to build quantitative models and contrast them directly to the data. These quantitative menu cost models are able to generate sizable monetary non-neutralities, while capturing micro evidence on firm pricing behavior (Golosov and Lucas Jr, 2007; Nakamura and Steinsson, 2010; Midrigan, 2011).

We extend the workhorse menu cost models by introducing news shocks (Barsky and Sims, 2011) to idiosyncratic demand dispersion to study how firms' pricing strategies respond to heightened uncertainty. To this end, our work contributes to the literature also aiming to examine the interaction between uncertainty and price-setting behavior (Vavra, 2014; Baley and Blanco, 2019; Drenik and Perez, 2020; Ilut et al., 2020; Klepacz, 2021; Alvarez and Lippi, 2021).[3] In particular, using models with information frictions and learning, Baley and Blanco (2019) and Ilut et al. (2020) conclude that higher uncertainty raises the responsiveness of prices and hence amplifies the real effects of nominal shocks. In contrast, we find that prices become less flexible under increased uncertainty and that a menu cost model is able to qualitatively match the data. As such, our findings echo that of Drenik and Perez (2020) who empirically estimate larger price dispersion after an increase in uncertainty about inflation.

Our quasi-natural experiment approach is especially useful when studying uncertainty shocks.[4] In fact, previous studies on pricing and uncertainty either focus on theoretical models, such as Baley and Blanco (2019) and Alvarez and Lippi (2021), or encounter the empirical challenge of isolating the pure effect of uncertainty from higher realized volatility of

[3] We also relate to explanations for sticky prices at the micro level based on uncertainty, such as customers anger in Rotemberg (2002) and rational inattention (Maćkowiak et al., 2021).

[4] Other event studies include the analysis by Hobijn et al. (2006) on the introduction of the Euro, the study of Gagnon (2009) on high inflation in Mexico, and Alvarez et al. (2019) analysis of the hyper inflation in Argentina.

shocks, such as Vavra (2014) and Klepacz (2021)). We show that the pure uncertainty effect induces less price adjustments through a "wait-and-see" effect as put forth by Bloom (2009). Moreover, our model features strategic pricing complementarity through a Kimball (1995) demand system. Previous works (Klenow and Willis, 2006) have shown that large shocks to idiosyncratic productivity are necessary to match the observed relative price movements in the presence of micro real rigidity. In contrast, our model featuring both demand and productivity heterogeneity is able to match the data without relying on excessively large shocks. Finally, the importance of demand shocks in our study can be related to the empirical study of Gagnon and López-Salido (2020) showing the effect of large demand changes on pricing behavior.

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

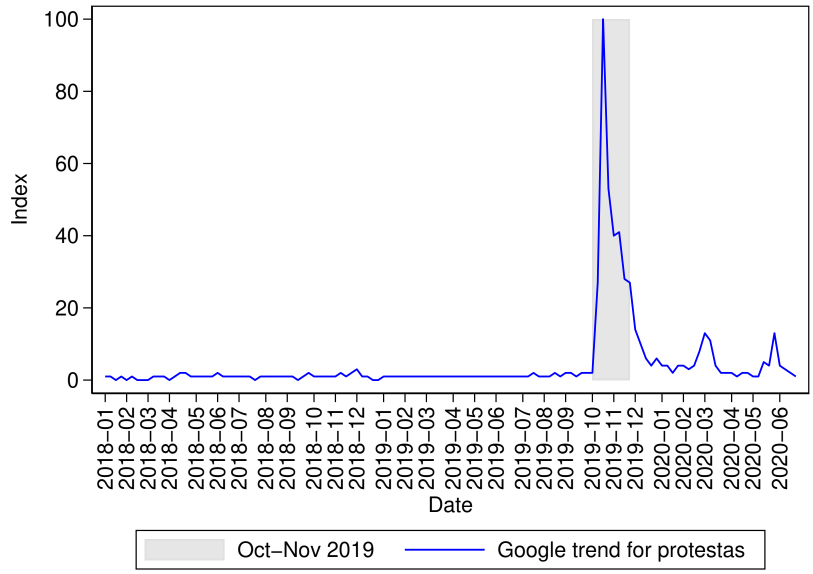
2 The 2019 Episode of Riots in Chile

On October 6, 2019, Santiago's subway fare was raised by 30cs, a 4% increase. 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 share 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. This culminated with mobs attacking military facilities on the night of November 12. A few days later, on November 15, a turning point in the escalation of violent riots materialized, with a broad political agreement across several parties on a course of action to change the constitution. To a large extent, this brought a stop to the violence and launched a political process that is now underway to draft a new Constitution, expected by 2023.

From the perspective of our work, there are three distinctive characteristics of this episode of riots that took place in Chile in late 2019. First, the episode was fully unexpected yet relatively short-lived. Figure 2 plots a daily index for the number of Google searches for "protestas" (protests in Spanish). It clearly documents how, by this metric, riots were not something that Chileans expected as the index increases 100-fold between October 17 and October 19. This episode was, nonetheless, relatively short-lived, and within the 31-day window after the riots began – the shaded region in the Figure – the index falls to the pre-October 18 levels.

Figure 2: Google trends for *"protestas"* (protests)

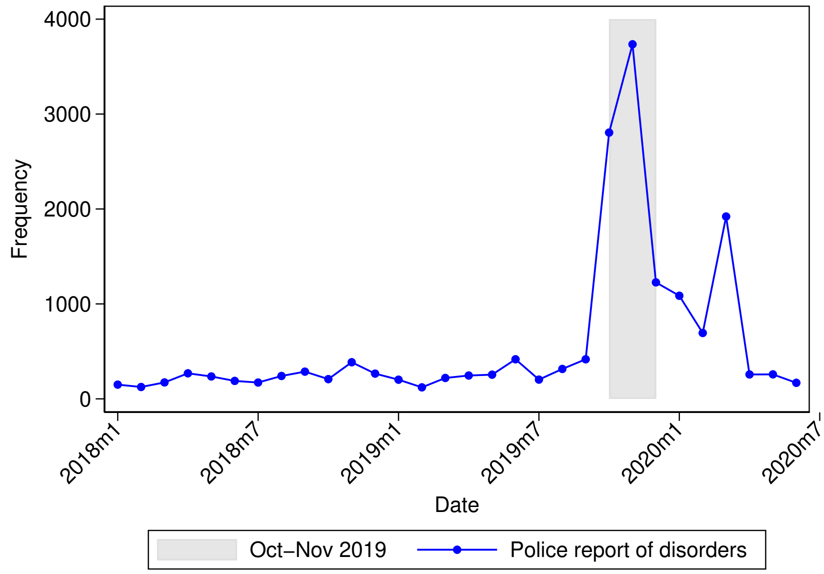


Note: The figure displays a daily index for the number of Google search for "protestas" (protests in Spanish), where the maximum daily searches in the whole sample, which happens to be on October 19, 2019, is normalized to 100. Shaded period between Oct-18-2019 and Nov-17-2019.

A second distinctive characteristic of this episode is that it was violent in nature. Figure 3 plots the number of monthly police reports of "desordenes" (public disorders in Spanish), an official definition that involves the destruction of private and/or public property. There is a clear spike within the month that the riots took place with a ten-fold increase in the number of reported events. To further illustrate this, Figure 4 complements this with some of the pictures taken during the riots which depict the violent clashes with police that characterized the massive events of social unrest, and the destruction and looting of private and public property among several other acts of violence.

A third and final salient characteristic of this episode is that riots were quite widespread in Chile, although with various degrees of intensity across regions. This fact is documented in Figure 5 which contains the map of Chile split into its 346 communes. More intense colors denote locations where the increase in the number of burglaries, the category of crime that

Figure 3: Police Reports of *"desórdenes"* (public disorders)



Note: The figure presents the number of monthly police reports of "desordenes" (public disorders in Spanish). Oct and Nov 2019 shaded.

includes supermarkets lootings according to police classification, was stronger. As it is clear from inspecting this Figure, there was a fair amount of heterogeneity in the intensity of the riots with no distinctive geographical pattern across regions.

3 Pricing Data

Appendix A.2 describes details in the construction of the dataset of daily prices. It also presents descriptive statistics and compares the properties of the Chilean data to the literature (Nakamura and Steinsson, 2008; Eichenbaum, 2014). We construct two alternative samples. The "baseline sample" includes 7.1 million observations of daily prices for unique triplets of $25,108$ products sold by 67 supermarkets in a total of 494 different locations. The "matched sample" merges daily prices with those paid by supermarkets to 228 different suppliers at specific locations. As a result, this sample has 2.3 million observations of daily

Figure 4: Riots in Chile: Oct.18 - Nov.17

(a) Riot 1

(b) Riot 2

(c) Riot 3

(d) Riot 4

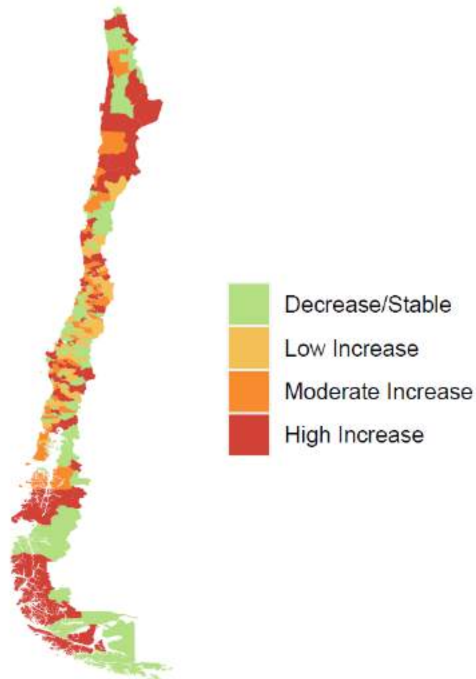
Notes: (a) Property damage as consequence of looting and public disorders (b) Violent demonstrations (c) One million Chileans march in Santiago (d) Supermarket looting.

prices charged for 8,478 specific products by 37 supermarkets in a total of 349 different locations.

