# Pricing Under Distress

PRELIMINARY AND INCOMPLETE - DO NOT CITE

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April 20, 2021

## 1 Introduction

Pricing decisions of firms have become increasingly central in macroeconomics. To give a well-known example, the effectiveness of a monetary expansion depends crucially on how firms react – the more prices react, the less quantities do and hence the less expansionary is the policy. We contribute to the broader literature by introducing a dataset from Chile that is available in higher frequency than most existing studies and that covers the universe of transactions in the economy. In this note, we use this dataset to understand the behavior of supermarket prices during a very important recent episode for Chile, the riots of October 2019. By doing so we shed some light on how firms react to periods of social and political distress, which paves the way for studying theoretically the effect of these large events on pricing dynamics and the economy as a whole.

Chile experienced major riots in October 2019, which were triggered by a seemingly benign increase in subway fares in Santiago and eventually led to an overhaul of its 40-year old constitution a year later. Similar events occur regularly in other developing countries (e.g. the Arab Spring demonstrations in early 2010s) and developed countries (e.g.the yellow vest protests in France in 2018). This episode in Chile provides an excellent laboratory to study how firms react to

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large events like this for at least two reasons. First, the riots gathered steam in a very short time and were thus largely unanticipated. Second, our data is exceptionally detailed and covers the universe of transactions in Chile. In particular, we use the administrative data collected by the tax authority in Chile for value-added tax (VAT) purposes where every transaction is recorded with price, quantity and identifiers for the parties of the transaction.

In this note we report our baseline results which show that the prices became more "sticky" during the riots: fraction of prices that increased on a given day fell from 2.1% to 1.5% during the one-month period that start with October 18, 2019, while fraction of prices that decreased fell from 1.7% to 1.2%. While the frequency of price changes fell during this period, when we look at the magnitude of price changes conditional on a price change, both positive and negative price changes became larger in absolute value, increasing from 14% to 16.1% and from 11.2% to 12.5%, respectively.

Our larger research project provides more detailed results about both the unconditional properties of prices as well as the riots period. We also study the implications of these findings in the context of a state-of-the-art menu cost model along the lines of Vavra (2014) where we interpret the riots as an unanticipated uncertainty shock and discuss the implications for effectiveness of policy.

## 2 Data Description

On January $31^{st}$ 2014, Chile passed a law (number 20.727) of electronic invoicing for business-to-business transactions to fight tax avoidance. Every transaction is electronically recorded and automatically reported to the tax authority. The implementation of the law was gradual, with larger firms starting first. It took three years for every firm in the economy to be subject to this new reporting system. This law effectively created a high-frequency database of every firm-to-firm transaction in the Chilean economy.

We focus on the supermarkets. Because of their well-defined input and output prices, supermarkets have been traditionally used when studying pricing and mark-up in the literature. The identity of the firms in the database are masked and thus we cannot use the names of companies to limit our sample. Instead, we limit our sample to firms whose economic activity is primarily described as ”Retail trade in non-specialized stores” according to the official Central Bank of Chile’s classification. Following the literature, we further restrict the sample to medium and large retailers (average annual sales higher than USD$4 million). This last feature also guarantees that the firms analyzed have information even in the early stages of the electronic invoicing law’s implementation. Finally, to ensure the identification of supermarkets, we require that the analyzed firms have a concentration of at least 50% of their sales in a specific set of product categories.[1]

These restrictions generate a database of more than 48 million individual electronic invoices between January 2015 and December 2019. Each electronic invoice contains the issuer’s (seller) id, the buyer’s id, the buyer’s municipality (as registered with the tax authority), and a unique code of the supermarket branch in which the transaction took place. Because the tax authority does not audit the branch information, some supermarkets do not distinguish their branch locations. We impose four criteria on the branch information to ensure that the branch identifiers indeed refer to unique branches:

1. A proper branch must report positive sales on at least 50% of the days between their first and last observation in the dataset before October 18, 2019.

2. A proper branch must have at least 80% of their weeks classified as *valid weeks*. We consider a valid week as one in which at least 50% of branch code’s buyers were registered in the same municipality.

