Scraped Data and Sticky Prices: Frequency, Hazards, and Synchronization

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Abstract

This paper introduces *scraped online data* to study price stickiness in developing countries. Scraped data constitute a unique source of price information in terms of detail, sampling frequency, and country availability, allowing simultaneous cross-country analyses in a variety of macroeconomic settings. Using a dataset with more than 21 million prices in four Latin American countries during a time of high inflation (from October 2007 to October 2008), I present patterns of price stickiness yielding three main empirical results. First, the distributions of the size of price changes are bimodal, with few changes close to zero, as predicted by menu cost models. Second, hazard functions are upward-sloping or hump-shaped in all countries, consistent with state-dependent pricing. Third, there is strong daily price synchronization within narrow categories, suggesting that strategic complementarities play an important role in price-setting decisions. These results differ considerably from previous findings in the literature and highlight the importance of studying stickiness across different macroeconomic settings.

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1 Introduction

Since the early 1970s, a large amount of theoretical research has focused on the micro foundations of sticky prices, a key element in modern explanations of the real effects of monetary policy. The empirical literature on price stickiness, by contrast, has been relatively thin. Bils and Klenow (2004) made an important contribution by studying disaggregated US Consumer Price Index (CPI) data from the 1990s and showing that the median retail price changed once every 4.3 months, more frequently than previously assumed.[1] Although other significant contributions followed, important empirical questions remain largely unanswered.[2] Are pricing decisions time-dependent or state-dependent? Is stickiness driven by menu costs, strategic complementarities, or imperfect information? Are there differences across countries or sectors, and what drives them? What roles do competition and price synchronization play? More generally, how do the macroeconomic environment, past inflation experiences, and institutional frameworks influence the way prices adjust? Insights into these questions are vital to constructing better models that can match the response of aggregate data to shocks, helping us understand how policy should react and what the impact will be on sectoral prices and output.

The main problem in the current empirical research is that product-level data are limited in terms of the frequency, countries, and contexts in which they are collected. US and European CPI data have recently become available to researchers on a limited basis.[3] Although

[1]The typical assumption was that retail prices changed once a year on average, following work by authors such as Carlton (1986), Cecchetti (1986), Kashyap (1995), and Blinder et al. (1998).

[2]See Mackowiak and Smets (2008) and Klenow and Malin (2009) for a review of the recent empirical literature. The main conclusion from early papers is that individual prices are more flexible than previously assumed and that standard state-dependent models calibrated with the observed firm-level flexibility do not generate enough real effects of monetary policy to match patterns in the aggregate data. Subsequent papers focused on improving the interpretation of the data. For example, Nakamura and Steinsson (2008) show that prices are stickier when sales are excluded, while Eichenbaum et al. (2008) show there is considerably stickiness in *reference prices*, measured as the most common price within a quarter. Other authors, such as Burstein and Hellwig (2007) and Klenow and Willis (2006), have extended state-dependent models with strategic complementarities and real rigidities, which can potentially deliver more aggregate stickiness.

[3]US CPI data are used by Bils et al. (2003), Nakamura and Steinsson (2008), Klenow and Kryvtsov (2008), and Klenow and Willis (2007). European CPI data are used by Dhyne et al. (2005), Boivin et al. (2007), Wulfsberg (2008), among others.

these datasets are detailed and cover a wide range of products, they are typically available only for a few developed countries with data collected during times of stable macroeconomic environments, where aggregate shocks are mild and micro-price mechanisms harder to detect. To determine which stylized facts are robust, the literature needs comparable data from different countries, under various inflation settings, macro volatilities, and institutional arrangements.

This paper makes contributions on two fronts. First, I show that there is a unique and valid source of data in scraped online prices, which can be used to extend the empirical analysis into a much larger set of countries and economic conditions.[4] Second, I look for empirical evidence of sticky prices in four developing countries, with a focus on frequencies of adjustment, hazard functions, and price synchronization, introducing results that differ considerably from previous findings in the literature.

Section 2 describes a methodology that I developed to efficiently "scrape" price information from online sources. For the purposes of this paper, I constructed a dataset with more than 21 million supermarket prices in Argentina, Brazil, Chile, and Colombia, between October 2007 and October 2008. The information is comparable across countries, with the same type of products and time periods. Prices are available with *daily* frequency, which reduces measurement errors and makes it easier to study sales, hazards, and price synchronization. In addition, the data contain detailed information on each product (including a sale and price control indicator) and were collected during a period of high inflation and aggregate volatility.

To show that scraped prices are a valid source of information, I compare simultaneous surveys of *online* and *offline* prices in all supermarkets. Although price levels are seldom identical, price changes behave similarly in terms of timing and size of adjustment. In addition, daily price indexes generated with online data provide estimates of annual inflation

[4]Together with Prof. Roberto Rigobon at MIT Sloan, I started the "Billion Prices Project" that is extending the data collection and analysis to a sample of over 50 countries in five categories: supermarkets, furniture, electronics, apparel, and real estate. See www.billionpricesproject.org.

of 22.5% in Argentina, 6.4% in Brazil, 7.5% in Chile, and 7.7% in Colombia. These values closely match official statistics in every country, with the only exception of Argentina, where official price indexes have become widely discredited in recent years.[5]

Sections 3 to 5 use this data to study price stickiness in all countries and present three main results:

First, there is evidence of bimodal distributions in the size of price changes in Argentina, Chile, and Brazil, with few changes close to zero percent. This is consistent with state dependent menu cost models, which predict that very small changes are not optimal in the presence of adjustment costs. Furthermore, in Argentina the distribution has an asymmetry that is characteristic of a Golosov and Lucas (2007) menu cost model in the presence of strong positive aggregate shocks. These results differ from what Klenow and Kryvtsov (2008) and Midrigan (2005) found in US CPI and scanner data respectively, where very small price changes are common and distributions are symmetric.[6]

Second, I use duration analysis to find evidence of upward-sloping and hump-shaped hazard functions in individual price adjustments. Hazards measure the probability of a price change *conditional* on the time passed since the previous adjustment. In state-dependent models, hazard functions tend to be upward-sloping when there are persistent aggregate shocks, because prices move further away from their optimum as duration increases.[7] Empirically, hazard functions are upward-sloping in Argentina and Colombia. In Chile and Brazil, they are upward-sloping for the first month and then present a hump-shaped pattern which is consistent with state-dependent models in the presence of stronger temporary shocks. These results also differ from what other authors such as Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008) found with US CPI data, where hazard functions

[5]Since January 2007, the government has been interfering with the construction and publication of price indexes at the National Statistics Institute (INDEC). See www.inflacionverdadera.com for more up-to-date inflation estimates in Argentina using some of the data in this paper.

[6]The differences are likely due to aggregation across retailers in CPI data and/or lower sampling frequency of the data in a context with relatively more temporary shocks.

[7]By contrast, hazard functions are constant in time-dependent models such as Calvo (1983) because the probability of price change is fixed over time.

are either downward-sloping or flat.

Finally, I find strong daily price synchronization within narrow categories or "aisles". Synchronization is independent of sales and is stronger for price increases than price decreases. Aisles with more synchronization also have less variability in the size of simultaneous price changes, which suggests that firms are acting like strategic complements by matching both the timing and size of their price changes.[8] Synchronization, however, is not linked to any *real rigidities*. The data show that synchronization tends to increase the frequency of price adjustments at the aisle level in Argentina, Brazil, and Chile, consistent with Ball and Romer's (1991) model of coordination failure under strong aggregate shocks.

Overall, this paper provides empirical evidence in support of state-dependent pricing in developing economies. Most of the findings differ considerably from previous results in the literature that uses US and European data.[9] This highlights the importance of using scraped data to study stickiness in a larger sample of countries and economic settings, allowing us to understand which facts are robust and how they should influence the design of theoretical models.

2 Scraped Data: a New Approach with Online Sources

2.1 Main Characteristics

This paper uses a new database of more than 21 million supermarket prices in four Latin American countries: Argentina, Brazil, Chile, and Colombia. The data come from the online price tables of four different retailers, one in each country, and cover the period from October 2007 to October 2008.

All the supermarkets included in this paper are major players in their respective countries, with hundreds of physical stores. They also sell online in large cities such as Buenos Aires,

[8] Other causes of synchronization are common shocks and economies of scale in menu costs.
[9] See Klenow and Malin (2009) for a review of the main results in this literature.

Santiago, Rio de Janeiro, and Bogotá. Since buyers cannot physically see the products they are purchasing online, retailers make an effort to display detailed information on each item, including the price, the product's identification number (id), name, brand, package size, category, and whether it is on sale or under price control.

Every day, during the course of a year, I connected to these online shopping platforms and recorded all available information for each good on display. I built and used an automated procedure that scans through the code of publicly available webpages and records all the relevant price information. This technique is commonly called "web scraping" and hence I use the term *Scraped Online Data*.[10]

Table 1 provides details on each country's database. There are roughly 18000 daily prices for each country in Argentina, Chile, Brazil, and 5000 in Colombia. The initial date for each database differs by a few days around October 2007, but they all end on October 12th 2008. To compare results for the same product categories across countries, I matched each supermarket's classifications into 95 standardized categories containing a large variety of foods and household items.[11] Products are further classified into "aisles", which are narrow product categories that include only close substitutes displayed next to each other.[12]

To conduct the price stickiness analysis, I treated the data following common procedures in the literature. I replaced missing values *within* price series with the previous price available for that product. These missing values are typically caused by items that go out of stock or failures in the scraping software that tend to last for only a few days. For those results that exclude sales, I created a *regular* price series by replacing all sale prices with the previous *non-sale* price available for that product. I also removed all price changes exceeding 500%. These

[10]All over the world, a large and growing share of retail prices are being posted online. Retailers show these prices either because they want to sell their products online or simply to advertise their prices with offline buyers. This source of data represents a important opportunity for economists wanting to study prices, yet it has been largely untapped because the information is hard to obtain, widely dispersed across sites, and needs to be collected on a regular basis. The technology to efficiently do this on a large scale is only now becoming available.

[11]See Table A6 in the Appendix for a complete listing. These categories are based on ELI classifications used by the US Bureau of Labor Statistics to construct CPI statistics.

[12]The aisle is an url or web address for a single page of products, corresponding to the narrowest grouping of items displayed by each supermarket.

represent a negligible number of observations, as shown in Table 1, but can bias statistics related to the magnitude of price changes.[13]

2.2 Comparison to other Data Sources

There are two other sources of data commonly used for sticky-price studies: CPI data and scanner data. The differences with scraped data are summarized in Table 2.