Daily prices are constructed from transactional data registered in VAT invoices, which in turn account for about 13% of total sales by supermarkets. Supermarkets cannot discriminate among customers based on the request of filling VAT invoices although they can use coupons and other forms discount prices. Following the literature, we eliminate such discount prices from the dataset. To do so, we first collapse prices at transactional frequency to daily frequency by taking the highest price registered in VAT invoices for the triplet product, supermarket and location. Then we apply the filter proposed by Kehoe and Midrigan (2015) to eliminate high-frequency variation in prices across days.

Figure 6 offers a first look a the descriptive statistics of the riots in our baseline sample, by

Figure 5: Intensity of Burglaries Across Regions During Riots



Note: This map of Chile displays the intensity of riots at the municipality level. This measure is constructed by the increase in police reports for burglaries 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.

displaying the time series of the daily number of products sold in 2019. This figure show that the riots had real effects, as the number of products dropped by about 20%. Importantly, however, because of our continuity filter we still retain most of the products, allowing us to identify the effects of riots on the pricing behaviour of supermarkets by observing prices of products sold before *and* during the episode of riots.

Figure 7 presents the daily frequency of price changes –i.e the share of prices that change among the products analyzed. As it is clear from the Figure, riots were characterized by a change in the pricing behaviour of supermarkets which materialized in a reduction in the frequency of price changes. We turn to a more formal analysis of this finding next.

Figure 6: Number of Products Sold Daily: baseline sample

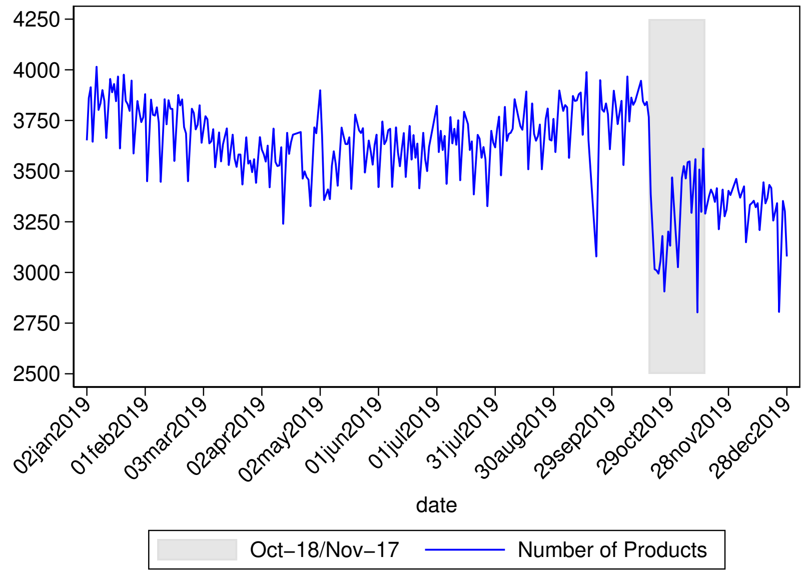
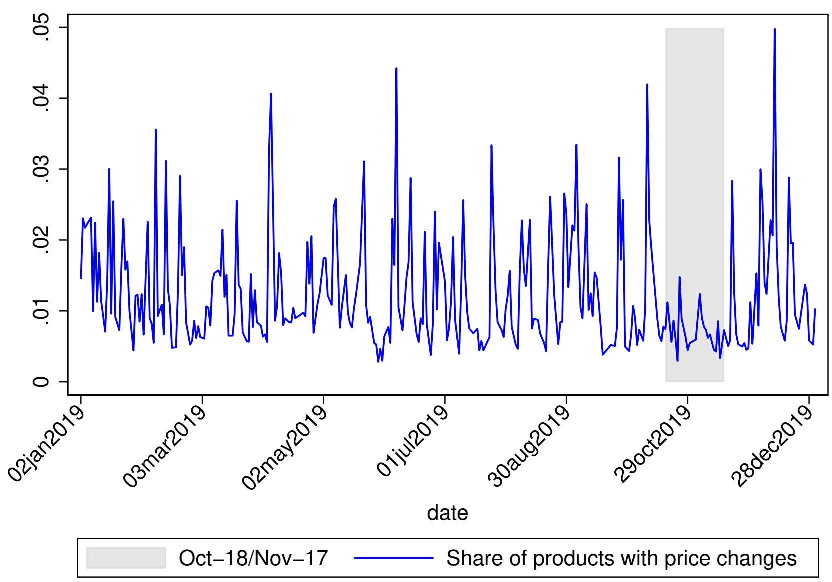


Figure 7: Frequency of Price Changes



4 Empirical Analysis

The exogenous and sudden nature of the Chilean riots and our high frequency pricing data constitutes a quasi natural experiment to study the pricing strategy of supermarkets when facing social turmoils. Section 3 uses raw data to show that supermarkets exhibit a sharp decrease in their frequency of price changes during the riots, we use the following empirical model to explore the robustness of this result and extend the analysis to other pricing outcomes.

$$y_{it} = \alpha + \beta D_{riots} + \gamma X_{i,t} + h(FE) + \varepsilon_{it}^{y}, \tag{1}$$

where y_{it} is the dependent variable of interest and $X_{i,t}$ is a vector of product-location controls and $h(FE)$ is a vector of fixed effects. When studying the frequency of price changes, the dependent variable is a dummy variable that indicates the occurrence of a price change (a "break"), we also study the magnitude of price changes using as dependent variable the absolute percentage change of a price change conditional on the occurrence of a price break on the filtered price. We study positive and negative price changes independently, therefore, we have in total four specifications for Equation (1). The dummy D_{riots} takes the value of 1 for the 30 days after the start of the riots in October 18, 2019. Therefore, the coefficient of interest β captures the change in the pricing behavior of supermarkets at the product-location level during the Chilean riots. The vector $X_{i,t}$ captures time variant product-location specific controls that can affect the pricing behavior of supermarkets. In particular, we control for a third order polynomial of the number of days since the last price change was observed, and the number of price breaks of the product in the last 30 days. These controls are meant to capture any product-specific pricing dynamics that are time variant. Finally, the vector of fixed effects $h(FE)$ contains location-product, week day, month, number of the week, and non-mandatory holiday fixed effects. This exhaustive set of fixed effects captures a potential time invariant pattern, for example, this would capture a systemic pattern every first Monday of the third month there is a systematic change in prices. Our estimation clusters standard errors at the seller-location level allowing for a location-specific pricing

Table 1: Supermarket Analysis: baseline Sample

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_{riots}	-0.00296***	-0.00346***	0.0188***	0.0200***
	(0.000458)	(0.000346)	(0.00656)	(0.00601)
Observations	7,246,966	7,246,966	43,646	34,204
Adjusted R-squared	0.002	0.002	0.390	0.432
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00694	0.00559	0.114	0.0987

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

behavior. The sample excludes mandatory holidays and only considers product-dates where transactions took place.

Table 1 presents the results of the OLS estimation of Equation (1) for the full sample of product-locations. Columns (1) and (2) show that the frequency of positive and negative price changes fell during the riots. The fall in frequency is economically significant when compared to the unconditional frequency of daily price changes. In fact, positive price changes decrease their frequency by more than 40% while the decrease in the frequency of negative price changes is even larger, at more than 60%. Columns (3) and (4) study the size of price changes conditional on a price break occurring. During the riots, although price changes were less frequent, realized price changes were significantly larger in absolute terms. in fact, price increases and price decreases were 50% larger during the 30 days that followed October 18 of 2019.[5] Furthermore, we do not find systematic differences in the responses of price-setting behavior between large and small supermarket, as documented in Table 17 in the Appendix, suggesting that the riots affected the pricing strategies of supermarkets uniformly.

[5]We also analyze the robustness of our findings when the dependent variables are constructed based on the unfiltered price series, which includes high frequency price fluctuations that are not filtered out. While the results on the frequency of price changes results remained in the analysis with unfiltered prices, the statistical significance of riots on the magnitude of these changes disappears. Table 16, in the Appendix, presents these results.

Table 2: Supermarket Analysis: Matched Sample

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_riots	-0.00416***	-0.00521***	0.0470***	-0.000960
	(0.000713)	(0.000605)	(0.0157)	(0.00960)
Observations	2,324,403	2,324,403	14,288	12,706
Adjusted R-squared	0.002	0.003	0.321	0.453
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00715	0.00647	0.118	0.0986

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

Could these changes in the pricing dynamics of supermarkets have been triggered by changes in the pricing behavior of their suppliers? In particular, could supermarkets just be transmitting less frequent and more violent price changes from their suppliers? Next, we make use of the matched supplier-location-product panel to explore the possibility of supply shocks driving the pricing dynamics of supermarkets.

4.1 Supply Factors

Because we observe the universe of business to business transactions we can retrieve the purchases of goods at the supermarket level. As detailed in Section 3, we build a product-location-supplier panel using name matching at the product level. This database allows us to directly study if supply effects can explain the unusual pricing behavior of Chilean supermarkets during the riots. First, we replicate the baseline supermarket results with this smaller sample.

Table 2 presents the results of the baseline estimation on this sub-sample. Note that the frequency of price increases and decreases is also lower during the riots for this sub-sample. In terms of size, we find that price increases are significantly larger after the riots while we lose significance on this sub sample for the size of price decreases, which likely comes from

Table 3: Supplier Analysis: Matched Sample

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_{riots}	0.000575	0.000670	-0.0460*	-0.00996
	(0.00232)	(0.00138)	(0.0240)	(0.0254)
Observations	1,982,065	1,982,065	12,063	8,718
Adjusted R-squared	0.008	0.010	0.354	0.495
Controls	Yes	Yes	Yes	Yes
FE	yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00700	0.00517	0.159	0.136

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

the fall in the number of observations for the sub-sample.