3. We calculate the most common municipality for all costumers of a given branch in every week. A proper branch must have 95% of weeks registering the same municipality as the most recurrent among its buyers.

4. A proper branch has to report at least 80 days with positive sales.

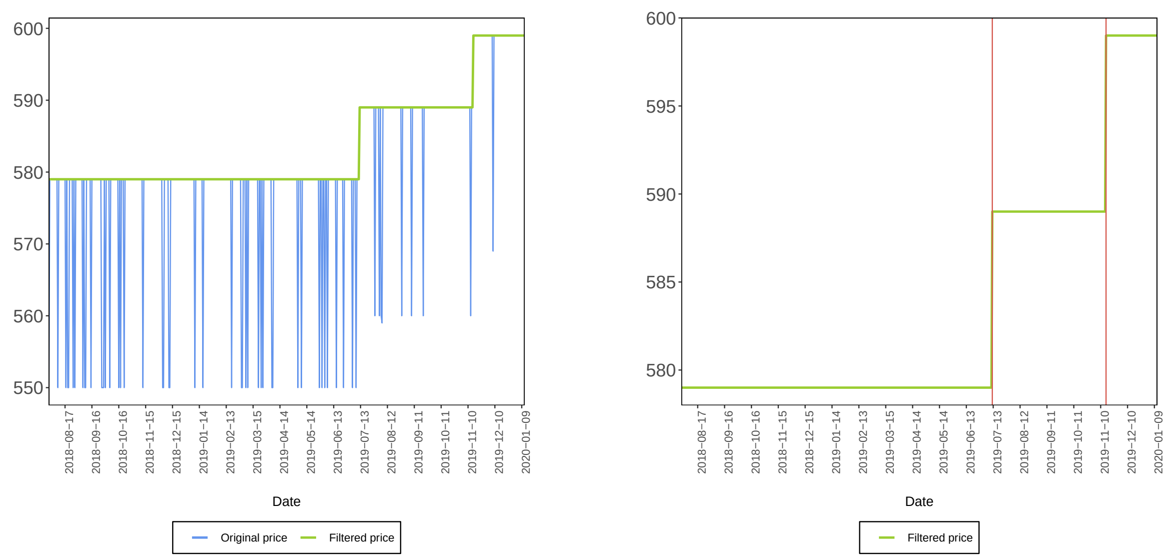
Having this cleaned set of invoices, we build our panel data. The unit of analysis is a unique combination of a supermarket (seller’s id), location (branch code), and product description (from

[1] These product categories are wheat, rice, barley, oats, other cereals, vegetables, eggs and other livestock products for consumption, milk, poultry, nuts, citrus fruits, oil, drinkable plants and spices, tobacco, foliage, nursery products, live plants, flowers and seeds, raw vegetable materials for textile use, perfumery and medicine, other raw vegetable materials, wine grape, table grape, kiwi and other subtropical and tropical fruits, olives, raw animal materials, textile use and other animal products unsuitable for food, auxiliary services for agriculture, hunting, forestry and fishing, plantations, trunks and logs of insignis pine and other conifers, wood and other forestry products.

now on, this triplet is referred as a product). Because a given product can appear in several invoices on a given day for a particular branch, we use the intra-day maximum price as the relevant daily price. The reason for using the maximum is that price deviations are small and likely to be due to the use of coupons or other specific discounts (e.g., cash versus credit, veteran discount, etc.). We only consider products bought at least 3 days per week (minus holidays on weekdays) for at least 20 consecutive weeks.[2] For each of the product-stints for which this continuity restriction is verified, we fill any gaps in daily prices using the last observed daily price.

We complete the cleaning process by applying the filter proposed by Kehoe and Midrigan (2015), which removes short-term price fluctuations. Panel (a) of Figure 1a shows the filtered and the original price for a particular product.