Scraped data have two main disadvantages. First, they cover a much smaller set of retailers and product categories than CPI prices. This limitation can be overcome over time, as a growing number of firms start posting their prices online. For this particular paper, this is not a major limitation because supermarket products represent over 40% of all CPI expenditure weights in these Latin American countries. Second, scraped data do not include information about quantities sold, which scanner datasets tend to include. This prevents me from getting market shares and estimate elasticities or markups directly.[14]

Despite these limitations, scraped datasets have some key advantages that make them a unique source of information for sticky-price analyses:

First, scraped data contain daily prices. This reduces measurement error biases in frequency calculations and is especially useful for the analysis of sales, price controls, hazards, and price synchronization.[15]

Second, the data are available for a much larger set of countries, because they can be collected in any place where online prices are available. In this paper, I focus on *developing* countries, where scanner data are scarce and product-level CPI prices are unreliable or seldom disclosed.[16]

Third, the data are comparable across countries, with prices on the same categories of goods and time periods. This makes it possible to perform simultaneous cross-country

[13]See Section A.1 in the Appendix for more details on data treatments.

[14]There are other variables, such as the number of substitutes in an aisle, which can be used to estimate the degree of competition and its impact on frequencies of adjustment. See section A.4 in the Appendix.

[15]See section A.3 in the Appendix for an analysis of how monthly data can change frequency results.

[16]The study of stickiness in developing countries is rare in the literature. A recent exception is Gagnon (2007), who provides a detailed analysis of sticky prices in Mexico using disaggregated CPI data.

analyses.

Fourth, there is more detailed information on each product. In particular, the aisle indicator is unique to this type of data. It identifies products displayed next to each other and plays a key role in measuring price synchronization among close substitutes.

Fifth, there are no *forced* item substitutions (which commonly occur in official statistics) or missing information when products are not purchased (as it happens with scanner data).[17]

Finally, scraped data are available on a real-time basis, without any delays to access the information. This can be used to provide real-time estimates of stickiness that immediately reflect changes in the underlying economic conditions. For this paper, this also allowed me to collect prices during a period of aggregate volatility and inflation across the world without having to wait several years to access the data.

2.3 Online vs. Offline Prices

A major concern with scraped data is that they may not be representative of a country's pricing behaviors, because online purchases are still a small share of transactions in most countries. In this section, I explore this issue in two parts. I first consider whether online and offline prices behave similarly in each retailer. I then examine whether these supermarkets are representative of each country's aggregate pricing trends.

2.3.1 Matching Offline Price Behaviors

Between December 2008 and February 2009, I conducted simultaneous surveys of *offline* and *online* prices in all the supermarkets where I collect the data. These surveys took place in Buenos Aires, Santiago, Rio de Janeiro, and Bogotá, with the help of four local volunteers.

[17]Forced substitutions occur in official statistics when the agent surveying prices does not find the item she was looking for, and decides to replace it with another product, which becomes the surveyed item from then on. In practice, if the old item is supplied again and/or the new product was being supplied before, official statistics ignore their prices, effectively censoring the price series. In scraped data, prices are recorded from the first moment they enter the sample until the last day they have been offered to consumers, which solves substitutions for items that go temporarily out of stock. Note, however, that I do not attempt to link price series of goods that are discontinued with those of similar goods that may replace them. Such substitutions could be attempted with this data.

They were asked to select any branch of the supermarket and randomly buy 100 products, divided in 10 pre-defined categories. These categories were chosen to ensure some variety in the type of goods purchased: Dairy, Bakery, Beverages, Cereal and Flours, Fats and Oils, Meats, Pasta and Rice, Fruits and Vegetables, Cleaning Products, and Bath Products.

After the first purchase, we determined which of these random products were also being sold online by comparing product ids and descriptions.[18] Those items that could not be matched to the online database were removed from the product list for subsequent purchases.

In total, four purchases took place in each supermarket, at 15-day intervals, always in the same branch. The same items were bought every time, with identical flavors and package sizes. If a product was out of stock, no price was recorded for that day, but we attempted to buy the product again in subsequent purchases.

Table 3 shows the results from this validation exercise. The percentage of offline products that were also available online is very high in all countries. It ranges from 74% in Colombia to 100% in Argentina. Most of the products that could not be matched are raw-food items, which tend to be re-packaged for online sales and have different id numbers and descriptions.

I compared prices both in terms of their *levels* and the timing and size of *changes*. The behavior of changes is more important for stickiness purposes, so I constructed a price change series for each product, with a value of 1 if the price increased, 0 if the price remained constant, and -1 if the price dropped.

In the case of Chile, the online-offline price matching is extremely close. 361 out of 388 comparable prices were exactly the same. The 27 price discrepancies, which averaged 2% in size, were concentrated in only 12 goods (mostly raw-food products), so that 89% of products have identical price levels across samples. The matching of price *changes* is even better: 94% of products have matching price change series. Taking all products together, the ratio of changes over total observations is 0.274 offline and 0.249 online, while the mean *size* of changes is 1.4% offline and 1.3% online.

[18] In Argentina, Brazil, and Colombia, the matching was based exclusively on product ids. In Chile the matching was based on the item's name, description, and package size.

In Argentina, prices are typically higher online: 252 out of 323 comparable prices were higher in the scraped database. In nearly every case, there was a difference of 5% across samples. Fortunately, this constant markup means that price *changes* are highly correlated: 93% of products that have identical price *change* series. Furthermore, the ratio of all price changes over total observations is 0.215 in both samples, and the mean size of these changes is 1.6% offline and 1.4% online.

The cases of Brazil and Colombia are more complex, but the samples still show similar price change behaviors. The evidence suggests these supermarkets treat their online stores as independent branches, with similar strategies in terms of price adjustments.

In Brazil, price levels are identical 42% of the time. Unlike Argentina, online prices can be either higher or lower depending on the product. In terms of price changes, the matching is much better because most of the timing differences are concentrated in a small share of products: 75% of all goods have identical price change series across samples. For all products, the ratio of changes over total observations is 0.356 offline and 0.411 online, while the mean size of changes is 4.9% offline and 5.3% online.

In Colombia, the matching of price levels, at 29%, is lower than in Brazil. However, price differences are small, while the matching of price changes is high, with 67% of identical price changes series. The ratios of changes over total observations match perfectly, at 0.433 in both samples, while the mean size of changes is 8.1% offline and 8.2% online.

Therefore, even though price levels are not the same across samples, online and offline price *changes* behave similarly in terms of timing and size of adjustments in all countries.[19]

2.3.2 Tracking CPI Statistics

Online price changes in these supermarkets are also representative of country-level inflation trends. I show this by comparing scraped price indexes with official price statistics.

[19]In addition, Table 3 shows that offline price changes occur more frequently in Brazil and Colombia, consistent with the results on stickiness reported in Table 7 with scraped data. Furthermore, Appendix Figure A13 shows that Colombia has a larger share of offline price changes close to 0%, consistent with the results in Section 3.3.

Figure 1 plots a daily supermarket index (constructed with scraped data) and the official CPI index in each country.[20] I focus the comparison on CPI indexes to emphasize aggregate levels of inflation; in Section A.2 of the Appendix I provide similar results comparing only a subset of food indexes.[21]

Figure 1 shows that daily online indexes closely track the official CPI series in nearly every country. Table 4 compares the annual inflation rate in both indexes. In Brazil, the scraped inflation was the same as the CPI inflation, at 6.4%. In Colombia, scraped inflation was 7.7% and CPI inflation 7.9%.[22] In Chile, scraped inflation was 7.5% (with sales included), while CPI inflation was 9.8%.

Argentina is the only country where scraped indexes are not consistent with official statistics. The scraped data show a supermarket inflation rate of 22.6%, but the official CPI inflation was only 8.4% for this period. However, the difference is not surprising because official data have become widely discredited since January 2007, when the government started interfering with the construction and publication of price indexes at the National Statistics Institute (INDEC).[23]

Overall, these results support the validity of scraped data as a source of price information. Online prices behave like offline prices and can closely track aggregate inflation trends.

3 Evidence of Price Stickiness

In this section I use the data to document sticky-price facts in all four countries and empirically evaluate some predictions in standard theoretical models.

[20]These daily scraped indexes are simple unweighed averages of non-sale price changes. These averages assign equal importance to all products within categories (geometric mean) and to all categories in the aggregate index (arithmetic mean). See the Appendix for more details, including similar price indexes that include sale prices.

[21]Food and household products sold in supermarkets represent over 40% of CPI weights in all these countries, and were the main driver of inflation during this time period.

[22]In Colombia I measure inflation from November 2007 to October 2008 in both indexes, because I started collecting scraped prices on November 13th, 2007.

[23]See www.inflacionverdadera.com for up-to-date inflation estimates in Argentina using some of the data in this paper.

Many microeconomic mechanisms have been proposed to explain why prices are sticky. Most of them can be broadly classified into two types of models: time-dependent and state-dependent models.

In time-dependent models, the timing of price adjustment is exogenously determined. A firm is able to set the optimal price after a given number of periods (as in Taylor, 1980), or randomly every period (as in Calvo, 1983). With random adjustments, price changes of any size are possible, and there is a stable fraction of firms adjusting every period, regardless of how much time has passed since their previous price change. This creates a tractable, exogenous staggering of individual price changes that can generate considerable aggregate stickiness.

State-dependent models, starting with the menu cost models of Barro (1972) and Sheshinski and Weiss (1977), and more recently Dotsey et al. (1999) and Golosov and Lucas (2007), tend to have stronger micro foundations. They are based upon the assumption that firms are able to change their prices at any time, but must face adjustment costs to do so. These adjustments costs, which I broadly refer to as "menu costs" in this paper, may include labor costs to change prices, managerial costs to make the decision, or even "customer anger" costs linked to the consumer's reaction after a price adjustment.[24] In state-dependent models there are few small price changes (because it is not worth paying the menu cost) and adjustments tend to occur more frequently in "older" prices (where the deviation from the optimum is likely larger).

As Klenow and Kryvtsov (2008) explain, the implications for real output and inflation can differ dramatically in time and state-dependent models, so it is important to empirically distinguish between them. Even though there is a large degree of heterogeneity in price changing behaviors, I find mostly evidence in support of state-dependent pricing in these

[24] An example of models that include the latter are "Fair Pricing" models, such as Rotemberg (2005), Rotemberg (2008) and L'Huillier (2009). These models build on the idea that prices are sticky because firms do not want to antagonize customers. Blinder et al. (1998) found in a survey of price setters that this was a major concern for firms setting prices in the US. I explore some evidence for this type of models in the Appendix, using data from Argentina.

developing countries, in contrast to previous results based on US and European data.