The first step to analyze potential supply side effects is to study if the suppliers changed their pricing behavior towards supermarkets during the riots. To this end, we estimate equation (1) at the supplier-product-location. All dependent and independent variables are now calculated with the pricing data of suppliers. Additionally, we include a fixed effect controlling for the supplier-product-location link.

Table 3 show the results of this analysis indicating that suppliers did not change their frequency of prices changes during the riots. In terms of size adjustments, we see that price increases were less violent during the riots and no effect on price decreases. Interestingly, the only slightly significant pattern is on the size of price increases and it has the opposite sign. Therefore, there is no evidence that the behavior of supermarket is just a reflection of their supplier's pricing decisions during the riots. Nevertheless, it could be the case that riots made supermarkets change the way they reacted to changes in their suppliers prices. In this sense, even if suppliers did not change their pricing behavior, it could still be the case that supermarkets reacted differently to the pricing behaviour of their suppliers during the riots. To examine this possibility we extend Equation (1) to include a measure of replacement cost at the supermarket-location-product level. In particular, we estimate the supermarkets'

Table 4: Supermarket Analysis: Matched Sample and Supplier Controls

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_{riots}	-0.00408***	-0.00533***	0.0506***	0.00219
	(0.000786)	(0.000648)	(0.0160)	(0.00975)
$PCPS$	0.00286***	-0.000933**	0.0185***	-0.0804**
	(0.000896)	(0.000376)	(0.00559)	(0.0398)
$PCPS$*D_{riots}	-0.000699	-0.0180	1.338	5.847*
	(0.0171)	(0.0148)	(0.853)	(3.186)
Observations	2,210,719	2,210,719	14,000	12,421
Adjusted R-squared	0.003	0.003	0.332	0.466
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
Mean of Dependent Variable	0.00740	0.00668	0.117	0.0988
Mean of PCPS_15	0.00686	0.00686	0.0295	-0.00825

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

pricing decisions

$$y_{it} = \alpha + \beta D_{riots} + \delta_0 PCPS_{i,t} + \delta_1 D_{riots} PCPS_{i,t} + \gamma X_{i,t} + h(FE) + \varepsilon^y_{it}, \tag{2}$$

where the new independent variable $PCPS_{i,t}$ controls for the percentage change in the product specific supplier price in the last 15 days. The coefficient δ_0 reflects the normal time pass through of supplier prices into supermarket prices, and δ_1 reflects any differential pass through during the riots.

Table 4 shows the results of this estimation. First, the coefficient δ_0 provides validation to our matching procedure: as suppliers increase their price pressure on supermarkets, we observe more frequent price increases, less frequent prices decreases, larger price increases and smaller price decreases. Therefore, the link between supplier prices and supermarket prices conforms well with economic logic. Second, the estimation of δ_1 shows that supermarkets did not respond differently to suppliers' pricing behaviour during the riots. Only the response of the size of price increases is statistically significant at the 90% confidence level. Third, when comparing the estimates of β in Tables 2 and 4 we see that the inclusion of suppliers prices

Table 5: Supermarket Analysis: Baseline Sample with additional controls

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_riots	-0.00298***	-0.00347***	0.0187***	0.0210***
	(0.000467)	(0.000347)	(0.00666)	(0.00622)
log of last week Purchases to suppliers	0.000207	0.000465	0.000609	0.00922***
	(0.000256)	(0.000327)	(0.00259)	(0.00281)
Observations	7,203,155	7,203,155	43,475	34,088
Adjusted R-squared	0.002	0.002	0.386	0.431
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

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

does not alter the strong significance of this coefficient. Therefore, the pricing behavior of supermarkets during the riots cannot be explained by changes in the pricing behavior of their suppliers or changes in how supermarket react to changes in their costs.[6]

4.2 Concurrent Demand Changes

Having discarded supply shocks as a source of the differential pricing behavior of supermarkets during the Chilean riots, we turn to the analysis of changes in the demand due to the concurrent turmoil. Our premise is that if the riots changed product demands then we should expect price dynamics to respond to actual changes in demand. We design two strategies to explore this hypothesis. First, we directly control for all the purchases of goods and services at the supermarket level to proxy for changes in demand. Second, we use geographical variation in the intensity of the riots to see if riots themselves could have caused concurrent changes in demand.

Table 5 shows the results for the fist approach. When we use the total purchases of the supermarket during the last week, β remains statistically and economically significant.[7]

[6]In addition to the wholesale cost of merchandises, the costs of supermarkets also include labor costs. To further explore potential supply channels Table 18 in the Appendix uses the supermarket Wage Bill in the month as a control. Once again, changes in wages cannot explain the pricing patterns documented in the regressions.

[7]These results are also robust to using total daily purchases as presented in Table 19 in the Appendix.

Table 6: Supermarket Analysis: Baseline Sample and Riot's Intensity

VARIABLES	(1) Positive Breaks	(2) Negative Breaks	(3) Delta Positive Breaks	(4) Delta Negative Breaks
D_{riots}	-0.00315***	-0.00355***	0.0158***	0.0140**
	(0.000647)	(0.000473)	(0.00592)	(0.00678)
$D_{riots}*Intensity$	0.000431	0.000183	0.00694	0.0155
	(0.000914)	(0.000571)	(0.0143)	(0.0128)
Observations	7,246,775	7,246,775	43,646	34,204
Adjusted R-squared	0.002	0.002	0.390	0.432
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
mean of Dependent Variable	0.00694	0.00559	0.114	0.0987

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

The second approach uses the geographical variation depicted in Figure 5. In particular, we group municipalities according to the severity of the riots. If riots affected supermarket pricing decisions by disturbing contemporary demand, we should expect that the effects of the riots are more pronounced in supermarket locations that saw more riot intensity. To explore this hypothesis, we build a dummy that indicates if the municipality saw an increase in the number of riot related incidents above the median increase and include an interaction between the riots dummy and the intensity dummy. Note that the intensity dummy by itself is absorbed by the product-location fixed effect.

Table 6 shows the results of the intensity analysis. Interestingly, there is no differential effect in the pricing behavior of supermarkets located in municipalities where the violence was more intense. Therefore, any effect due to the riots has to be independent of actual economic conditions triggered by the turmoil.

Taking stock, we have discarded several potential channels linking riots and supermarkets' pricing behavior. First, because suppliers did not change their pricing strategy, we can discard any actual or expected supply shock as the driver of supermarkets' changing pricing

Because of the more lumpy nature of supermarket purchases on a daily bases, we prefer the weekly sales control.

behaviour. Moreover, we found no evidence of supermarket changing their reaction function to supplier's prices during the riots. Thus, any transmission mechanism has to be completely independent from supply forces. From a demand perspective, because the baseline results are unaffected by the volume of economic activity at the supermarket level during the riots and because the effect of the riots is not more pronounced in municipalities where riots were more intense, we can discard actual changes in demand triggered by the episode.

We thus conjecture that expected changes in future demand could drive the pricing dynamics of supermarkets during the riots. The next section develops a quantitative pricing model and shows that news about future demand dispersion can trigger a reduction in the frequency of price changes and an increase in the absolute size of price changes akin to those observed in the data.

5 Quantitative Model

In the previous empirical analysis, we documented a reduction in the frequency of price adjustments and an increase in the size of price changes conditional on adjustment among supermarkets in Chile during the 2019 riots. The empirical analysis does not find support for this change in pricing behavior being driven by supply-side factors nor by supermarkets reacting to current changes in their demand. Other kinds of shocks are unlikely to generate the simultaneous reduction in the frequency of price adjustments *and* the increase in the size of price change. A shift in the level of any aggregate shock will necessarily shift the desired prices of firms in one direction, leading to opposite effects for upward and downward adjustments. For instance, a negative shock to aggregate demand puts downward pressure on prices. This would lead to more firms adjusting their prices down and less firms adjusting their prices up. This suggests that, in order to replicate the patterns observed in the data, a second-moment shock is necessary.

We hypothesize that riots can bring about heightened uncertainty surrounding *future* product demand. Due to the spontaneity of riots and the unpredictable political climate, the near future becomes highly uncertain and supermarkets can reasonably expect volatility of demand to increase, while, crucially, nothing happens today. For instance, demand for basic necessities may increase abruptly in the near future because of a closure of a nearby competitor. On the other hand, it is also likely for demand to plummet as consumers decide to shelter at home as a safety precaution.

To explore this hypothesis, we develop a quantitative menu cost model based on Vavra (2014), augmented with a news shock regarding idiosyncratic demand volatility. Using the model, we test whether a news shock to demand dispersion is able to generate the observed patterns in the data. Finally, we turn to the policy implications of such a shock.

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. They solve problem

$$\max \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\log\left(C_t\right) - \omega n_t\right] \tag{3}$$

subject to the budget constraint:

$$P_t C_t + \mathbb{E}_t\left[q_{t+1} B_{t+1}\right] \leq B_t + W_t n_t + \Pi_t \tag{4}$$

where B_{t+1} delivers the net payoffs from the state-contingent assets purchased in period t and they are priced using $q_{t,t+1} = \beta \frac{C_t}{C_{t+1}}$. P_t and W_t are the price of final goods and nominal wage, respectively, both of which are taken as given by the households. Π_t denotes the total dividends received by the household.