A critical part of our study is to evaluate the characteristics of price changes. To identify "breaks" in price regimes we use the process proposed by Stevens (2020). Panel (b) of Figure 1b shows the implementation of the procedure for the same example. Note that we ignore price changes that are smaller than one peso – all post-tax prices are integers and no coins for less than one peso exists in Chile – or less than 0.5% of the previous price.




**(a)** Kehoe and Midrigan (2015) Filter

**(b)** Stevens (2020) Procedure

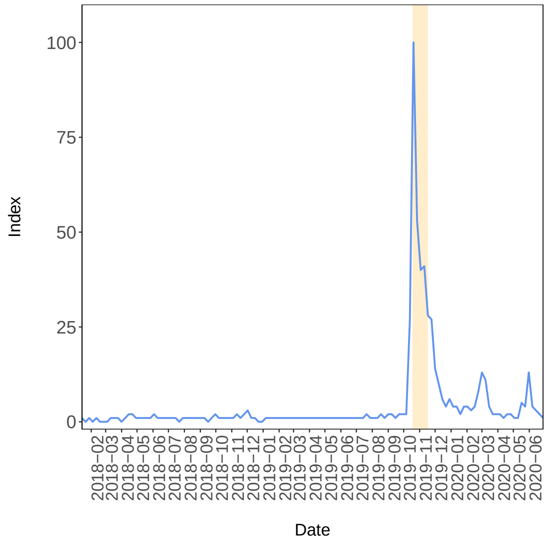
**Figure 1:** Filters

[2]On days where the total sales of a location is exactly zero, indicating that the location was likely closed that day, product-level prices are filled with the previous day's information and quantities are set to zero.

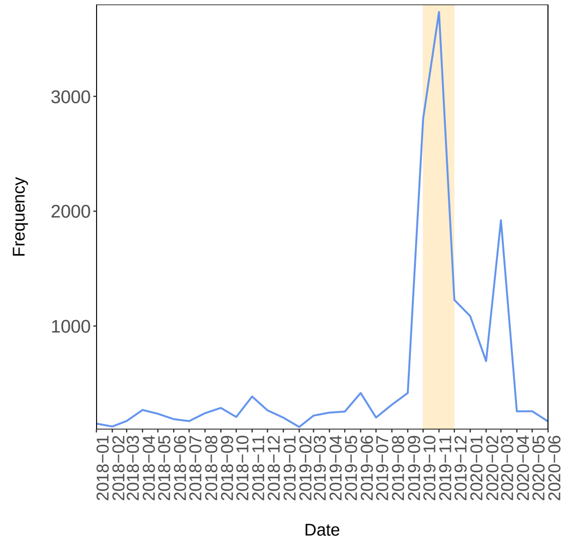
## 3 The Riots as an Unexpected Event

Santiago's subway fare was raised by $30CLP (about $0.04USD) on October 6, 2019. In the days that followed, high school students reacted with demonstrations in subway stations against this fare increase with minimal disruptions on the subway service. Government officials and other public figures made statements against the demonstrations. The momentum of the demonstrations slowly grew until October 18, 2019, when some limited disruptions in Santiago's subway service was met with a strong police response. On the night of October 18, 2019 massive riots broke out with mobs attacking, sacking and burning subway facilities. On that night and the following nights, the riots spread to all major cities supermarkets, churches, museums, restaurants and other local business were all affected. The riots found their turning point on November 15, 2019 when almost the whole political spectrum announced an agreement aiming for a referendum about changing the 1980 Constitution. This announcement immediately calmed the intensity of the riots and they slowly faded away.

We argue that this episode was sudden and unexpected. Panel (a) of Figure 2 shows searches in Google for the word "protestas" (demonstrations, in Spanish) by internet users based in Chile where the maximum daily searches in the whole sample, which happens to be on October 19, 2019, is normalized to 100. The yellow area marks the time window from October 18 to November 17, 2019. Panel (b) of Figure 2 shows a similar pattern using monthly data on police reports related to "desórdenes" (disturbances, in Spanish).




**(a)** Google Trend for ”protestas”




**(b)** Police Reports of ”desórdenes”

**Figure 2:** Riots

Note: Weekly Google trend, shaded period between Oct-18-2019 and Nov-17-2019. Monthly police reports, oct and nov 2019 shaded.