3.1 Price Change Statistics

This section presents general price change statistics in each country. Table 5 shows that a large percentage of goods changed their prices twice or more within a year, ranging from 80% in Brazil to 56% in Chile. The median good changed its price 8.1 times a year in Brazil, and 4.2 times in Chile. This relative flexibility in Brazil and stickiness in Chile is common across most results in this paper.

Figure 2 shows that price changes occur nearly every day, but that the daily fraction of goods that changes prices is highly volatile. It ranges from 0 to 10% in Argentina and Chile, and from 0 to 15% in Brazil and Colombia. This can be evidence of strong price synchronization on daily prices, which I explore in detail in section 5.

Table 5 also shows that price decreases are a significant share of total price changes in each country. This is particularly surprising in Argentina, where price *decreases* are 31% of all price changes and inflation is three times higher than in other countries.[25] What explains this large share of price decreases? Sales play an important part in the answer for Argentina, as can be seen in Table 5. When I remove sales, the share of price decreases in Argentina falls to 16%.[26]

Sales can have significant impact on most sticky-price facts. Therefore, in Table 6 I present detailed sales statistics in all countries where sale data are available. In all cases, sale events tend to last only a few days, with a median length between 6 to 13 days.[27] Sales represent between 8.8% and 14% of all price changes, and between 22% and 45% of all price decreases.

Surprisingly, many sales are not associated with a reduction in prices at all. If we con-

[25] Nakamura and Steinsson (2008) found a similar share in the US, with CPI data collected during a period of much lower inflation.

[26] The percentages for Brazil and Colombia are only slightly different because sales are a smaller share of price decreases in these two countries.

[27] This is an important cause of measurement error when using monthly prices because many sales are either not recorded at all, or assumed to last over a month. See the Appendix for more details.

sider a three-day window around the announcement of a sale, between 13% and 29% of sale events are not related to any price changes. [28] Even more surprisingly, in Argentina and Colombia 3% of sales are linked to price *increases*. This suggests that an important degree of asymmetric information exists between retailers and consumers, with sale announcements sending misleading signals to consumers who are unable to monitor prices on a daily basis. This behavior is stronger in high-inflation Argentina, where sales also tend to be shorter, more v-shaped, and smaller in size (given a price decrease). As inflation rises, sales also become relatively more important as a share of all price decreases. These facts suggest that sales play a role in pricing strategies that standard sticky-price models cannot fully explain.[29] In the following sections I provide results both including and excluding sale prices, where appropriate, and discuss any relevant differences.

3.2 Frequency and Implied Durations

To measure the degree of price stickiness in each country, I follow the frequency approach now standard in the empirical sticky-price literature.[30] This method provides a single parameter to reflect the unconditional probability that a firm will change its price over a given period of time (a day in this case).

To obtain country-level frequencies, I first obtain the daily frequency per individual good by computing the number of daily price changes over the number of total valid change observations for a particular product. Next, I calculate the *median* frequency per good category, and finally, the *median* frequency across all categories.[31] Given that CPI expenditure weights are

[28] Price changes occurring within +/- one day from the date a sale indicator appears next to the product. If multiple changes were present during that period, only price decreases were counted.

[29] Sales could potentially play a role in "fair pricing" models such as Rotemberg (2008), as a way to reduce the negative impact that price increases are having on customer anger. I explore this in the Appendix. In addition, Guimaraes and Sheedy (2008) present a recent model consistent with the fact that sales remain important even with strong aggregate shocks, because sales are strategic substitutes across retailers.

[30] See Bils and Klenow (2004), Nakamura and Steinsson (2008) and Gopinath and Rigobon (2008)

[31] I follow Gopinath and Rigobon (2008) (GR) and take the *median* frequency within each good category. For comparison, in the Appendix I also report the results of the Bils and Klenow (2004) (BK) approach used by most papers in this literature. The BK method computes the weighted ***mean*** frequency within good categories, before obtaining the weighted median frequency across all categories. The use of the two methods

different across countries, I use unweighed medians to facilitate cross country comparisons.[32] In addition to frequencies, I estimate implied durations by computing $1/frequency$.[33] Implied durations provide another intuitive way to compare the degree of price stickiness across countries.

Table 7 presents each country's frequency and duration estimates. On one extreme, prices are stickiest in Chile, with the lowest median frequency of 0.006 and an implied duration of 166 days. On the other extreme, prices are most flexible in Brazil, with the highest median frequency of 0.019 and an implied median duration of 52 days.[34] The exclusion of sales increases durations considerably in most countries, as Nakamura and Steinsson (2008) show with US data.

A puzzling result is that, counter to standard predictions in sticky-price models, countries with higher inflation rates also tend to have stickier prices. Argentina is the most curious example: the annual inflation rate is three times the level of any other country in the sample, but price changes are relatively sticky with an implied median duration of 90 days, 30% longer than Colombia and 70% longer than Brazil.[35]

The median frequencies of price increases and decreases, when considered separately, also

yield different results in the overall *level* of frequencies, but it does not significantly alter the cross-country comparisons in this paper. In general, BK leads to higher frequencies (less duration or stickiness) in this sample because the distribution of frequencies within categories is right (or positively) skewed, so that the mean frequency is larger than the median. This is driven by those goods with no price changes, some of which are censored in the one-year sample period. In principle, with longer samples, both methods should give similar results.

[32]Since most papers in the literature conduct single-country analyses, the standard procedure is to use weighted medians.

[33]This method makes the simplifying assumption of constant hazards, where the probability of a price change is independent from the amount of time elapsed since the previous adjustment.

[34]Overall, prices are stickier than what has previously been reported for similar products in more developed economies. Eichenbaum et al. (2008), for example, compute durations of only 2.5 weeks (18 days) for US supermarket prices collected between 2004 and 2006, even though inflation averaged only 3% annually during that period. The difference are surprising because daily data tends to *increase* durations considerably, as I show in the Appendix. The difference can partially explained by different methodologies (GR frequency) and a wider set of product types available in these Latin American supermarkets (not just food).

[35]Argentina's low frequency is not explained by a difference in the type of goods being sampled in each country. As can be seen in Table A6, Argentina is stickier than Brazil in 54 out of 60 common categories (or 90%). Additionally, the high frequency in Brazil is not the result of the two exceptional days in December 2007 where 90% prices were changed. When I exclude these days, Brazil's implied median duration rises from 52 to 61 days, still much shorter than Argentina's.

fail to significantly correlate with inflation levels. The only frequency statistic that is strongly correlated with inflation across countries is the relative frequency of increases over frequency of decreases. This is also the case in the cross-section of products within each country.[36]. In essence, it suggests that the overall degree of stickiness is less important than the relative flexibility of increases over decreases to predict the short-term effects of monetary policy on inflation and output.

Indeed, the overall degree of stickiness may be affected by country-level factors, such as the popularity of sales and other marketing practices, the degree of idiosyncratic shocks, and the importance of strategic interactions for pricing decisions. It could also be affected by the country's inflationary experiences in the past, which may have influenced price changing behaviors over time. In fact, the overall median frequencies in Table 7 seem positively related to the recent *history* of inflation experienced by each country. Chile has a history of price stability that none of the other countries share, and official statistics show that the surge of inflation is a recent phenomenon; this could explain why frequencies are still low. Brazil by contrast, experienced high inflation levels in the 80s that culminated in a hyperinflation in 1994; this is consistent with its levels of price flexibility. Finally, although Argentina also has a history of chronic inflation, it experienced a full decade of price stability in the 1990s which may explain the current low frequency of adjustment.[37]

3.3 Size of Adjustments: Bimodal Distributions

Frequencies give only a partial view of pricing behavior. To understand the micro-mechanisms behind price changes, one also needs to study the *size* of changes, measured

[36]See Table A7 in the Appendix

[37]Even though Argentina's government has been imposing price controls since 2002, Table A6 in the Appendix shows that Argentina is stickier than Brazil *even* in categories which are never under price controls. Also, in section A.4.2 of the Appendix, I find that price controls are correlated with *higher* frequencies at the individual good level. If price controls are playing a role, they must be affecting pricing behaviors in unrelated goods categories. This is possible if firms are afraid of being "selected" by the government for future controls, or concerned about boycotts and other negative consequences associated with frequent price changes. I explore the case of Argentina in more detail in section A.6, where I find some evidence in support of fair pricing concerns.

in percentage change over the previous price. Table 8 shows basic statistics of the size of daily price changes.

As expected, higher inflation countries have higher mean size of price changes. The mean size of changes is 5.1% in Argentina, but only 1.8% in Brazil. However, when price increases and decreases are considered separately, the mean size of changes is very similar across countries. Therefore, the size of increases and decreases is not sensitive to the level of inflation.[38] This means that the explanation for Argentina's high inflation is not that price increases tend to be larger, or price decreases tend to be smaller, but rather that there is a greater number of price increases than decreases.

A more detailed understanding can be achieved by looking at the distribution of the size of all price changes. The daily nature of the data allows me to plot detailed histograms in Figures 3 and 4, with bins that are only 0.1% wide.

The most interesting feature of these distributions is their *bimodal* shape. Argentina, Chile, and Brazil have distributions with a sharp dip in the density of changes close to zero percent. This is consistent with state dependent menu cost models, which predict that very small changes are not optimal in the presence of adjustment costs. Time-dependent models, by contrast, predict that price changes of any size would take place when firms are able to adjust.

In Argentina and Brazil, there is also an asymmetry in the distribution, with more price increases than decreases. This is predicted by menu cost models such as Golosov and Lucas (2007) in the presence of strong positive monetary shocks. The dip reflects the menu costs, while the asymmetry shows how positive aggregate shocks lead to a disproportionate amount of price increases. This asymmetry is especially strong in the case of Argentina, which explains why inflation is so high.[39]

[38] This is consistent with "customer regret" costs that increase with the size of changes, as in Rotemberg (2009).