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

$$\int G\left(\frac{n_t^i y_t^i}{Y_t}\right) di = 1 \tag{5}$$

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

$$G\left(\frac{n_t^i y_t^i}{Y_t}\right) = \frac{\omega_p}{1+\psi_p}\left[(1+\psi_p)\frac{n_t^i y_t^i}{Y_t} - \psi_p\right]^{\frac{1}{\omega_p}} + 1 - \frac{\omega_p}{1+\psi_p} \tag{6}$$

The parameter $\psi_p \leq 0$ controls the curvature of the demand curve and hence the degree of strategic complementarity in pricing between intermediate firms. Together with ψ_p, the parameter ω_p 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

$$\max_{y_t^i} \quad 1 - \int \frac{p_t^i y_t^i}{P_t Y_t} di \quad \text{subject to} \int G\left(\frac{n_t^i y_t^i}{Y_t}\right) di = 1 \tag{7}$$

The optimality condition of the final good producer's maximization problem yields

$$\frac{n_t^i y_t^i}{Y_t} = \frac{1}{1+\psi_p}\left(\left(\frac{p_t^i}{\lambda_t n_t^i P_t}\right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p\right) \tag{8}$$

which implicitly defines the demand for each variety, where λ_t is the Lagrangian multiplier on the Kimball aggregator, which can be obtained by substituting the optimal demand into

(5) as

$$\lambda_t = \left[\int \left(\frac{p_t^i}{n_t^i P_t} \right)^{\frac{1}{1-\omega_p}} di \right]^{1-\omega_p} \tag{9}$$

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

$$P_t = \frac{1}{1+\psi_p} \left[\int \left(\frac{p_t^i}{n_t^i} \right)^{\frac{1}{1-\omega_p}} di \right]^{1-\omega_P} + \frac{\psi_p}{1+\psi_p} \int \frac{p_t^i}{n_t^i} di \tag{10}$$

When $\psi_p = 0$, $G(.)$ collapses to the Dixit-Stiglitz constant elasticity of substitution (CES) aggregator yielding the familiar expressions

$$y_t^i = \left(n_t^i\right)^{\frac{1}{\omega_p - 1}} \left(\frac{p_t^i}{P_t} \right)^{\frac{\omega_p}{1-\omega_p}} Y_t \tag{11}$$

$$\lambda_t = 1 \tag{12}$$

$$P_t = \left[\int \left(\frac{p_t^i}{n_t^i} \right)^{\frac{1}{1-\omega_p}} di \right]^{1-\omega_P} \tag{13}$$

With the CES aggregator, optimal markup is constant and is independent of idiosyncratic or aggregate demand shifters. The use of the Kimball aggregator generates variable markups based on demand heterogeneity.

We assume that nominal aggregate expenditure $S_t = P_t Y_t$ grows deterministically at a fixed rate μ

$$\log\left(S_t\right) = \mu + \log\left(S_{t-1}\right) \tag{14}$$

Idiosyncratic demand n_t^i follows an AR(1) process

$$\log\left(n_t^i\right) = \rho_n \log\left(n_{t-1}^i\right) + v_t \sigma_n \epsilon_t^i \tag{15}$$

The dispersion of innovations to idiosyncratic demand depends on the time-varying state of aggregate volatility of demand v_t, which evolves according to the following process

$$v_{t+1} = \rho_v v_t + \sigma_v \epsilon^v_{t+1} + \sigma_{\text{news}} u^{\text{news}}_t \tag{16}$$

In the same spirit of the news shock specification of Barsky and Sims (2011), shocks to idiosyncratic demand dispersion consists of two components: an anticipated news component $\sigma_{\text{news}} \cdot u^{\text{news}}_t$ and an unanticipated component $\sigma_v \cdot \epsilon^v_t$. In the current period, agents receive news about future demand dispersion which has no immediate impact today. Conditional on a positive news shock today, the probability that demand dispersion will be higher in the next period becomes higher, but the actual realized level of demand dispersion ultimately depends on the realization of the unanticipated shock to dispersion.

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

$$y^i_t = z^i_t l^i_t \tag{17}$$

Firm idiosyncratic productivity z^i_t follows an autoregressive process. Following Midrigan (2011) and Vavra (2014), we assume that shocks to firm productivity arrive probabilistically according to a Poisson process

$$log\left(z^i_t\right) = \begin{cases} \rho_z log\left(z^i_{t-1}\right) + \sigma_z \epsilon^{z,i}_t; \quad \epsilon^{z,i}_t \sim N\left(0,1\right) & \text{with probability } p_z \\ log\left(z^i_{t-1}\right) & \text{with probability } 1 - p_z \end{cases} \tag{18}$$

5.3.1 Pricing Decision

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. In the spirit of Calvo (1983), firms face a chance of a free adjustment with probability α, so that the menu cost is given by:

$$f_t^i = \begin{cases} 0 & \text{with probability } \alpha \\ f > 0 & \text{with probability } 1 - \alpha \end{cases} \tag{19}$$

This feature allows the model to better match the distribution of price changes, especially the fraction of small price adjustments that is observed in the data.

Pricing decisions are chosen to maximize the present discounted value of profits net of price adjustment costs

$$\max_{p_t^i} \quad \mathbb{E}_t \sum_{t=0}^{\infty} q_{t,t+1} \left(\pi_t^i - f_t^i \frac{W_t}{P_t} \mathbb{I}_{p_t^i \neq p_{t-1}^i} \right) \tag{20}$$

where the period profit is given by

$$\pi_t^i = \left(\frac{p_t^i}{P_t} - \frac{W_t}{z_t^i a_t P_t} \right) \frac{Y_t}{n_t^i} \cdot \frac{1}{1 + \psi_p} \cdot \left[\left(\frac{p_t^i}{\lambda_t n_t^i P_t} \right)^{\frac{\omega_p}{1-\omega_p}} + \psi_p \right] \tag{21}$$

To keep the state space of the problem bounded, all nominal prices (p_t^i, P_t) are normalized by total nominal expenditure S_t. At the beginning of each period, firms observe their current price p_{t-1}/S_t which is the price they inherit from the last period normalized by the current level of nominal expenditure. They also observe their idiosyncratic states n_t^i and f_t^i, as well as aggregate states v_t and u_t^{news}. In order to evaluate the profit function and to make pricing decisions, firms also need to know λ_t and P_t/S_t, which are determined by the aggregation of all firms' pricing decisions. We assume that the joint distribution of idiosyncratic states $g(\frac{p^i_{t-1}}{S_t}, n^i_t, f^i_t)$ is common knowledge and therefore firms are able to perfectly forecast λ_t and P_t/S_t given the distribution g and the optimal pricing rules. However, this makes the firms' state space an infinite-dimensional object.

To make the state space of the problem finite, we use the strategy of Krusell and Smith (1998) and conjecture that $\frac{P_t}{S_t}$ can be predicted by a linear function

$$\log\left(\frac{P_t}{S_t}\right) = \beta\left(u^{\text{news}}_t\right) \cdot X_{P,t} \tag{22}$$

where

$$X_{P,t} = \begin{bmatrix} 1 & \log\left(v_t\right) & \log\left(v_t\right)^2 & \log\left(\frac{P_{t-1}}{S_t}\right) & \log\left(\gamma_t\right) & \log\left(\gamma_t\right)^2 & \log\left(\frac{P_{t-1}}{S_t}\right) \times \gamma_t \end{bmatrix} \tag{23}$$

is a vector of aggregate state variables, and β a vector of coefficients dependent on the aggregate news state.

Similarly, we conjecture that λ_t can be predicted by

$$\log\left(\lambda_t\right) = \alpha\left(u^{\text{news}}_t\right) \cdot X_{\lambda,t} \tag{24}$$

where

$$X_{\lambda,t} = \begin{bmatrix} 1 & \log\left(v_t\right) & \log\left(v_t\right)^2 & \log\left(\frac{P_{t-1}}{S_t}\right) & \log\left(\gamma_t\right) & \log\left(\gamma_t\right)^2 & \log\left(\frac{P_{t-1}}{S_t}\right) \times \gamma_t \end{bmatrix} \tag{25}$$

In X^{λ}_t and X^P_t, we include a variable $\gamma_t \equiv \int \frac{p_{t-1}(i)/S_t}{n_t(i)} di$ which summarizes the joint distribution of firms' prices at the beginning of the period and their idiosyncratic demand states. γ_t is then included in the state space of the firms' problem and we conjecture that it's law of motion can be approximated by

$$\gamma_{t+1} = \delta\left(u_t^{\text{news}}\right) \cdot X_{\gamma,t} \tag{26}$$

where

$$X_t^{\gamma} = \begin{bmatrix} 1 & \log\left(v_t\right) & \log\left(\frac{P_t}{S_{t+1}}\right) & \log\left(v_{t+1}\right) & \log\left(v_{t+1}\right)^2 & \gamma_t \end{bmatrix} \tag{27}$$

Given the conjectured laws of motion, the firms' problem can be written recursively. The value of not adjusting its prices is simply the flow profit at the existing price p_{t-1}^i/S_t plus continuation value.

$$\begin{aligned} V_N\left(\frac{p_{t-1}^i}{S_t}, n_t^i, z_t^i; \chi_t, \gamma_t, v_t, u_t^{news}\right) &= \pi\left(\frac{p_{t-1}^i}{S_t}, n_t^i, z_t^i; \chi_t\right) \\ &+ \mathbb{E}_t\left[\beta \frac{P_{t+1}/S_{t+1}}{P_t/S_t} V\left(\frac{p_t^i}{S_{t+1}}, n_{t+1}^i, z_{t+1}^i, f_{t+1}^i; \chi_{t+1}, \gamma_{t+1}, v_{t+1}, u_{t+1}^{news}\right)\right] \end{aligned} \tag{28}$$

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

$$\begin{aligned} V_A\left(n_t^i, z_t^i, f_t^i; \chi_t, \gamma_t, v_t, u_t^{news}\right) &= -f_t^i \frac{\omega}{P_t/S_t} + \max_{p_t^i}\left\{\pi\left(\frac{p_t^i}{S_t}, n_t^i, z_t^i; \chi_t\right)\right. \\ &\left. + \mathbb{E}_t\left[\beta \frac{P_{t+1}/S_{t+1}}{P_t/S_t} V\left(\frac{p_t^i}{S_{t+1}}, n_{t+1}^i, z_{t+1}^i, f_{t+1}^i; \chi_{t+1}, \gamma_{t+1}, v_{t+1}, u_{t+1}^{news}\right)\right]\right. \end{aligned} \tag{29}$$