Riots were also widespread in Chile. To see this, Figure 3 shows a map of Chile with 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. Figure 4 shows the Santiago Metropolitan Area in detail. We classify municipalities in four categories: green for those crime remained equal or decreased, and yellow, orange and red respectively for increase in crime with increasing intensity. We observe that all large and medium-scale cities in the country where affected by riots. Only rural areas remained unaffected. In Santiago, all municipalities but two showed an increase in crime reports.

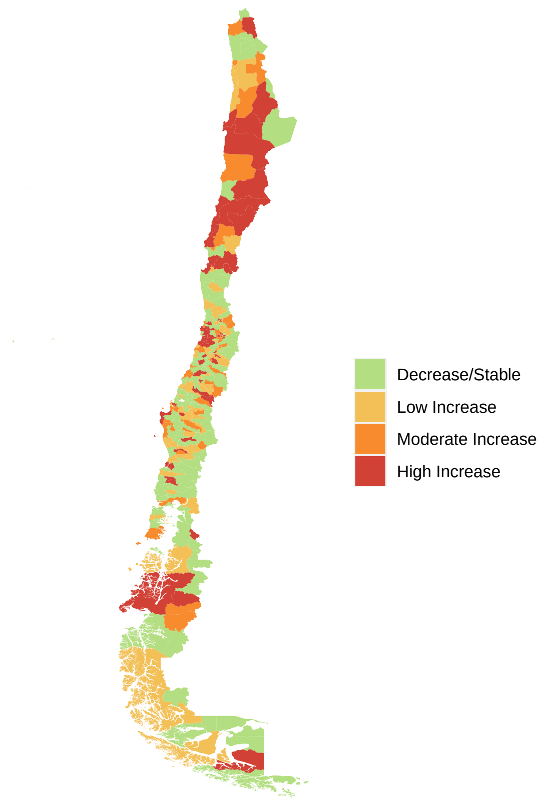



**Figure 3:** Geographical variation of burglaries in the country

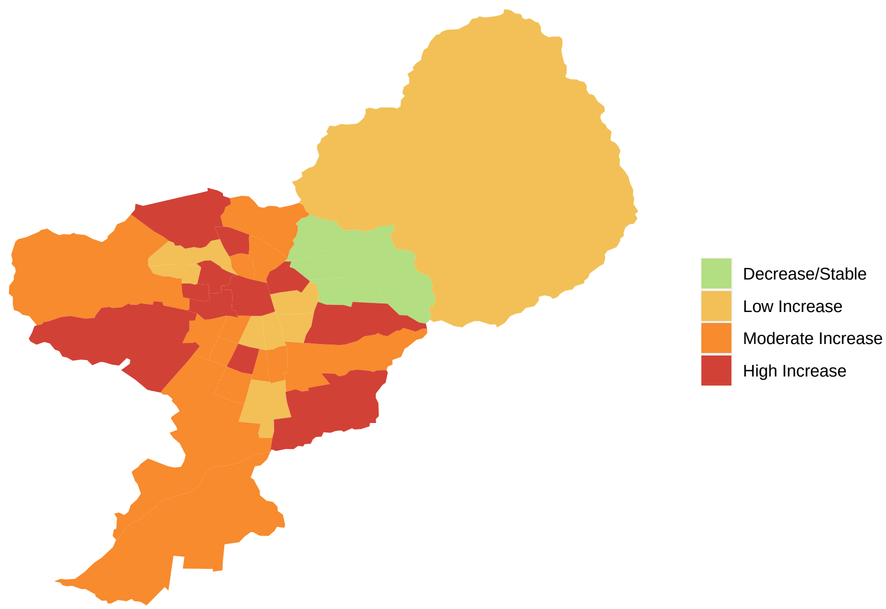



**Figure 4:** Geographical variation of burglaries in Santiago

To give an idea about the effect of the riots on economics activity, Figure 5 shows the number of products (recall, again, that this refers to product-store-branch triplets) available in our sample on non-Sunday and non-holiday days. Those are the total number of prices recorded in a day in our sample after all exclusions and filters described above are applied. Before the riots, number of available goods fluctuate around 3,500 where this fluctuations reflect both the high-frequency fluctuation that happen within months but also lower-frequency fluctuations reflecting the natural churning of products. The gray shade indicates the time window between October 18, 2019 and November 17, 2019, during which the number of available goods instantly fall by 1,000, or by about 30%.