[39] Another pattern emerging from these graphs is that all countries have multiple *spikes* in their distributions. Argentina and Colombia have the largest spikes at -5% and +5%. In Chile, they occur at -10% and +10%, and in Brazil at approximately -2% and +2% (if we include the two days in December 2007 where nearly all prices in the supermarket changed by small amounts, nearly 8% of all price changes are increases

The distribution is smoother in Colombia, where small price changes are common. Although this shape could be an indication of time-dependent pricing in this supermarket, it is also consistent with menu costs under certain conditions. For example, there could be different menu costs for different goods (as in Dotsey et al., 1999), one menu cost for a large number of goods (as in Midrigan, 2005), or simply negligible menu costs in online pricing.[40]

The bimodal shape of the distributions in Argentina, Chile, and Brazil differ significantly from what Klenow and Kryvtsov (2008) and Midrigan (2005) found with US data, where distributions are smoother and small price changes common. The differences may be driven by aggregation across retailers, with some retailers behaving like the colombian supermarket in this sample. It could also be caused by a lower frequency of data sampling with temporary shocks. In particular, monthly or weekly sampling of price data could have an impact if there are temporary price changes (such as sale events) that are closely -but not completely- reversed. Consider a hypothetical example of a price that drops from \$10 to \$9 and a few days later returns to \$10.1. With daily data we observe two price changes, one with size -10% and another one with size +11%. With monthly or weekly sampling of the data, we may only observe the price changing from \$10 to \$10.1, a variation equivalent to 0.01%. A similar effect can be caused by average weekly prices, which are also common in scanner datasets. Nevertheless, a more conclusive explanation for the differences in findings can only be obtained by extending the scraped data collection to US and European data, and directly comparing the results with CPI and scanner datasets.

Overall, these results provide evidence for a key prediction in state-dependence menu cost models: that very small price changes are not optimal in the presence of adjustment costs. In the next section, I focus on another basic prediction of state-dependence for which no

of 2%). One interpretation for these spikes is that supermarkets, once they decide that they need to change prices, simply use integer numbers to implement them. Another interpretation is that these are the limits of S-s bands, typical of most state-dependent models. The fact that Argentina's bands are smaller than Chile's would be consistent with the higher level of inflation.

[40] In addition, this particular supermarket has a price matching policy with its main competitor, which may be forcing it to make tiny price adjustments when products are advertised. This type of marketing practices is not important for macroeconomic purposes, but it can significantly affect the price stickiness statistics.

evidence has been found yet in the literature: that "older" prices are more likely to change because they tend to deviate more from the optimal price.

4 Duration Analysis: Upward-Sloping Hazards

The frequency approach in the previous section computes implied durations with the assumption that the daily probability of price change is independent from the time past since the previous adjustment, or in other words, that the hazard rate of price changes is constant over the whole sample period.[41] Although this method is a simple and effective way to compare the degree of stickiness across sectors and countries, one of the most contrasting predictions of time-dependent and state-dependent models lies precisely in the shape of the hazard function.

The hazard is the *instantaneous* probability of price change at time t, conditional on the price not changing until that point in time. In time-dependent models such as Calvo (1983), the hazard function is constant because the probability of price change is fixed and exogenously determined. In state-dependent models, by contrast, hazard functions tend to be upward-sloping, because non-stationary shocks increase deviations from the optimal price over time. As the price moves away from the optimum, the conditional probability of a price change rises.

In this section, I study the shape of hazard functions using *Duration Analysis*. This technique, also called Survival Analysis, is widely used in the life sciences to study the time elapsed from the "onset of risk" until the occurrence of a "failure" event.[42] In a price-setting context, we are interested in the time between the firm's optimal price adjustments. Therefore, both the "onset of risk" and the "failure event" occur when a firm optimally changes prices. The set of constant prices between these two dates is called a "price spell",

[41] For example, consider a good that changes its price 3 times within a year. The frequency approach computes 3/365 as the daily probability of price change, and assuming that this is constant over time, the implied duration is approximately $365/3 = 121$ days.

[42] Economists mostly use duration analysis to study unemployment spells. Its use in the sticky-price literature has been limited by the lack of suitable high-frequency data.

and the duration is the length of the spell, measured in days.

The hazard function is the corner-stone of Duration Analysis. Formally, if T is a random variable measuring the duration of the price spell, with density function $f(t)$ and cumulative density $F(t)$, the hazard $h(t)$ is the limiting probability that a price change occurs at time t, conditional on the price not changing up to that point in time:[43]

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t < T < t + \Delta t | t < T)}{\Delta t} = \frac{f(t)}{1 - F(t)} \tag{1}$$

This hazard function measures the instantaneous "risk" of a price change, conditional on survival. We can add all hazard rates over time and obtain the total risk of price change accumulated up to time t. This is represented by the Cumulative Hazard Function, H(t):[44]

$$H(t) = \int_0^t h(u)du = -\ln(1 - F(t)) \tag{2}$$

H(t) is an increasing, unbounded function of t, that accumulates the conditional probability of price changes over time. In the context of repeated "failures" (price changes), it can be interpreted as the expected number of price adjustments from 0 to t. The Cumulative Hazard receives a lot of attention in Duration Analysis because it is easier to estimate than the hazard function itself.

To empirically estimate $H(t)$ and $h(t)$, I use a simple non-parametric approach due to Nelson (1972) and Aalen (1978), which requires no distributional assumptions.[45] It provides a simple estimate of the cumulative hazard function $H(t)$, given by:

[43]The connection between $h(t)$ and the density function can be obtained using Bays' Law and noting that:

$$f(t) = [1 - F(t)]h(t)$$

[44]Note that

$$h(u) = \frac{f(t)}{1 - F(t)} = -\frac{\partial \ln(1 - F(t))}{\partial t}$$

[45]I chose this method because I want to study the *shape* of the hazard function $h(t)$, not the effects of any covariates. In the Appendix, I show robustness with a semi-parametric Cox model that can incorporate covariates and account for unobserved heterogeneity at the category level.

$$\widehat{H}(t) = \sum_{j|t_j \leqslant t} \frac{c_j}{n_j} \tag{3}$$

where c_j is the number of price changes at time t_j and n_j is the number of price spells that can still change at time t_j. The incremental steps c_j/n_j are an estimate for the probability of price change at t_j, taking into account only those price spells that have survived until that point in time.

To obtain the smoothed hazard function $\widehat{h}(t)$, I take the discrete changes in $\widehat{H}(t)$ and weight them using a kernel function:

$$\widehat{h}(t) = \frac{1}{b} \sum_{j \in D} K\left(\frac{t - t_j}{b}\right) \Delta \widehat{H}(t_j) \tag{4}$$

where K is a symmetric kernel density, b is the smoothing bandwidth, and D is the set of times with price changes.[46]

An important characteristic of duration spells in a price-setting environment is that there are multiple price spells available per product. To estimate hazards, I follow the literature and treat all duration spell individually, with each price being "at risk" until the next price change takes place. I consider only uncensored price spells whose duration is known with certainty, and exclude all sale prices (with the exception of Chile, where sale indicators are not available).

Figure 5 shows the estimated hazard functions with 95% confidence intervals for all countries. Hazards are smoothed with a 60-day bandwidth and only the first 150 days are shown.[47] There are some important differences across countries.

In Argentina, hazard functions are consistently upward-sloping. As prices get older, the conditional probability of a price change rises. This is compatible with the fact that the country had the highest inflation rate, at 22.6%. In this context, fixed prices move further

[46] See Wang (2005) for more on alternative smoothing algorithms.

[47] Using uncensored spells implies that all durations will last less than the sample period of 334-371 days. Hazard functions will necessarily be upward-sloping as they approach this limit, so I focus only on the first 150 days. Figure 7 shows that most durations lie in this interval.

away from their optimum every day, increasing the firm's gains from adjusting and the likelihood of a price change.

In Chile and Brazil, hazard functions are initially upward-sloping, but after approximately 30 days they fall and become relatively flat. In Colombia, the hazard function tends to be upward-sloping, but a similar hump-shaped pattern appears after a month. There are several possible reasons for these hump-shaped functions.

First, the estimates in Figure 5 implicitly assume that the shape of the hazard is the same across products. In practice, heterogeneity tends to flatten hazard rates, because there is a "survival" bias that arises naturally in this context. Those goods or categories that survive are precisely the ones that have low hazard rates.[48]. Indeed, a high degree of heterogeneity in hazards can be seen in Figure 6, where I plot the estimated hazard functions for all categories in each country. An even higher degree of heterogeneity is present among products *within* categories.

Second, short duration spells are more important in these countries, as can be seen in Figure 7. These short-price spells can be caused by sales (which could not be removed in Chile due to the lack of a sales indicator), or temporary shocks (which are more important in these lower inflation countries than in Argentina). In addition, the baseline estimation emphasizes short durations because it includes all price spells individually. This means that products with more price changes, and therefore shorter durations spells, are contributing a larger number of spells to the hazard estimates.[49] Short durations can significantly increase the effect of unobserved heterogeneity on aggregate hazards, because products with high hazard rates disappear quickly from the sample, increasing the survival bias that flattens hazard rates.

Finally, as Nakamura and Steinsson (2008) point out, state-dependent models can also

[48]See Chapter 6 in Aalen et al. (2008)

[49]For example, a good with 10 price changes in the whole period will contribute 9 duration spells to our hazard estimates, while another good with two price changes will show up only once. An alternative approach is to use a single price spell for each product. This can mitigate the bias, as shown in Figure A16 in the Appendix, where only the first price spell available for each product are included.

generate hump-shaped hazard functions. In fact, the shape of hazard functions can depend on the relative importance of temporary and permanent shocks in these models. Permanent shocks, like those experienced in highly inflationary settings, will cause persistent deviations from the optimal price that accumulate over time, increasing the probability of price changes and leading to strictly upward-sloping hazards. However, if temporary shocks are relatively more important, then most of the risk of price change can accumulate within a short period of time, leading to hump-shaped hazards like those observed in Brazil and Chile.

As with previous results, the hazard functions in Figure 5 differ considerably from other findings in the literature. Nakamura and Steinsson (2008) found evidence of downward sloping hazards in US CPI prices, while Klenow and Kryvtsov (2008) found mostly flat hazard functions in similar data. Part of the difference can be explained by the fact that these papers use prices from low inflation settings, were hazards tend to be less upward-sloping, as my own country comparisons show. As inflation rises, individual hazards become increasingly upward-sloping, and while the survival bias caused by unobserved heterogeneity is still present, it may not be strong enough to make the aggregate functions appear flat or downward sloping.

In summary, the upward-sloping and hump-shaped hazard functions in this section provide support for state-dependent pricing in these countries. In all cases, the probability of price change is not independent of the "age" of the price spell, as standard time-dependent models tend to predict. The evidence is stronger in Argentina, where aggregate shocks are more persistent and cause larger deviations from the optimal price over time.

An advantage of duration analysis is that it can easily be extended to study the effect of covariates on hazard rates, by using semi-parametric estimation methods.[50] Although that is beyond the scope of this paper, it is important to emphasize that the level of detail available in scraped data makes this type of analysis possible.

[50]See the Appendix for a semi-parametric Cox model that can incorporate covariates.

5 Synchronization and Strategic Complementarities

In the previous sections, I found evidence for state-dependent pricing in the bimodal size of changes and upward-sloping hazard functions. Another pricing mechanism that has received attention in the state-dependent literature is the effect of *strategic complementarities*. Broadly defined, a strategic complementarity exists if the action of one agent is an increasing function of the action of another agent. In terms of pricing decisions, two goods are considered strategic complements if it is optimal to increase (decrease) the price of one good when the price of another good rises (falls).