The firm chooses whether or not to adjust by comparing the value of adjusting against not adjusting

$$V\left(n_t^i, z_t^i, f_t^i; \chi_t, \gamma_t, v_t, u_t^{news}\right) = \max\left\{V_A, V_N\right\} \tag{30}$$

To solve the firm's problem, we first start with a guess for the law of motion of $(P/S, \lambda, \gamma_t)$ and we solve the firm's recursive problem using value function iteration. Using the optimal pricing policy functions from the solution to the value function iteration problem, we use the histogram method to simulate the economy non-stochastically following the methodology of Young (2010) and obtain the time-series for $(P/S, \lambda, \gamma_t)$. We iterate on this process until the conjectured law of motion is sufficiently close to the law of motion from the model simulated data.[8]

5.4 Calibration

The model frequency is monthly. We externally calibrate the set of parameters shown in Table 7 using monthly data from Chile. The discount rate β is set to 0.997. 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 treat the supplier price of a good sold by the supermarket as the TFP of the firm. 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 shock (ρ_z, σ_z), we take the monthly panel of supplier price series and drop periods in which there are no price changes. Then, with the trimmed series, we estimate a panel AR(1) using the Arellano and Bond (1991) estimator with supplier fixed effects. Lastly, the parameter ω_p, which governs the average level of markup, is set to 1.34 to reflect the average markup of 34% that we observe in the Chilean data.[9]

The remaining parameters in the model are internally calibrated to match data moments that are obtained from our micro data. The parameter ψ_p which governs the curvature of the demand function, or the degree of strategic complementarities in pricing, is chosen so that the price-cost pass-through in the model matches that from the data. From the supplier-

[8] The R^2 for all regressions exceed 0.999.

[9] Although we are able to match supermarket products to the supplier, we do not observe the units of the transactions. For example, a supermarket could purchase a 12-pack of beer for $12 and then sell the beers in separate bottles for $2 each. 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 7: External Calibration

Parameter	Description	Value	Source
β	Discount Rate	0.997	Literature
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 AR(1)	0.31	Supplier price dynamics
σ_z	Idio. TFP AR(1)	0.14	Supplier price dynamics
ω_p	Kimball EOS	1.34	Average markup

supermarket matched data, we first trim observations where we do not observe a change in the supermarket price. With the trimmed dataset, we estimate the following regression

$$\Delta \log \left(p_t^i\right) = \beta \cdot \Delta \log \left(c_t^i\right) + \text{Firm FE}_i + \epsilon_t^i \tag{31}$$

where c_t^i denote the supplier price for product i.

Our pass-through regression yields a value of 0.29 which is in line with short and medium run estimates of price-cost pass-through in the literature. 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. We choose $\psi_p = -1.5$ so that the model-based version of the same regression yields the same pass-through.

The set of parameters $(f, \alpha, \rho_n, \sigma_n, \rho_v, \sigma_v)$ 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 monthly frequency of price changes, the fraction of small price change where a small price change is defined as one which is smaller than half of the average adjustment size, the fraction of changes that are positive, the average size of price changes, and estimates of an AR(1) process on aggregate price dispersion.

Table 20 report the calibrated parameter values next to their empirical counterpart. Comparison of the data and model moments show that the model is able to match the

Table 8: Internal Calibration

Parameter	Description	Value	Moment	Data	Model
f	Menu Cost	0.40	Freq. Price Change	0.30	0.29
ψ_p	Kimball	-1.5	Cost Pass-through	0.28	0.29
α	Calvo-plus	0.25	Frac. Small Price Change	0.42	0.35
ρ_n	Idio. Demand AR(1)	0.60	Frac. Pos. Price Change	0.52	0.64
σ_n	Idio. Demand AR(1)	0.10	Size Price Change	0.118	0.090
ρ_v	Demand Disp. AR(1)	0.50	Agg. disp. AR(1)	0.80	0.84
σ_v	Demand Disp. AR(1)	0.65	Agg. disp. AR(1)	0.018	0.016

price data well. Although we jointly calibrate the parameters as each parameter affects all empirical moments, each parameter is tightly linked to a specific empirical moment. 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. The probability of receiving a free price adjustment α is linked to the fraction of small price changes. This is because in the presence of adjustment, firms do not adjust unless the deviation of the current price is sufficiently large from the optimal price. On the other hand, when price adjustment is free, firms will adjust as long as their current policy deviates from the desired price however small the deviation is. The size of idiosyncratic demand shocks is informative about the average size of price adjustments since larger innovations to demand result in larger changes in a firm's desired price. Finally, the law of motion for aggregate demand volatility (ρ_v, σ_v) are chosen to match the AR(1) process of aggregate price dispersion in the data. In the supplier-supermarket match sample, we first normalize the price of each product in every period by its time-series mean. Next, we compute the cross-sectional standard deviation of the normalized prices in each period which results in a time-series of price dispersion. We then estimate an AR(1) process with the log of this time-series. Because higher demand volatility across firms lead to an increased dispersion of desired prices, the time-series properties of aggregate price dispersion allows us to calibrate the demand volatility process in the model.

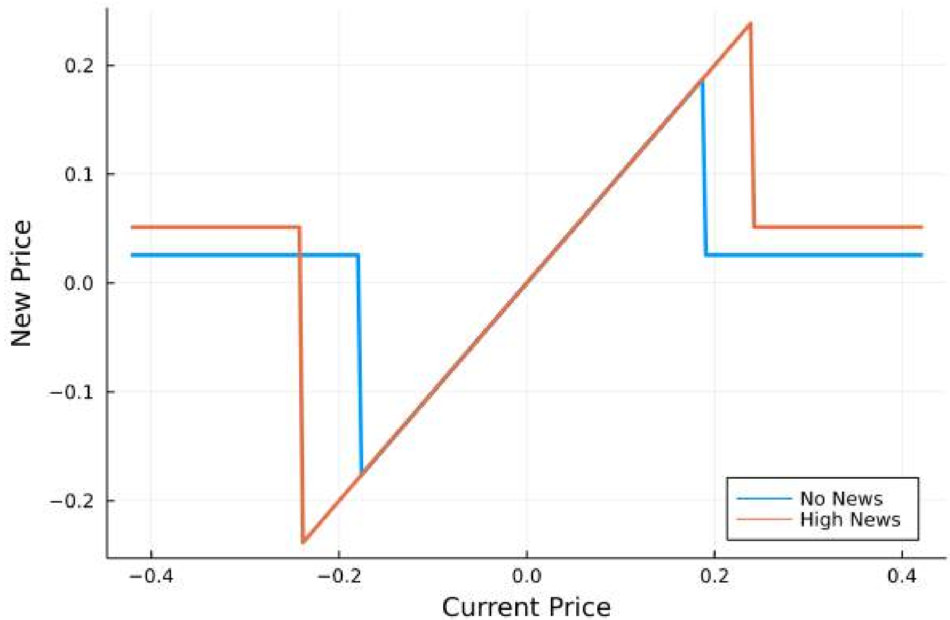
5.5 Results

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). When idiosyncratic demand shocks are expected to be larger in the future and because the optimal price depends on demand, higher uncertainty means that firms are more likely to be left with a large price deviation from the desired price in the next period. In other words, if firms adjust today, the new price is more likely to become obsolete immediately in the next period. 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 8 plots a representative slice of the pricing decision for a firm conditional on the current news state, with the current 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. The blue line shows the decision rule when $u^{news}_t = 0$ and the orange line shows the decision rule when $u^{news}_t > 0$. There are two things to note from the decision rules. Firstly, there is a widening of the inaction region which is represented by the upward-sloping 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 it price to the desired level shown by the flat parts of the decision rule near the two edges. When there is a positive news to future demand volatility, the inaction region widens as illustrated in the orange line.

Interestingly, the size of the inaction region widening is asymmetric. Firms whose current

Figure 8: Pricing Decision Rule Conditional on u_t^{news}

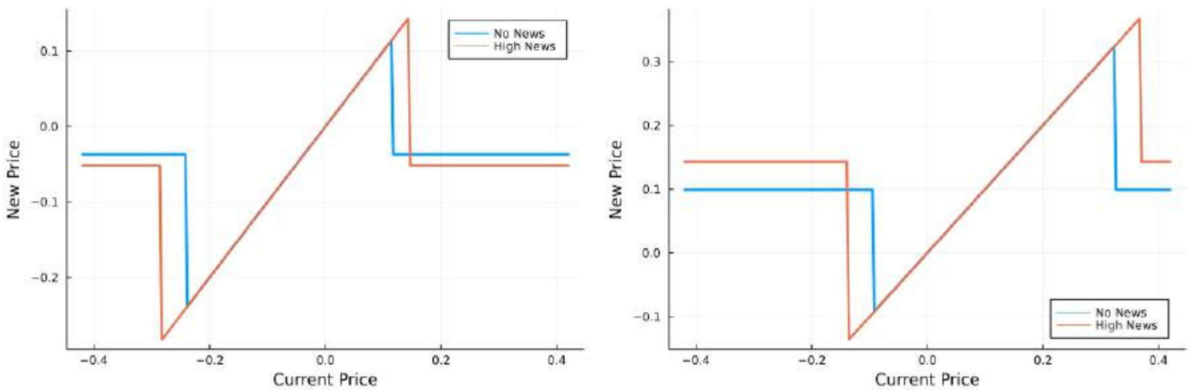


price is below the desired price are more hesitant to re-optimize as compared to firms whose current price is above the desired level. This can be attributed to the shape of the profit function under Kimball demand. Figure 10 plots the profit function under Kimball demand and CES demand. In a Kimball demand system, the profit function exhibits strong asymmetry as over-pricing is more costly than under-pricing. As a result, firms with a current price that is too high suffers larger current profit losses and have stronger incentive to adjust today.