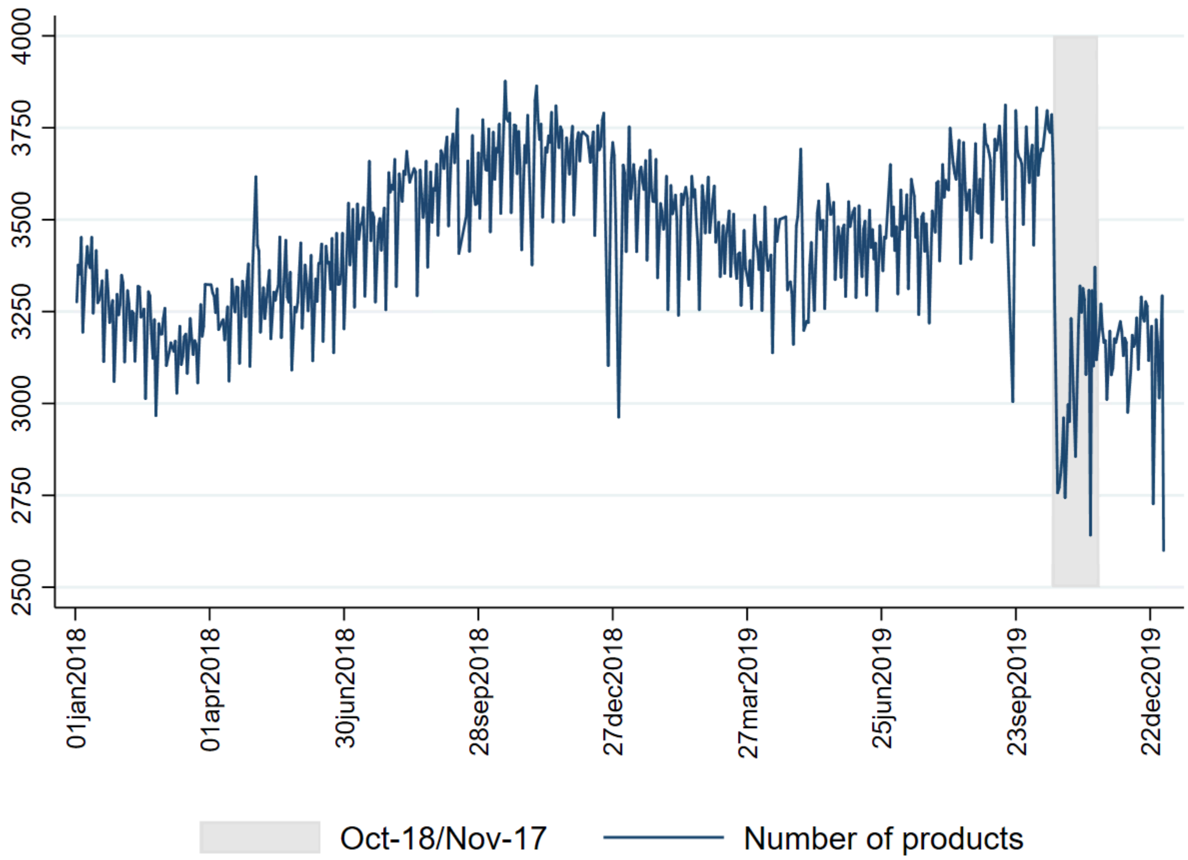



**Figure 5:** Number of product-store-branch

## 4 Empirical Results

We proceed to examining the pricing behavior of supermarkets during the Chilean Riots. Figure 6 shows the fraction of products experiencing price breaks every non-Sunday non-holiday day during the sample. Some seasonal patterns are evident in this figure – prices tend to change on certain days and on certain weeks of the month. The period of the riots, which is represented by the gray shading, stands out as a clear outlier in this graph where the share of products with a price change falls significantly and the seasonal variation seems to disappear.