Strategic complementarities have been introduced in state-dependent models as a form of *real rigidity*, in the spirit of Ball and Romer (1990), to increase the real effects of nominal frictions.[51] The intuition is that while some firms are free to adjust their prices, they may decide to wait until competitors react to the shock. The fact that some firms have not yet adjusted (due to a nominal friction like menu costs), may be enough to make other firms delay their own price changes (a real rigidity).

Empirically, strategic complementarities can be inferred from the pricing interactions among firms that produce similar products. In particular, firms selling strategic complements will imitate each other's actions by closely synchronizing the timing of their price changes.[52]

In this section, I measure aisle synchronization on a daily basis, discuss some of the possible causes including strategic complementarities, and show that, although prices are highly synchronized, there is no evidence of real rigidities in these data.

5.1 Measuring Price Synchronization

Scraped data are especially well suited to find close competitors who may be synchronizing price changes because an aisle indicator is available to identify products displayed next to each other. In addition, the daily nature of the data is important for price interactions in

[51] See Klenow and Willis, 2006 and Burstein and Hellwig, 2007.

[52] See Cooper and Haltiwanger (1996) for a general discussion of how agents have an incentive to synchronize discrete decisions under strategic complementarities.

these high-inflation contexts because, as Lach and Tsiddon (1996) noted, a sufficiently long sampling interval would ensure that all prices change simultaneously *regardless* of the degree of synchronization.

Since the goal is to focus on strategic complementarities between competing firms, I consider the price changes of one product *per brand* in each aisle. This eliminates simultaneous price changes caused by the same good with different package sizes and flavors, or different goods sold by the same firm under a single brand.[53]

To measure the degree of synchronization in each aisle, I use a simple method based on the binomial distribution.[54] I start by looking at Y_{jt}, the number of products that change their price in aisle j on day t:

$$Y_{jt} = \sum_i X_{ijt} \tag{5}$$

X_{ijt} is a binary indicator equal to one if good i changed its price at time t. Let $P_{ijt} = Pr(X_{ijt} = 1)$ be the probability that the price of that product changes that day. Then X_{ijt} is a Bernoulli random variable, with success probability p_{ijt}. Assuming all products in an aisle are identically distributed with a constant probability of price change, then $p_{ijt} = p_j, \forall i, t$.

If there is no synchronization in price changes, then X_{ijt} is independent across products, and Y_{jt} is distributed as a $Binomial(N_j, p_j)$, where N_j is the number of products in the aisle. Therefore, to determine whether prices are synchronized or not, we can observe the distribution of Y_{jt} in each aisle and compare it to the binomial distribution. This is done by computing the *implied probabilities* under the assumption of a binomial distribution. That is, given the number of products N_j in a particular aisle, we can find the individual probability p_j

[53]For each brand, I keep the product with the largest number of price observations available. The results are qualitatively robust to a random selection criteria per brand, or the inclusion of all products in an aisle. This sample still includes products from the same manufacturer that are sold under different brands (within the same aisle). We should ideally eliminate these products to measure strategic complementarities, but there is no manufacturer information for individual products or ways to link brands to manufacturers.

[54]Similar results can be obtained with probits, as shown in Table A8, or the Fisher-Konieczny index (Fischer and Konieczny, 2000). I use the binomial methodology because it provides an estimate of synchronization in each aisle which can be compared to median aisle frequencies.

that would generate the observed frequency of simultaneous changes under the assumption of a binomial distribution. If price changes were really independent, then these implied probabilities would be constant; however, if there are incentives to synchronize changes, the implied probabilities would increase with the number of items adjusting at the same time.

To illustrate this methodology, I use the "Rice" aisle in each country as an example. First, I compute the distribution Y_{jt} in Figure 8, by plotting the fraction of days with a given number of synchronized price changes. For example, the value at two (e.g. 0.046 for Argentina) indicates the fraction of days where only two products in that aisle changed their price, or $Y_{jt} = 2$.

Second, under the hypothesis of a binomial distribution, I calculate the implied probabilities. For example, since there are 25 products in the "Rice" aisle for Argentina, when $Y_{jt} = 2$ the implied probability p solves the equation:

$$\Pr[Y_{jt} = 2] = 0.046 = \begin{pmatrix} 25 \\ 2 \end{pmatrix} p^2(1-p)^{25-2} \tag{6}$$

In this case, p is equal to 0.0145. The same calculation is repeated for all values of Y_{jt}, up to $Y_{jt} = 10$.[55]

Figure 9 plots the implied probabilities for the "Rice" aisle in all countries. In all cases, the probabilities increase with the number of simultaneous price changes, consistent with synchronization.

For a single aisle, we can measure the degree of synchronization by fitting a linear trend and obtaining the slope of implied probabilities. The higher the slope, the larger the deviation from the binomial distribution and, therefore, the stronger the synchronization.

We can further generalize the analysis and average all aisle slope coefficients to get a

[55] To obtain a unique solution, I solve for p in:

$$\frac{\Pr[Y_{jt} = k]}{\Pr[Y_{jt} = 0]} = \begin{pmatrix} N_j \\ k \end{pmatrix} \left(\frac{p}{1-p}\right)^k \ , \ \forall k \in [1, 10]$$

country-level measure of synchronization.[56]

Table 9 shows high levels of synchronization in all countries. The average slope of implied probabilities is 0.012 in Argentina, 0.007 in Chile, 0.009 in Brazil and 0.010 in Colombia. Compared to the median frequencies (the *unconditional* probabilities of daily price change reported in Table 7), these coefficients imply that the probability of price change increases by 63% in Argentina, 73% in Brazil, 100% in Chile, and 80% in Colombia every time an additional price change occurs at the same time.

Table 9 also shows that synchronization is not affected by the exclusion of sales. There is, however, a large difference between price increases and decreases, when considered separately. In Argentina, Brazil, and Chile, price increases are 50% to 100% more synchronized than price decreases.

5.2 What is the cause of synchronization?

There are several possible causes for price change synchronization within aisles. First, prices could change on the same day because of a common sectoral shock affecting the aisle. Although a common shock is unlikely to make firms change prices on exactly the same day, it is still possible that the supermarket is accumulating wholesale price changes over a few days and applying them to retail prices simultaneously.

Second, even with no common shocks, supermarkets may choose to change the prices of many products at the same time in order to save on adjustment costs. For example, when there is a fixed cost to walk to an aisle and manually change prices, or connect to a database and input the new values, but low marginal costs to change the price of additional items within the aisle.[57] This is the case of increasing returns to scale in adjustment costs, studied by Midrigan (2005).

A third possible cause for price synchronization is the existence of strategic complemen-

[56]Only aisles with at least 3 products are considered. In addition, aisles with slope coefficients that are not statistically significant in a 95% confidence interval are assumed to have no synchronization.

[57]This is a literal definition of menu costs. Sheshinski and Weiss (1992) explicitly differentiate these from decision costs that require an adjustment cost for each individual price change.

tarities. As mentioned before, if two products are strategic complements, firms will try to match the timing of each other's price changes. Although it is hard to empirically differentiate it from the other causes of synchronization, some evidence in favor of strategic complementarities can be obtained if we look at the interaction between the *timing* and the *size* of price changes. Firms that want to keep a stable relative price will not only try to synchronize the timing of changes but also match the size of these changes. This implies that aisles with more synchronization should have less variability in the size of simultaneous price changes. By contrast, if synchronization was caused by economies of scale in menu costs, synchronized changes would take place regardless of their size.[58]

To test this prediction, I estimate the correlation between price synchronization and size variability at the aisle level. I obtain a measure of size variability per aisle by looking at days where there are at least 2 simultaneous price changes, computing the daily coefficients of variation in the absolute size of changes (standard deviation divided by the mean), and averaging them over all days.

Table 10 shows a negative correlation between synchronization and size variability in Argentina, Brazil, and Chile. As prices become more synchronized, they also tend to have similar change sizes, as expected in the presence of strategic complementarities.[59]

5.3 Strategic Complementarities and Real Rigidities

Although the previous results show that prices are highly synchronized, likely due to strategic complementarities, there is no evidence of real rigidities in these data. This can be seen in Table 11, where I show the results of an OLS regression of the degree of aisle synchronization on the median aisle frequency. I include aisles where there is a positive degree of synchronization and use aisle dummies to control for unobserved aisle effects. In Argentina,

[58]Once the menu cost is payed for the whole aisle, all optimal price changes can take place. See Midrigan (2005).

[59]The timing and size of changes would also be similar with common shocks. However, the fact that the average degree of synchronization is relatively low in Argentina, where common shocks are likely stronger, casts doubt on the importance of shocks as the main cause of synchronization.

Chile, and Brazil, higher degrees of synchronization lead to higher median frequencies of adjustment. A positive coefficient is also estimated for Colombia, but it is not statistically significant.

These results may seem surprising because strategic complementarities are commonly introduced in state-dependent models to create real rigidities, but whether complementarities can affect frequencies in a state-dependent model depends on the environment in which firms are playing their strategic game.[60] Indeed, Ball and Romer (1991) showed that strategic complementarities in a menu cost model can lead to multiple equilibria in the degree of rigidity. The type and size of shocks can determine the final outcome. In a stable macro environment with small shocks, firms that face no nominal frictions will prefer to wait until "sticky" firms change their prices; this is the case of a real rigidity. By contrast, if shocks are sufficiently large, firms will tend to coordinate towards a full-adjustment equilibrium, quickly changing their prices because they know others will react the same way.[61]

In these four Latin American countries, firms that match their competitor's actions tend to adjust their prices quickly in response to shocks, increasing price flexibility. Therefore, even though strategic complementarities seem to play an important role in price setting decisions, they are not linked to real rigidities in these countries. Understanding the conditions under which real rigidities can arise is still an open empirical question, which will require extending the analysis to a larger set of countries and economic settings.

6 Conclusions

This paper makes a dual contribution by introducing a new way of collecting price data and using it to extend the study of price stickiness into developing countries.

[60] In a time-dependent context, synchronization unambiguously leads to less persistent monetary policy (See Taylor, 1980, Blanchard, 1982, and Lach and Tsiddon, 1996).

[61] Klenow and Willis (2006) also point out that synchronization at a very disaggregated level can reduce the effect of real rigidities on stickiness. In addition, in models with imperfect information the effect can also depend on the relative importance of idiosyncratic and aggregate shocks, and how well informed firms are about them. When aggregate shocks are evident to all firms, then there is no reason to delay the adjustments.