Secondly, there is a shift in the desired prices of the firms in response to the news shock. When there is a positive news shock, firms expect to receive more extreme realizations of idiosyncratic demands in the next period due to larger variability of the shock to demand. The change in expected demand induces firms to change its desired price. It turns out that firms with high (low) demand today react to the news shock by increasing (decreasing) their desired prices as illustrated in Figure 9.

The aggregate effect of a news shock on pricing depend jointly on the decision rules as

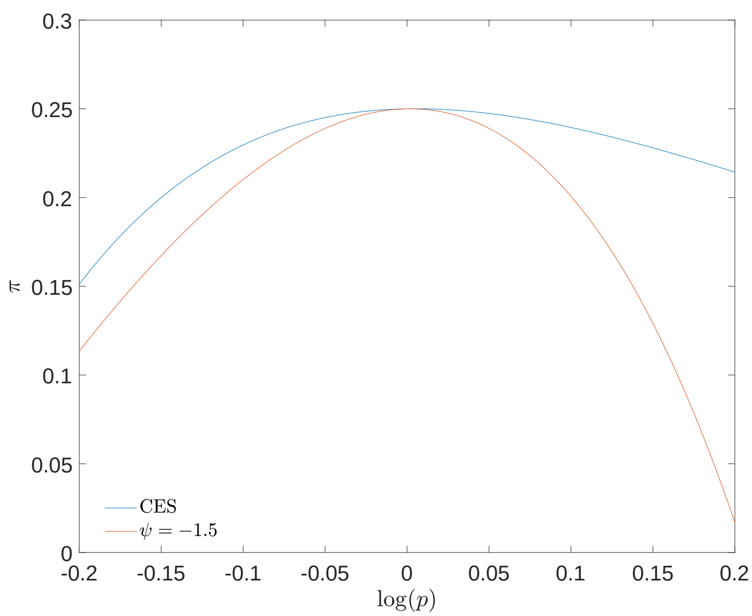
Figure 9: Decision Rule at Different Levels of Demand



(a) Decision Rule: $\log(n_t^i) = -0.16$

(b) Decision Rule: $\log(n_t^i) = 0.16$

Figure 10: Shape of Profit Function under Kimball Demand and CES Demand



well as the distribution of price deviations in the economy. To examine whether the model is able to replicate the empirical findings, we conduct an exercise where we compare the key pricing moments in an economy without any news shocks to an economy receiving a positive news shock to demand volatility. To do this, we first simulate an economy for 60 periods with news shocks turned off. We then take the same simulation and turn on positive news shock in the last period of the simulation. After repeating this 500 times, we compare the average frequency and size of adjustment between the shocked economies and unshocked economies. This corresponds to our empirical analysis where the riots occur near the end of our sample and we do not take a stand as to the realization of the increase in dispersion in the period after the news shock.

Table 9 show the result of the simulations where we hit the economy with a 3 standard deviation with $\sigma_{\text{news}} = 0.75 \cdot \sigma_v$. This is chosen such that the probability of a demand volatility increase goes from 20% to 90% relative to the case with no news shock, when current volatility is at its unconditional mean. In sum, the model is able to produce a decline in price adjustment frequency in both directions. The arrival of news about an expected increase in demand volatility leads to about a 0.7 p.p. in the fraction of firms adjusting up and a 0.2 p.p. in the fraction of firms adjusting down. The asymmetry in the size of the effects of frequency is a result of the asymmetric widening of the inaction region discussed earlier. Meanwhile, the model generates a 2 p.p. and 0.6 p.p. increase in the size of positive and negative price changes respectively. The magnitudes of these responses are larger when we increase the size of the news shock to $\sigma_{\text{news}} = 1.50 \cdot \sigma_v$. Comparing the model generated pricing responses with our empirical regression estimates, we conclude that our model is able to match the empirical results we found about riots qualitatively, with the idiosyncratic demand volatility shock as the driving force.

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 in idiosyncratic states.

Table 9: Supermarket Analysis: Data and Model

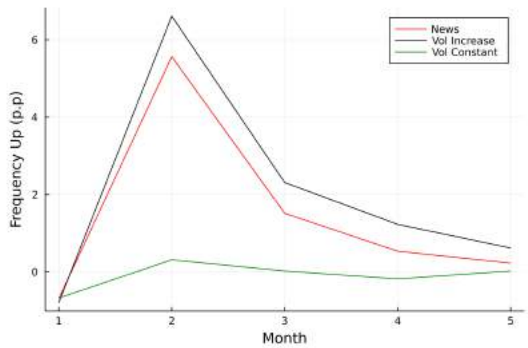
VARIABLES	(1) Pos. Breaks	(2) Neg. Breaks	(3) Delta Pos. Breaks	(4) Delta Neg. Breaks
D_{riots} (Model, $\sigma_{news} = 0.75\sigma_v$)	-0.007	-0.002	0.020	0.006
D_{riots} (Model, $\sigma_{news} = 1.50\sigma_v$)	-0.009	-0.002	0.037	0.012
D_{riots} (Data, Daily)	-0.003***	-0.003***	0.0188***	0.0200***
	(0.0005)	(0.0003)	(0.0066)	(0.0060)
D_{riots} (Data, Monthly)	-0.042*	-0.085***	0.043***	-0.007
	(0.024)	(0.018)	(0.013)	(0.016)

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.

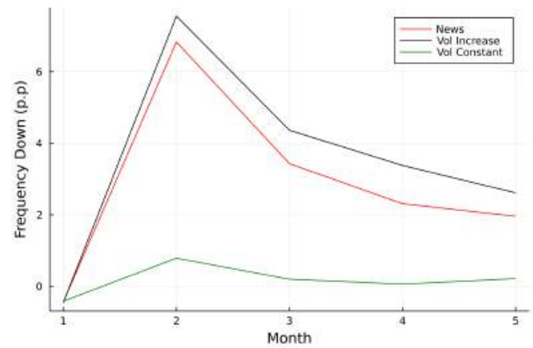
This is best seen in Figure 11, where we show the impulse response of various micro-pricing moments in response to a one-time unanticipated increase in news about future demand dispersion. In the red lines, demand volatility in periods 2 onwards are drawn unconditionally from its distribution. In the black lines, we force demand volatility to increase between period 1 and 2. Lastly, in the green lines, we force demand volatility to stay constant between period 1 and 2. On impact, the news shock reduces the fraction of firms adjusting in both directions and increases the average size of price changes conditional on a change being made. This is a result of the "wait-and-see" effect alongside the shifts in desired prices due to changes in the firms' expectations about future states. In period 2, if volatility actually increases, idiosyncratic demands become dispersed, resulting in a large increase in price adjustment frequency as well as larger adjustments. Meanwhile, this effect is muted if the news shock about volatility increase does not realize.

It is important to stress that alternative shocks are unable to replicate our empirical findings in the context of a menu cost model, as summarized in Table 10. First of all, a level first-moment shock will necessarily shift the desired price distribution in one direction. In

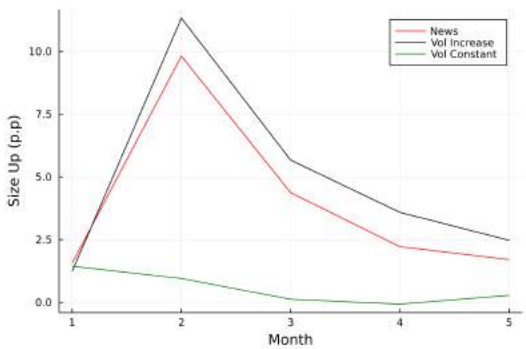
Figure 11: Impulse Response to a Positive News Shock



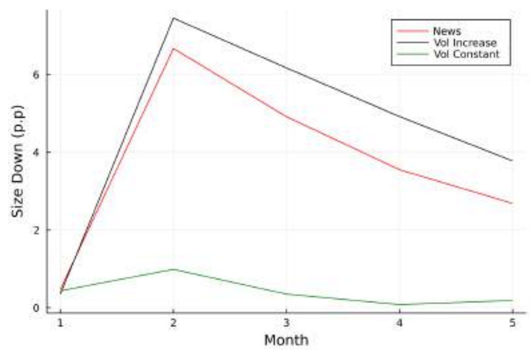
(a) Fraction of Firms Adjusting Up



(b) Fraction of Firms Adjusting Down



(c) Average Size of Upward Changes



(d) Average Size of Downward Changes

particular, upward and downward price responses will have asymmetrical signs. Consider a positive shock to aggregate TFP, which shifts the desired price distribution uniformly down as the optimal prices become smaller. This induces an increase in the fraction of firms adjusting down and a decrease in the fraction of firms adjusting up. Meanwhile, the average size of downward adjustments will be larger and upward adjustments smaller. By the same logic, a level shift in nominal expenditure S is also at odds with the empirical findings.

To generate symmetric signs in upward and downward adjustment responses, a second moment shock is needed. However, a simple one does not do the trick. Consider a simultaneous increase in idiosyncratic dispersion and anticipated increase in future volatility, similar to the one studied in Vavra (2014). Although anticipation of future volatility widens the inaction region as firms prefer to postpone price adjustments until uncertainty is resolved

Table 10: **Model Response to Alternative Shocks**

	Frac Up	Frac Down	Size Up	Size Down
Data - Riots	−	−	+	+
Agg. TFP Shock (−)	−	+	−	+
Expenditure Shock (−)	+	−	+	−
Demand Vol. Shock (+)	+	+	+	+
Vol. News Shock (+)	−	−	−	−
Menu Cost Shock (+)	−	−	−	−

which puts downward pressure on overall adjustment frequency, this effect can be counteracted by a widening of the desired price change distribution caused by a concurrent increase in idiosyncratic dispersion. Consistent with Vavra (2014), we find that the latter channel dominates, leading to a simultaneous increase in price adjustment frequency and size in both directions. Our news shock specification separates the "wait-and-see" effect stemming from a pure anticipation effect from the "realized volatility" effect caused by the actual realization of increased idiosyncratic dispersion. As a result, it is successful at replicating a decrease in price change frequency and increase in size on impact.