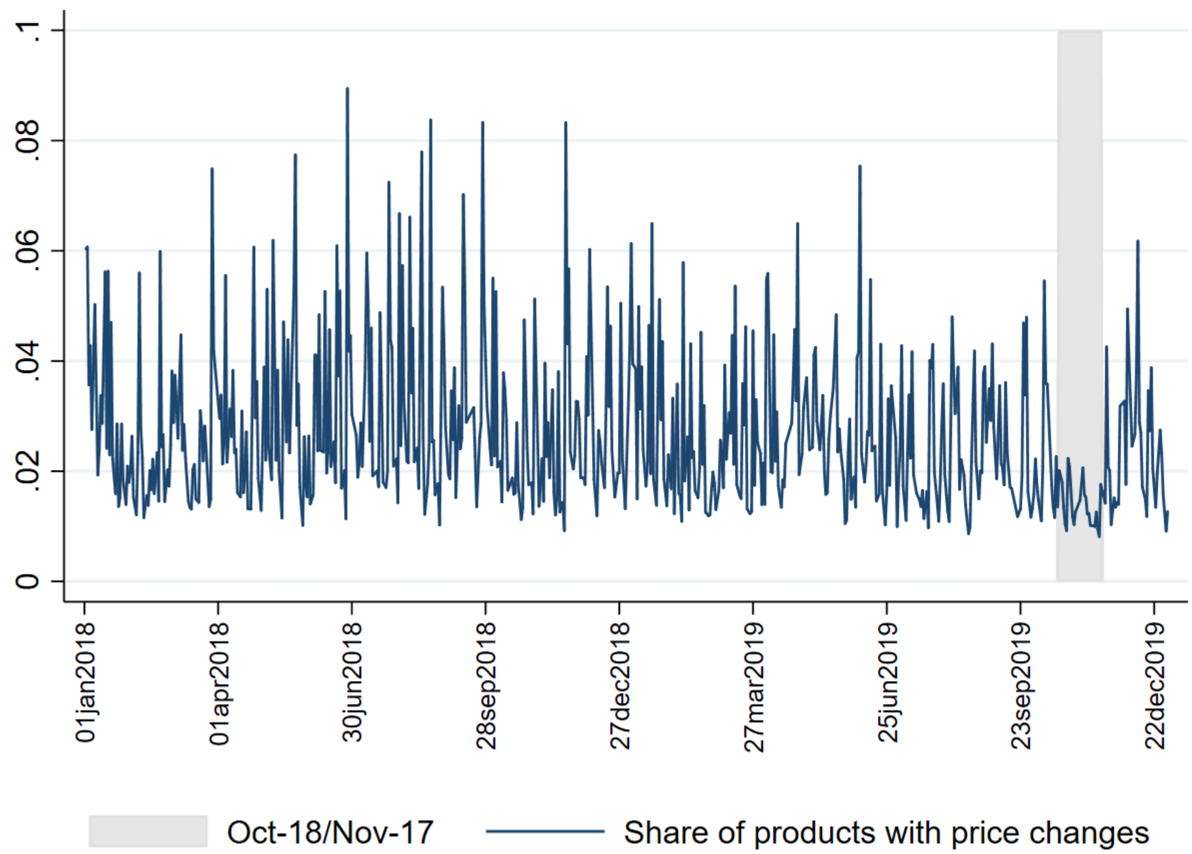



**Figure 6:** Share of Products with Price Changes

Table 1 reports some key statistics of price dynamics at the product level for seven weeks starting on October 18, 2019. As a reference, we also report average statistics for a sample between July 1, 2018 to October 17, 2019. We report four statistics: i) the share of goods in the sample that experience a price increase, ii) the share of goods in the sample that experience a price decrease, iii) average size of price increases in absolute value, and iv) the average size of price decreases in absolute value.