I first show that scraped data, obtained directly from online sources, are a unique and valid source of price information. The availability of daily prices in various economic settings and countries, and across a wide range of products, represents a major opportunity for economists that wish to understand how pricing decisions are made. The immediate access to the data allows us not only to extend the analysis into new countries but also to potentially provide *real-time* estimates of stickiness and other pricing statistics.[62]

I then use a scraped dataset to find new evidence of state-dependent pricing in developing countries. First, the distribution of the size of price changes tends to be bimodal, with few changes close to zero, as predicted by menu cost models like Golosov and Lucas (2007). Second, hazard functions tend to be upward-sloping, with the conditional probability of a price change increasing with the amount of time since the last adjustment. Finally, high levels of daily aisle synchronization suggest that strategic complementarities play an important role in price-setting decisions.

These results differ considerably from previous findings in the literature that use US and European data, suggesting that sticky-price patterns can change dramatically across macroeconomic settings.[63] Although there is a high degree of heterogeneity in pricing behaviors across categories of goods and countries, the evidence in this paper shows that time-dependent pricing mechanisms become important when there is high inflation and strong aggregate shocks.[64]

There are, however, many patterns in the data which are not consistent with either state-dependent or time-dependent models. There is a large share of price decreases and sales in

[62]With these objectives in mind, Prof. Roberto Rigobon at MIT Sloan and I started the "Billion Prices Project" in 2008. Every couple of days, we update and display a number of price statistics at www.billionpricesproject.org. Access to the demo page is currently available with the username "harvard" and password "economics".

[63]Some of the differences may also be explained by the special characteristics of scrape data (e.g., the daily frequency and product details) which make it possible to avoid sampling biases.

[64]The hypothesis that state-dependence mechanisms are more important in these macroeconomic settings is consistent with imperfect information models where price setters pay an information cost to change prices, as in Woodford (2009). Strong aggregate shocks may reduce the cost of constantly being informed about market conditions, so firms tend to continuously reconsider the optimality of their prices, as state-dependent models assume. On the contrary, if aggregate shocks are milder, firms may find it optimal to re-evaluate prices only after a given number of days, as standard time-dependent models assume.

all countries, even when inflation is over 20%. A large fraction of sale announcements does not lead to price changes, suggesting there is an important degree of asymmetric information among firms and buyers. Also, the size of price increases and decreases does not vary with inflation, as predicted by "Fair Pricing" models where customers worry about the size of changes.[65] Finally, a surprising result is that countries with higher inflation levels also tend to have stickier prices, which contradicts the basic intuition that firms increase their prices more often as inflation rises.[66]

To understand these puzzling patterns and their impact on stickiness, we need to expand the cross-section and time-series dimensions of the available price information, identifying only the price mechanisms that are relevant for macroeconomic purposes. The special characteristics of scraped data, such as the high level of product details, daily sampling frequency, wide country coverage, and real-time availability, make them an ideal source of information to achieve these goals.

[65]See Rotemberg (2008) and Rotemberg (2009).
[66]See Ball, Mankiw and Romer (1988).

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Tables

Table 1: Database Description

	Argentina	Brazil	Chile	Colombia
Total observations	6.8M	6.2M	6.4M	1.8M
Products per day	18427	17021	18094	5347
Initial date	10/7/2007	10/10/2007	10/24/2007	11/13/2007
Final date	10/12/2008	10/12/2008	10/12/2008	10/12/2008
Days	371	368	354	334
Categories	74	72	72	59
Aisles	683	298	292	122
Product Description	Yes	Yes	Yes	Yes
Sale indicator	Yes	Yes	-	Yes
Price Controls	Yes	-	-	-
Brand	Yes*	Yes*	Yes	Yes
Bulk Price	Yes*	Yes*	Yes	Yes*
Size of Package	Yes*	Yes*	Yes	Yes
Missing obs. within spells	14.66%	10.75%	19.69%	22.62%
Outliers (price change above 500%)	4	7	19	6
Obs with sales (% of total)	5.78%	2.94%	-	6.26%
Products with sales	8983	5161	-	2348
Products with price controls	443	-	-	-
Life of goods (in days, Mean/Median)	267/355	257/333	253/354	254/334
Obs per good (Mean/Median)	230/270	233/279	208/240	205/243

Notes: *Obtained from product descriptions.

Table 2: Alternative Data Sources

	Scraped Data	CPI Data	Scanner Data
Products Categories and Retailers Covered	Few	Many	Few
Quantities Sold	No	No	Sometimes
Data Frequency	Daily	Monthly - Bi-Monthly	Weekly
Countries Available for Research	∼50*	10-15	<5
Cross-Country Comparisons	Yes	Limited	No
Details: sale, price control, etc.	Yes	Limited	Limited
Eliminates *Forced* Substitutions	Yes	No	Yes
Few Time Gaps	Yes	Yes	No
Real-Time data availability	Yes	No	No

Notes: *Data from over 50 countries are currently being collected by the Billion Prices Project (www.billionpricesproject.org).

Table 3: Online vs. Offline Prices

	Argentina	Brazil	Chile	Colombia
Matching ids	Yes	Yes	No	Yes
% Available Online	100%	80%	90%	74%
PRICE LEVELS				
online=offline	18%	42%	93%	29%
online>offline	78%	34%	4%	32%
Price Difference (Mean %)	5	9	2	0
PRICE CHANGES				
Products with Identical Change Series*	93%	75%	94%	67%
Ratio of Changes over Observations				
Offline	0.215	0.356	0.274	0.433
Online	0.215	0.411	0.249	0.433
Mean Size of Changes (%)				
Offline	1.6	4.9	1.4	8.1
Online	1.4	5.3	1.3	8.3

Notes: *Indicator variable, with a value of 1 if the price increased, 0 if the price remained constant, and -1 if the price dropped.

Table 4: Annual Inflation (% per year)

	Online Supermarket Index	Official Consumer Prices (CPI)
	Oct 2008	Oct 2008
Argentina	22.6	8.4
Brazil	6.4	6.4
Chile	7.5*	9.8
Colombia**	7.7	7.9

Notes: *Includes sales. ** November 2007 to October 2008.

Table 5: Price Changes by Country and Sale Treatment

	Including Sales				Excluding Sales*		
	Arg.	Brazil	Chile	Col.	Arg.	Brazil	Col.
Goods with no price change	19%	11%	27%	16%	22%	11%	21%
Goods with 2 or more price changes	66%	80%	56%	72%	59%	78%	66%
Price changes per good (Mean/Median)	4.4/3	8.1/4	4.2/2	5/3	2.6/2	6.8/4	4/3
Price increases (% of price changes)	69%	60%	57%	55%	84%	63%	57%
Price decreases (% of price changes)	31%	40%	43%	45%	16%	37%	43%

Notes: *No sales information is available for Chile.

Table 6: Sale Events by Country

	Argentina	Brazil	Colombia
Life of sales (in days, median)	6	7	13
Sales as % of price changes	14%	8.8%	11%
Sales as % of price decreases	45%	22%	25%
"Sales" with no price change*	29%	13%	22%
"Sales" with price *increases**	3%	0%	3%
Sales that end with old price (v-shaped)	89%	66%	52%
Sales that end with higher price	6%	12%	20%
Mean size of sale, given price decrease	-13%	-18%	-22%

Notes: *Price changes occurring within +/- one day from the date a sale indicator appears next to the product.

Table 7: Median Frequencies by Country - Increases and Decreases

	Including Sales				Excluding Sales		
	Arg	Brazil	Chile	Col	Arg	Brazil	Col
Median Frequency (daily)	0.011	0.019	0.006	0.015	0.008	0.017	0.012
Implied Durations (days)	90	52	166	66	124	58	83
Median Frequency Increases (Freq+)	0.009	0.014	0.006	0.009	0.008	0.0113	0.006
Median Frequency Decreases (Freq-)	0.002	0.006	0.002	0.006	0	0.005	0.004
Freq+/Freq-	4.5	2.3	3	1.5	-	2.3	1.5

Table 8: Size of Price Changes by Country and Sale Treatment

	Including Sales				Excluding Sales		
	Arg.	Brazil	Chile	Col.	Arg.	Brazil	Col.
Size of changes (Mean*)	5.1%	1.8%	4%	2%	7%	1.6%	2.1%
Size of price increases (Mean*)	13%	10.8%	16.2%	12.2%	11.4%	8.9%	8.9%
Size of price decreases (Mean*)	-13.5%	-12.7%	-13.6%	-10.8%	-12.4%	-11.4%	-7.3%

Notes: *I take the mean size of changes per individual good, then the mean per category, and finally the mean across all categories.

Table 9: Mean Synchronization within Aisles

	Argentina	Brazil	Chile	Colombia
All Price Changes	0.007	0.014	0.006	0.012
Excluding Sales	0.006	0.013		0.011
Price Increases	0.006	0.011	0.004	0.006
Price Decreases	0.004	0.006	0.002	0.006

Notes: Results based on 465 aisles in Argentina, 259 in Brazil, 236 in Chile and 99 in Colombia.

Table 10: Aisle Synchronization and the Coefficient of Variation in Size of Changes

	Argentina	Brazil	Chile	Colombia
Correlation*	-0.24	-0.23	-0.27	-0.10
p-value	0.00	0.00	0.01	0.44

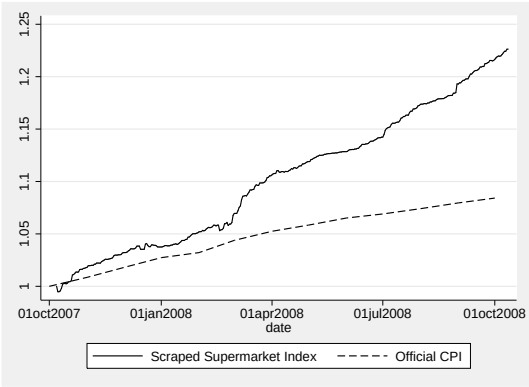
Notes: *Correlation between the degree of aisle synchronization and the mean coefficient of variation (CV) in the aisle. CV is the daily sd/mean of the absolute size of price changes. All price changes included in calculations, but CV is estimated only when there are two or more price changes in a day within an aisle. Only aisles with significant coefficients for synchronization (95% level) are included.