Lastly, and perhaps most interestingly, we find that a simple increase in the price adjustment cost is also unable to replicate the empirical results. This is relevant because one way to justify the empirical results can be by arguing that the supermarkets perceived the cost of changing prices to be higher than before – perhaps because of an increased stigma (the riots started with a change in prices) or perhaps the opportunity cost of price changes has increased. In the standard paradigm of menu cost models, an increase in the menu cost shifts the inaction bands outward. Holding the distribution of firm states fixed, this reduces the frequency and adjustments and increases the size of adjustments conditional on a change being made. However, in the presence of free adjustments which we introduce through the "Calvo-plus" setup, the negative correlation between frequency and size does not necessarily hold. In fact, we find that an unanticipated and permanent increase in the menu cost reduces both frequency and size. The key to understanding this is that the composition of price changes matter for the average size response. An increase in the menu cost reduces the frequency of adjustments and increases the size of price changes for firms who adjust by paying the menu cost. Because such changes occur less frequently, the proportion of price changes made through free price changes increases. On net, the conditional increase in size for changes made by firms paying the menu cost is overcome by the fact that they make up a relatively less fraction of all changes. The news shock specification introduces small changes in the desired price due to changes in firms' expectation about levels of future idiosyncratic demands as discussed before. This generates larger adjustments across both types of price adjustments and is crucial for the qualitative success of the model.

6 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, a nominal shock has no real effects because nominal prices will adjust and completely absorb the shock. However, when prices are inflexible, nominal shocks can have real effects as firms do not respond immediately to the shock.

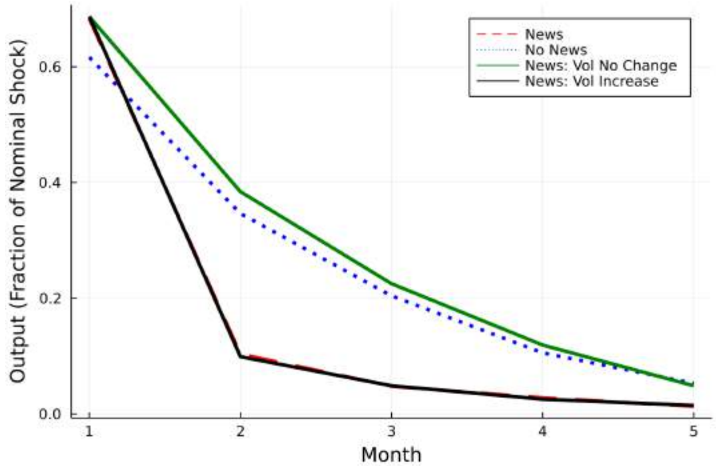
In this section, we explore the consequences of a news shock on monetary policy transmission. Firstly, we show that a positive news shock on idiosyncratic demand dispersion renders individual prices less flexible through a "wait-and-see" effect, which in turn raises the real transmission of a nominal policy shock. Secondly, we show that the 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 μ, which is a 0.37% increase to nominal expenditure. This mimics a monetary policy expansion where the central bank increases the money supply.

First, we consider how the nominal shock to S is transmitted to the real output C with and without the presence of a news shock. Figure 12 illustrates the output response, expressed as a fraction of the nominal shock, under four different experiments. Each impulse response compares the average responses in economies receiving the nominal shock against economies not receiving the nominal shock. The experiments differ by whether or not a news shock arrives simultaneously with the policy shock and the actual realization of demand volatility following the news shock.

In the first experiment, we consider the effect of a positive shock to nominal expenditure of size $\mu = 0.37\%$ only. Represented by the blue dotted line, real output increases on impact by 0.23% which is about 62% of the size of the nominal shock. The output response remains positive and slowly decays. In another experiment, we introduce a 3 standard deviation positive news shock (with $\sigma_{news} = 0.75 \cdot \sigma_v$) in period 1 and let the volatility path thereafter to be drawn unconditionally from its distribution. This is represented by the dotted red line, which is almost indistinguishable from the black line. On impact, real output increases by 0.26% which is a 68% real pass-through of the nominal shock. This shows that in the presence of a news shock, real transmission of nominal shocks are stronger – with the real pass-through increasing from 62% to 68%. This can be attributed to the fact that the news shock induces a "wait-and-see' effect and reduces price adjustments along the extensive margin. The real effect of the nominal shock is quickly tapered off in the second period because on average, the news shock materializes and actual idiosyncratic dispersion increases – leading to frequent and large price adjustments. When firms decide to adjust

Figure 12: Pass-through of Nominal Expenditure Shock to Real Output



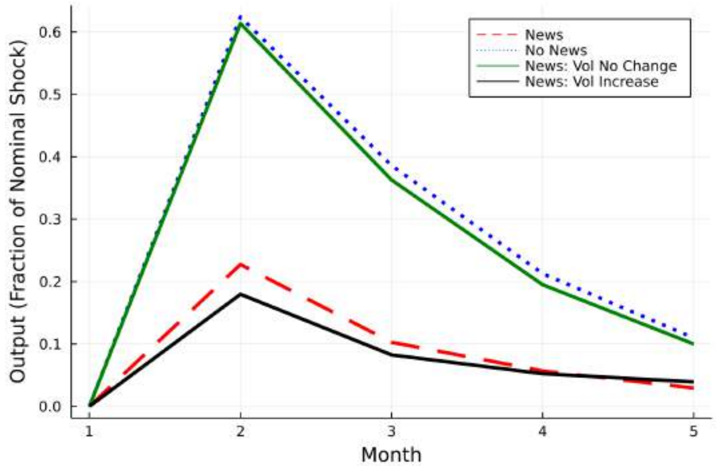
their price, they adjust both to their idiosyncratic states as well as the nominal shock, hence neutralizing much of the nominal shock. A similar result is obtained when we condition on an actual increase in idiosyncratic volatility between period 1 and 2, as represented by the solid black line. Interestingly, when we force volatility to stay constant between period 1 and 2, as shown in the solid green line, the nominal shock has a more persistent effect on real output. The effect of the initial nominal shock on real output remains strong in period 2 and only tapers off until 5 periods after. This is because the mismatch of firms' desired price and their actual price does not increase as much with the demand volatility increase not materializing, muting the price response in period 2 and onward.

Two important lessons can be drawn from this first set of experiments. Firstly, 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.

This motivates the second set of experiments where the arrival of the nominal expenditure shock is not synchronized with the news shock, but rather with a one period delay. The impulse responses from this exercise are shown in Figure 13. Similar to the previous exercise, each impulse response shows the average difference between an economy receiving a nominal expenditure shock in period 2 and an economy not receiving the nominal shock. The four impulse responses differ by whether there is a news shock occurring in period 1 and the realization of demand volatility.

In the dotted blue line, the economy is hit with only a nominal shock in period 2 and without a news shock. The nominal shock increases real output by 62% of the size of the nominal shock. Again, this is because in a menu cost model, firms do not immediately respond to a nominal shock due to pricing frictions, leading to monetary non-neutrality. The solid green line is drawn assuming there is a positive news shock arriving in period 1, but actual volatility is forced to remain constant between period 1 and period 2. In this situation, the real pass-through of the nominal shock in period 2 is slightly less than that from the experiment without a news shock. This is because when the news shock hits in period 1, some firms choose to hold off price adjustment until uncertainty is resolved. Therefore, in period 2, there are more firms that are due an adjustment as compared to the case without the initial news shock. This induces more adjustments in period 2 and slightly greater price flexibility. The dashed red line shows the impulse response when there is a news shock in period 1 and volatility is drawn unconditionally thereafter. On average, the news shock in period 1 results in higher demand dispersion in period 2. When that happens, more firms choose to adjust their price in response to changes in their idiosyncratic demand states. When they do so, they also take into account the monetary policy intervention. As a result, monetary intervention has a very low pass-through to real output – dropping from 62% in the case where volatility does not increase to about 22%. In the solid black line, we condition on volatility increasing between period 1 and 2. Unsurprisingly, the average pass-through of the

Figure 13: Pass-through of Nominal Expenditure Shock to Real Output: Nominal Shock at $T+1$ and News Shock at T

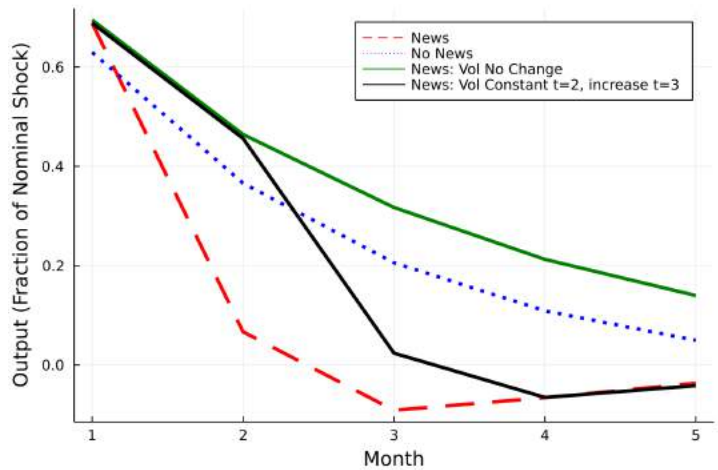


nominal is even lower in period 2, dropping below 20%. This result stresses the importance of timely monetary intervention in response to heightened uncertainty about idiosyncratic states. When news about higher idiosyncratic dispersion is realized, monetary intervention is not very effective. This echoes the findings of Vavra (2014), who shows that monetary policy is much less potent at stimulating the real economy when idiosyncratic dispersion is high.