Before the riots, on average 1.51% of products exhibit a positive price break, while 1.34% of of products experience negative price breaks. Conditional on a positive price break, the average size of the increase is 12.51% while price decreases conditional on a negative break are on average 9.47%. These statistics are broadly consistent with the literature (Nakamura and Steinsson, 2008). During the first week after the outbreak of the riots, we observe a large decrease in the share of products experiencing positive and negative price breaks – from 1.5% and 1.3% to 0.9% for both.

**Table 1:** Descriptive Statistics

| | Percentage of increases | Percentage of decreases | Magnitude of increases | Magnitude of decrease |
|---|---|---|---|---|
| Pre-Riots | 1.51 | 1.34 | 12.51 | 9.47 |
| Week of 18/10/2019 | 0.92 | 0.91 | 13.32 | 8.16 |
| Week of 25/10/2019 | 1.04 | 1.03 | 12.04 | 8.37 |
| Week of 11/01/2019 | 1.25 | 0.55 | 10.47 | 8.68 |
| Week of 11/08/2019 | 0.73 | 0.76 | 10.1 | 10.83 |
| Week of 11/15/2019 | 1.39 | 1.3 | 12.88 | 10.1 |
| Week of 11/22/2019 | 1.03 | 0.92 | 12.99 | 7.97 |
| Week of 11/29/2019 | 2.39 | 1.38 | 15.79 | 11.37 |

*Notes:* The pre-riots sample cover July 1, 2018 to October 17, 2019.

We also note a mild increase in the magnitude of positive price changes and a fairly large decrease in the magnitude of negative price changes. Similar results are obtained for the next three weeks, which are followed by an eventual correction in the week of November 29.

While, Figure 6 and Table 1 provide some convincing but casual evidence of a change in pricing dynamics, To more rigorously establish this we estimate the following panel regression:

$$\begin{aligned} y_{it} = \alpha_0 + \beta_1 D_{riots} + \Gamma_1 DSLB_{it} + \Gamma_2 DSLB_{it}^2 + \Gamma_3 DSLB_{it}^3 \\ + \Theta_1 ALDB_{it} + \Theta_2 SLDB_{it} + \Theta_3 ALDB_{it} * SLDB_{it} + \Psi_1 SB_{it} \\ + product_i + m_t + yq_t + nw_t + h_t + wd_t + product_i * nw_t + product_i * wd_t + \varepsilon_{it}^y \end{aligned} \tag{1}$$

The dependent variables are the same objects described in Table 1 – respectively labelled positive and negative breaks and positive and negative delta breaks. Table 2 describes the definition of all control variables used in the analysis. We use a third degree polynomial on the number of days that have passed since the last price change of a product. We also control for the magnitude and the direction of the last price break as well as for the number of price breaks that the product has experienced over the last 30 days. Besides the use of product fixed effects, we control for monthly seasonality and remove all quarterly aggregate fluctuations using time fixed effects. We also allow for weeks within a month and days within a week to have different price dynamics (for instance, the last week of the month, or Fridays in general, could be unusually active in terms of price changes for all products). We also allow for non-mandatory holidays to have an unusual price behavior, where some stores may be closed or some products may not be sold. Note that the daily frequency and the depth of the data allows us to use all these controls, which provide exceptional flexibility in the literature which typically uses weekly data for only one supermarket. The main variable of interest is the dummy $D_{riots}$, where the associated coefficient $\beta_1$ captures a potential change on the pricing behavior at the product level in a 30 days window after the start of the riots.