Table 11: Effect of Synchronization on Aisle Frequencies

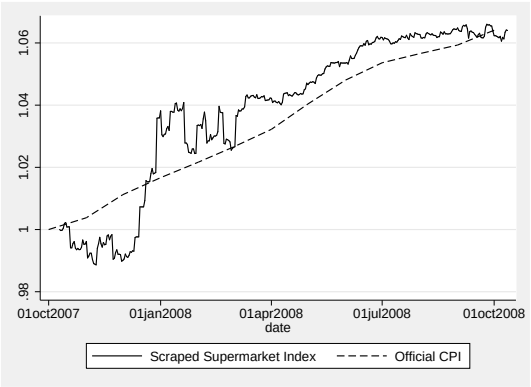
	(1) Argentina Aisle Frequency	(2) Brazil Aisle Frequency	(3) Chile Aisle Frequency	(4) Colombia Aisle Frequency
Aisle Synchronization	0.13*	0.43***	0.23**	0.07
	[0.071]	[0.12]	[0.11]	[0.09]
Observations	345	184	227	81
R^2	0.39	0.65	0.60	0.78

Notes: Dependent variable is the median frequency in each aisle. OLS regressions with category dummies and a constant (coefficients not shown). Only aisles where synchronization is estimated with 5% significance are included. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

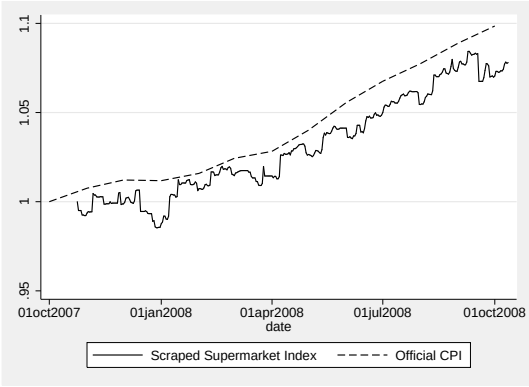
Figures



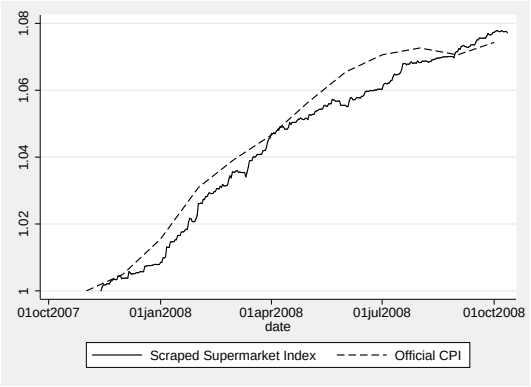
(a) Argentina



(b) Brazil



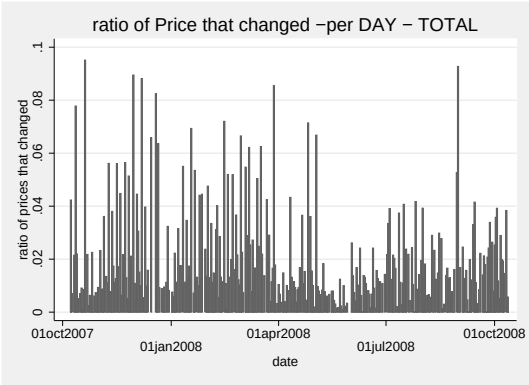
(c) Chile



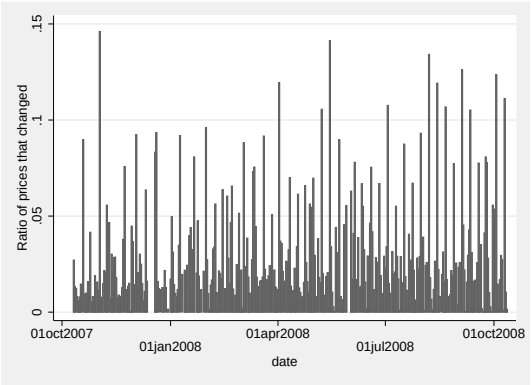
(d) Colombia

Figure 1: Daily Supermarket Index vs. the Official Monthly CPI

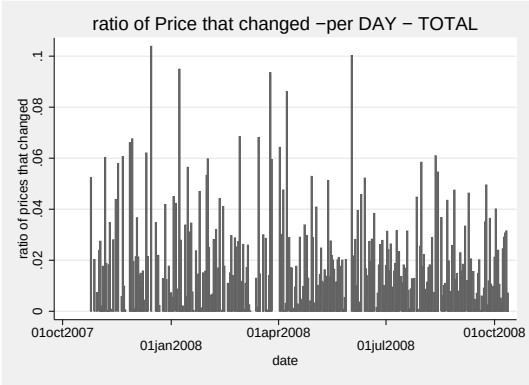
Notes: Sales are excluded from the Supermarket Index in all countries with the exception of Chile, where sales data is not available.



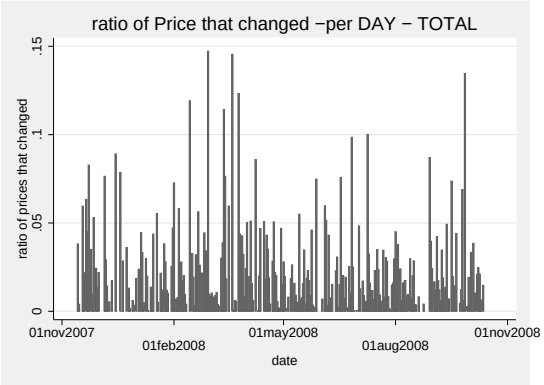
(a) Argentina



(b) Brazil*



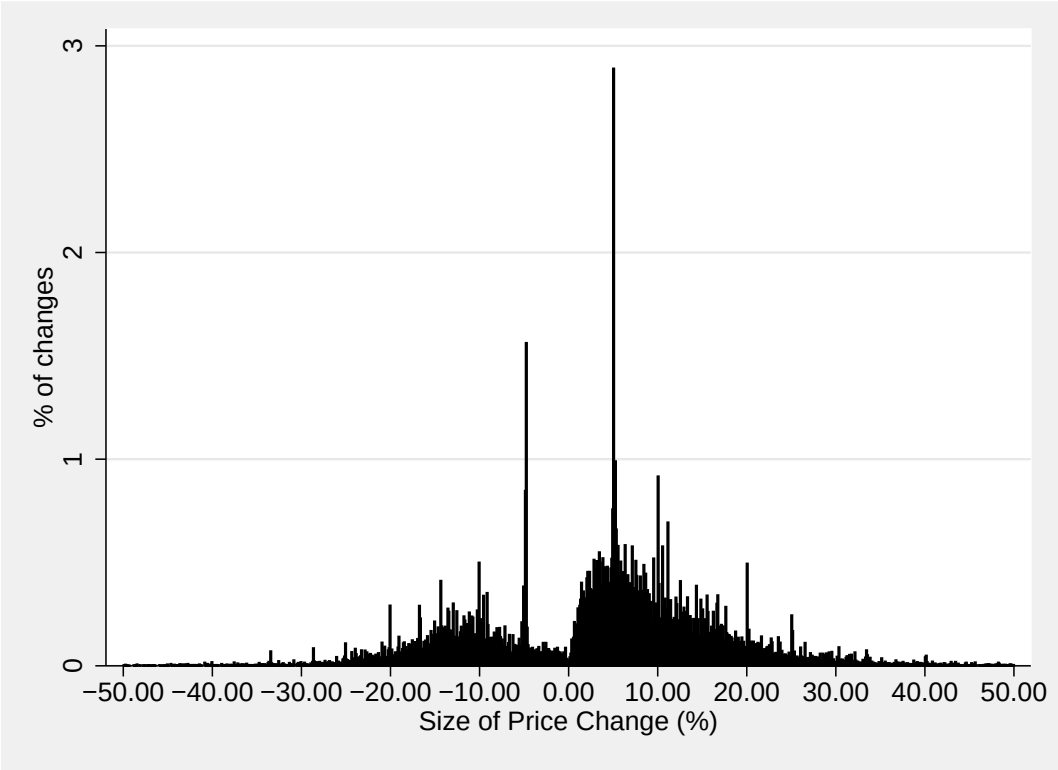
(c) Chile



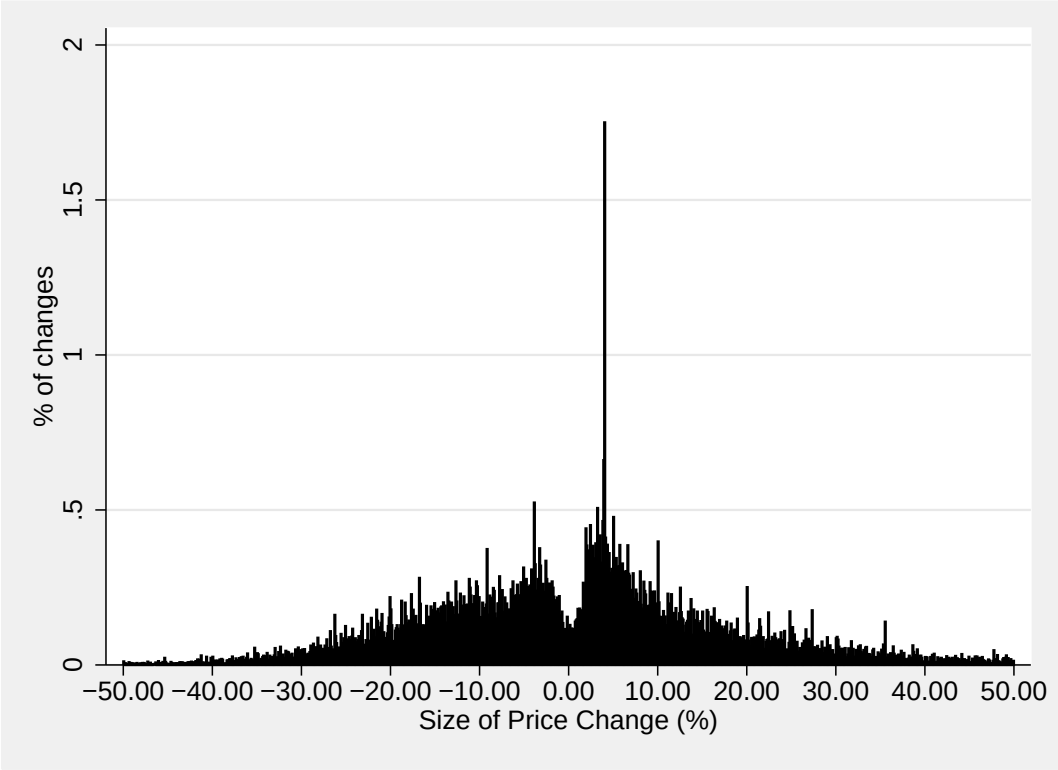
(d) Colombia

Figure 2: Fraction of Prices that Change each Day

Notes: *The graph for Brazil excludes two exceptionally large ratios in December 15th and 29th 2008, where over 90% of prices where adjusted by 2%.