Finally, we consider the real effects of a nominal shock when there is a persistent news shock. More specifically, we consider a positive news shock that lingers for 5 periods in a row, and examine how the realized path of actual dispersion affects the effectiveness of policy.

The blue dotted line in Figure 14 shows the response of real output to a one-time positive shock to nominal expenditure in period 1, without any concurrent news shock. Again, the nominal shock increases real output and its effects slowly decays over time. The solid green line shows the case where firms receive a positive news shock in periods 1 through 5, but volatility is conditioned to remain constant over the duration of the news shock. Simply put, every period firms are told that idiosyncratic demand could become more dispersed in the next period, but the increase in dispersion never materializes. Comparing the solid green

Figure 14: Pass-through of Nominal Expenditure Shock to Real Output: Persistent News Shocks



line and the dotted blue line, one can observe that the real effect of the nominal shock is persistently higher when firms anticipate an increase in dispersion in the future, due to the “wait-and-see” effect.

In drawing the red dotted line we assume that firms again receive the positive news shock 5 periods in a row, but the evolution of volatility is drawn unconditionally. On average, volatility immediately increases in period 2 following the initial news shock. As soon as this happens, monetary policy loses all its power. A similar pattern can be observed in the solid black line, where we force volatility to remain constant between period 1 and 2, then allows volatility to be drawn unconditionally from period 3 on-wards. Between period 1 and 2, monetary policy remains potent, but as soon as volatility increases in period 3, monetary policy no longer has any effects on the real economy.

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.

7 Conclusion

We use a unique daily dataset that covers supermarkets in Chile to study how firms change their pricing behavior when they face large and unexpected events. We use the riots in October-November 2019 in Chile as a quasi-natural experiment. Our empirical results show that during the one-month period following the first riots, supermarkets reduced the frequency of price adjustment by more than 40%, while increasing the size of price changes that do take place by around 50%. These results hold equally for price increases as well as decreases. Using various analyses we show that these results are not due to a change in the cost of the supermarket (a supply channel), nor it is due to a current change in demand. Given these empirical results, we extend the workhorse menu-cost model to allow for time-varying idiosyncratic demand and stochastic volatility in this 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. We model the riots as a news shock as in Barsky and Sims (2011) on the dispersion of idiosyncratic demand. That is, the firms receive the news that the dispersion of their idiosyncratic demand is going up in the near future. Doing so isolates the "wait-and-see" effect of Bloom (2009) and explains our empirical findings regarding the effects of the riots on the pricing behavior of supermarkets.

A policy implication of our findings is that real outcomes are more responsive to nominal disturbances such as monetary policy shocks in times of rising uncertainty. Because firms hold off price adjustments, aggregate price becomes less flexible and therefore 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 realized, prices become more flexible and thus, monetary policy looses 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.

References

Acemoglu, Daron, Tarek A Hassan, and Ahmed Tahoun, "The power of the street: Evidence from Egypt's Arab Spring," *The Review of Financial Studies*, 2018, *31* (1), 1–42.

Alvarez, Fernando and Francesco Lippi, "The Analytic Theory of a Monetary Shock," *Econometrica*, 2021, *forthcoming.*

_ , Martin Beraja, Martin Gonzalez-Rozada, and Pablo Andrés Neumeyer, "From hyperinflation to stable prices: Argentina's evidence on menu cost models," *The Quarterly Journal of Economics*, 2019, *134* (1), 451–505.

Arellano, Manuel and Stephen Bond, "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations," *The Review of Economic Studies*, 1991, *58* (2), 277–297.

Baley, Isaac and Andres Blanco, "Firm Uncertainty Cycles and the Propagation of Nominal Shocks," *American Economic Journal: Macroeconomics*, 2019, *11* (1), 276—-337.

Barro, Robert, "A Theory of Monopolistic Price Adjustment," *The Review of Economic Studies*, 1972, *39* (1), 17–26.

Barsky, Robert B and Eric R Sims, "News shocks and business cycles," *Journal of Monetary Economics*, 2011, *58* (3), 273–289.

Baskaya, Yusuf Soner and Sebnem Kalemli-Ozcan, "Sovereign risk and bank lending: evidence from 1999 turkish earthquake," Technical Report, National Bureau of Economic Research 2016.

Bloom, Nicholas, "The impact of uncertainty shocks," *Econometrica*, 2009, *77* (3), 623–685.

Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar, "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake," *Review of Economics and Statistics*, 2019, *101* (1), 60–75.

Burstein, Ariel and Gita Gopinath, "International prices and exchange rates," in "Handbook of international economics," Vol. 4, Elsevier, 2014, pp. 391–451.

Caballero, Ricardo and Eduardo M R A Engel, "Heterogeneity and Output Fluctuations in a Dynamic Menu-Cost Economy," *The Review of Economic Studies*, 1993, *60* (1), 95—119.

Calvo, Guillermo A, "Staggered prices in a utility-maximizing framework," *Journal of Monetary Economics*, 1983, *12* (3), 383–398.

Caplin, Andrew and Daniel Spulber, "Menu Costs and the Neutrality of Money," *The Quarterly Journal of Economics*, 1987, *102* (4), 703—725.

Dotsey, Michael and Robert G King, "Implications of state-dependent pricing for dynamic macroeconomic models," *Journal of Monetary Economics*, 2005, *52* (1), 213–242.

_ , Robert G. King, and Alexander L. Wolman, "State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output," *The Quarterly Journal of Economics*, 1999, *114* (2), 655–690.

Drenik, Andres and Diego J Perez, "Price setting under uncertainty about inflation," *Journal of Monetary Economics*, 2020, *116*, 23–38.

et al Eichenbaum Martin, "How frequent are small price changes?," *American Economic Journal: Macroeconomics*, 2014, *6* (2), 137–155.

Gabaix, Xavier, "Variable rare disasters: An exactly solved framework for ten puzzles in macro-finance," *The Quarterly journal of economics*, 2012, *127* (2), 645–700.

Gagnon, Etienne, "Price Setting during Low and High Inflation: Evidence from Mexico," *The Quarterly Journal of Economics*, 2009, *124* (3), 1221–1263.

_ and David López-Salido, "Small Price Responses to Large Demand Shocks," *The Journal of the European Economic Association*, 2020, *18* (2), 792–828.

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

Hadzi-Vaskov, Metodij, Samuel Pienknagura, and Luca Antonio Ricci, "The Macroeconomic Impact of Social Unrest," *IMF Working Papers*, 2021, *2021* (135), A001.

Harding, Martín, Jesper Lindé, and Mathias Trabandt, "Resolving the missing deflation puzzle," *Journal of Monetary Economics*, 2021.

Hobijn, Bart, Federico Ravenna, and Andrea Tambalotti, "Menu Costs at Work: Restaurant Prices and the Introduction of the Euro," *The Quarterly Journal of Economics*, 2006, *121* (3), 1103—1131.

Ilut, Cosmin, Rosen Valchev, and Nicolas Vincent, "Paralyzed by fear: Rigid and discrete pricing under demand uncertainty," *Econometrica*, 2020, *88* (5), 1899–1938.

Kehoe, Patrick and Virgiliu Midrigan, "Prices are sticky after all," *Journal of Monetary Economics*, 2015, *75*, 35–53.

Kimball, Miles S., "The Quantitative Analytics of the Basic Neomonetarist Model," *Journal of Money, Credit and Banking*, 1995, *27* (4), 1241–1277.

Klenow, Peter J and Jonathan L Willis, "Real rigidities and nominal price changes," *FRB of Kansas City Working Paper No. RWP06-03*, 2006.

Klepacz, Matthew, "Price Setting and Volatility: Evidence from Oil Price Volatility Shocks," *unpublished mimeo*, 2021.

Krusell, Per and Anthony A Smith Jr, "Income and wealth heterogeneity in the macroeconomy," *Journal of Political Economy*, 1998, *106* (5), 867–896.

Maćkowiak, Bartosz, Filip Matějka, and Mirko Wiederholt, "Rational Inattention: A Review," *The Journal of Economic Literature*, 2021, *forthcoming.*

Midrigan, Virgiliu, "Menu costs, multiproduct firms, and aggregate fluctuations," *Econometrica*, 2011, *79* (4), 1139–1180.

Nakamura, Emi and Jon Steinsson, "Five Facts About Prices: A Reevaluation of Menu Cost Models," *The Quarterly Journal of Economics*, 2008, *123* (4), 1415–1464.

_ and _ , "Monetary non-neutrality in a multisector menu cost model," *The Quarterly journal of economics*, 2010, *125* (3), 961–1013.

Rotemberg, Julio, "Customer Anger at Price Increases, Time Variation in the Frequency of Price Changes and Monetary Policy," *NBER Working Papers 9320*, 2002.

Sheshinski, Eytan and Yoram Weiss, "Inflation and Costs of Price Adjustment," *The Review of Economic Studies*, 1977, *44* (2), 287—-303.

Vavra, Joseph, "Inflation dynamics and time-varying volatility: New evidence and an Ss interpretation," *The Quarterly Journal of Economics*, 2014, *129* (1), 215–258.

Wieland, Johannes F, "Are negative supply shocks expansionary at the zero lower bound?," *Journal of Political Economy*, 2019, *127* (3), 973–1007.

Young, Eric R, "Solving the incomplete markets model with aggregate uncertainty using the Krusell–Smith algorithm and non-stochastic simulations," *Journal of Economic Dynamics and Control*, 2010, *34* (1), 36–41.