| Variable | Description |
|---|---|
| $D_{riots}$ | 1 in the period between October 18, 2019 and November 17, 2019 and 0 in other case. |
| $DSLB_{it}$ | Number of days since last price break. |
| $ALDB_{it}$ | Absolute value of last price break. |
| $SLDB_{it}$ | Sign of last price break (1 if positive). |
| $SB_{it}$ | Number of price breaks in the last 30 days. |
| $product_i$ | Product (supermarket-location-product) fixed effect. |
| $m_t$ | Month fixed effect. From 1 (January) to 12 (December). |
| $yq_t$ | Year-Quarter fixed effect. From 1 (2015q1) to 20 (2019q4). |
| $nw_t$ | Week number in a month starting from first Monday fixed effect. From 1 to 5. |
| $wd_t$ | Weekday fixed effect. From 0 (Sunday) to 6 (Saturday). |
| $h_t$ | Non-mandatory holiday fixed effect. |

**Table 2:** Independent Variables

Table 3 reports the estimation results. The first two columns show that during the riots the frequency of positive and negative price breaks fell by practically the same magnitude ($0.6$ percentage points). Conditional on observing a price change, price changes of both signs are larger in absolute terms. The increase in magnitude is asymmetric, with positive breaks changes increasing their magnitude by more (about $2.3\%$ versus $1.2\%$). These effects are large when compared to the unconditional moments computed using the same sample. Thus, under the distress of the riots, supermarkets decreased the frequency of price changes, but conditional on a price break, they adjusted their prices by a larger extend.

**Table 3:** Supermarkets price setting results

| | Positive breaks | Negative breaks | Delta positive breaks | Delta negative breaks |
|---|---|---|---|---|
| D_riots | -0.00623*** | -0.00547*** | 0.0225*** | 0.0124** |
| | (0.00104) | (0.000679) | (0.00653) | (0.00583) |
| DSLB | -0.0000133*** | -0.0000304*** | 0.0000613* | 0.000105*** |
| | (0.00000293) | (0.00000278) | (0.0000326) | (0.0000386) |
| DSLB2 | 1.99e-08*** | 4.60e-08*** | 0.000000247*** | -0.000000229 |
| | (6.77e-09) | (5.30e-09) | (9.24e-08) | (0.000000206) |
| DSLB3 | -4.34e-12 | -1.49e-11*** | -1.39e-10*** | 3.76e-10 |
| | (3.39e-12) | (2.31e-12) | (4.92e-11) | (2.35e-10) |
| ALDB | 0.0914*** | -0.0285*** | 0.743*** | -0.272*** |
| | (0.00835) | (0.00284) | (0.0229) | (0.0185) |
| SLDB | -0.0139*** | -0.0127*** | 0.0541*** | -0.0257*** |
| | (0.000651) | (0.000692) | (0.00212) | (0.00156) |
| SLDB*ALDB | -0.112*** | 0.0445*** | -0.924*** | 0.401*** |
| | (0.00802) | (0.00269) | (0.0217) | (0.0179) |
| SB | -0.000589*** | -0.00118*** | 0.00555*** | 0.00145*** |
| | (0.0002) | (0.000183) | (0.000697) | (0.000475) |
| Constant | 0.0276*** | 0.0124*** | 0.0627*** | 0.124*** |
| | (0.000827) | (0.000712) | (0.00291) | (0.00223) |
| product FE | Yes | Yes | Yes | Yes |
| wd FE | Yes | Yes | Yes | Yes |
| m FE | Yes | Yes | Yes | Yes |
| q FE | Yes | Yes | No | No |
| nw FE | Yes | Yes | Yes | Yes |
| h FE | Yes | Yes | Yes | Yes |
| product*wd FE | Yes | Yes | No | No |
| product*nw FE | Yes | Yes | No | No |
| Observations | 4491396 | 4491396 | 88831 | 76432 |
| Products | 17823 | 17823 | 12244 | 11162 |
| $R^2$ | 0.069 | 0.065 | 0.549 | 0.491 |
| Adjusted $R^2$ | 0.02 | 0.016 | 0.479 | 0.404 |

Note: Standard errors in parentheses
$^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

## References

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

**Nakamura, Emi and Jón Steinsson**, "Five facts about prices: A reevaluation of menu cost models," *The Quarterly Journal of Economics*, 2008, *123* (4), 1415–1464.

**Stevens, Luminita**, "Coarse pricing policies," *The Review of Economic Studies*, 2020, *87* (1), 420–453.

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