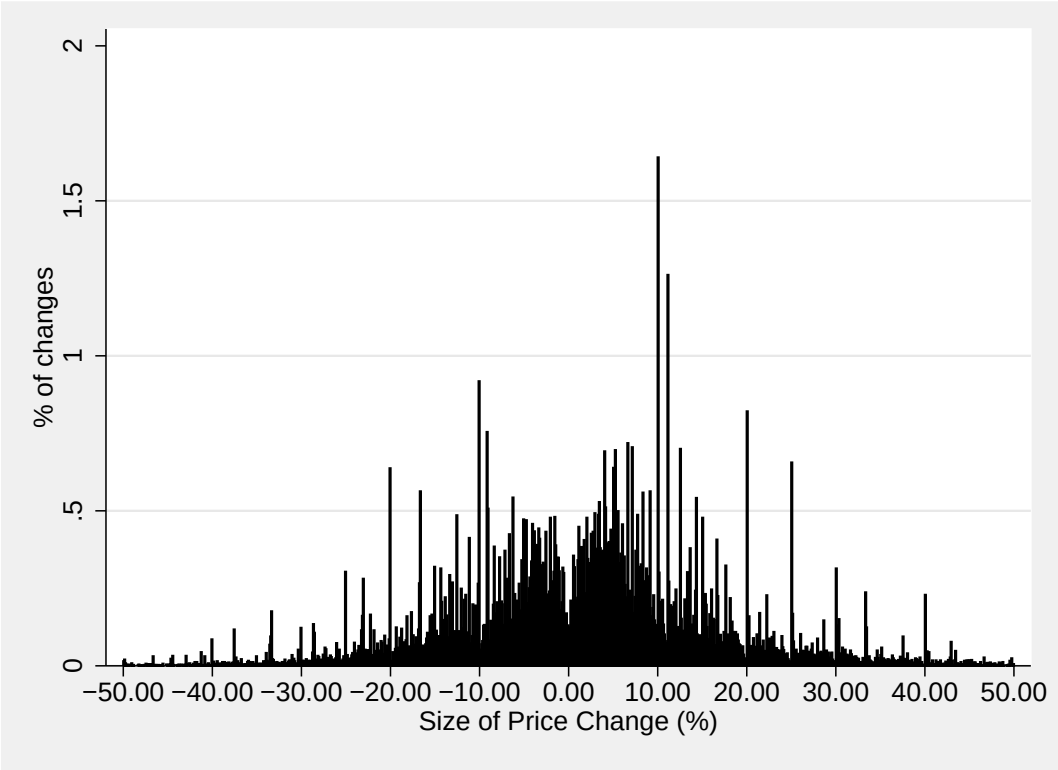
(a) Argentina



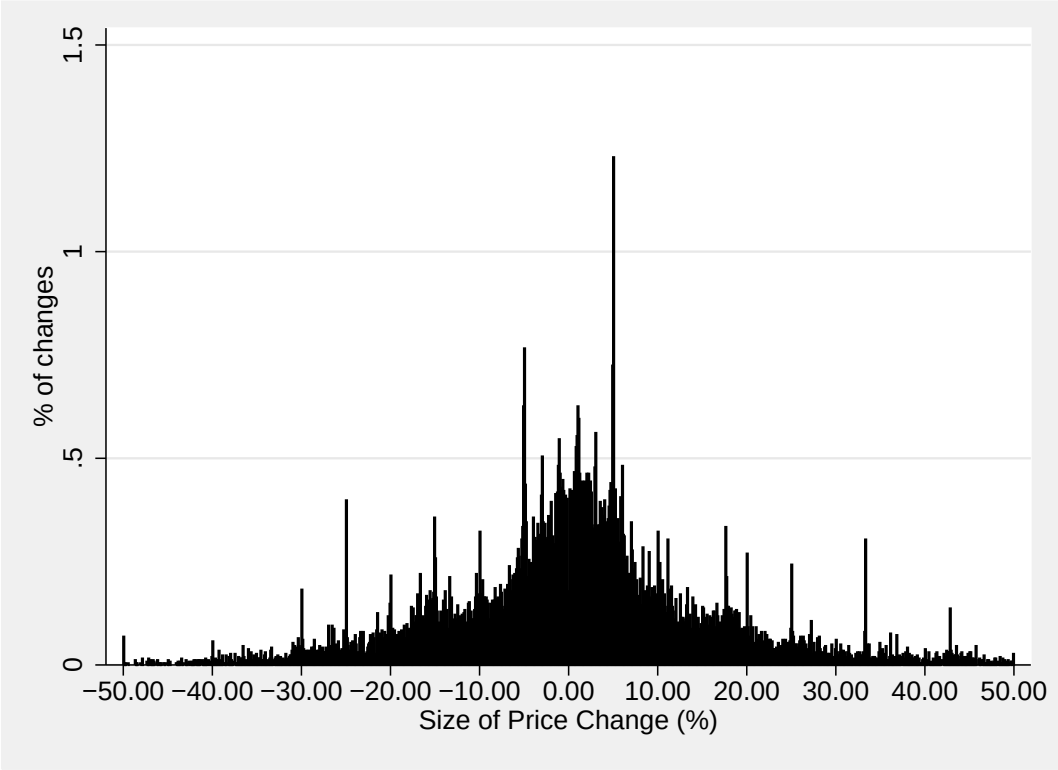
(b) Brazil

Figure 3: Size of Price Changes

Notes: Bin size is 0.1%. Brazil shown without changes on 15/12/07 and 29/12/07 (see Appendix for full distribution).



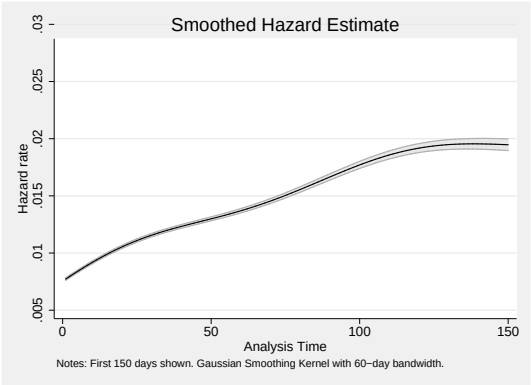
(a) Chile



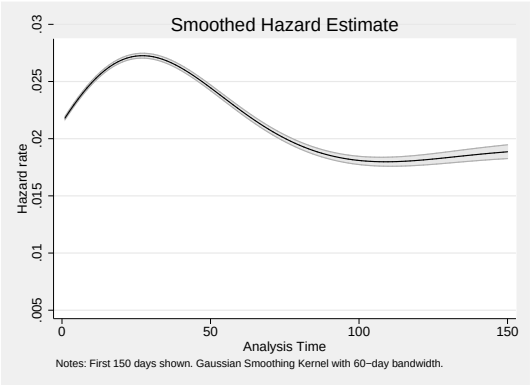
(b) Colombia

Figure 4: Size of Price Changes

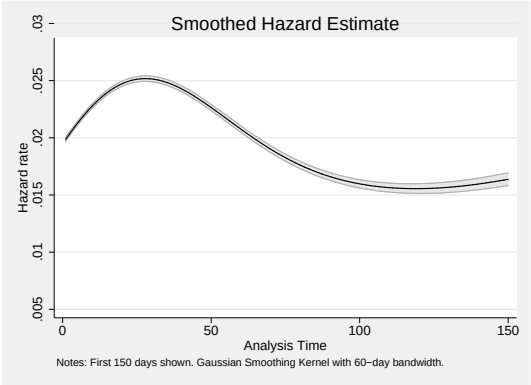
Notes: Bin size is 0.1%.



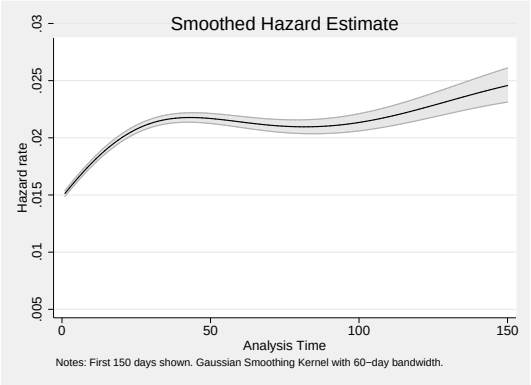
(a) Argentina



(b) Brazil



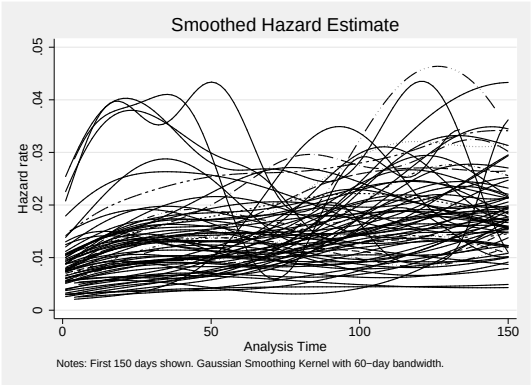
(c) Chile (with sales)



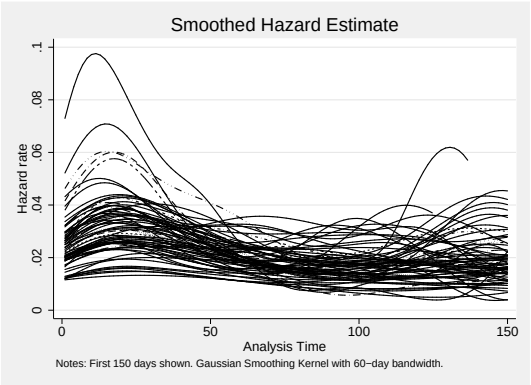
(d) Colombia

Figure 5: Smoothed Hazard Functions

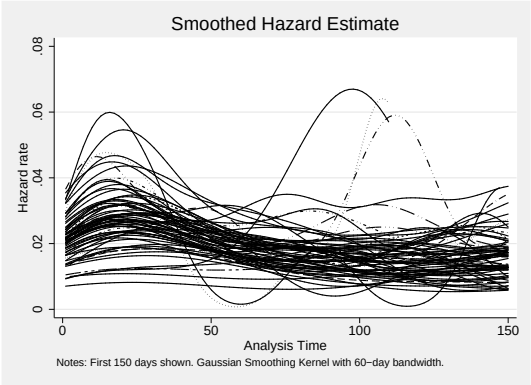
Notes: All uncensored spells are included. Sale events are excluded, with the exception of Chile where sales information is not available. Smoothing function with a Gaussian Kernel and 60-day bandwidth. First 150 days are shown.



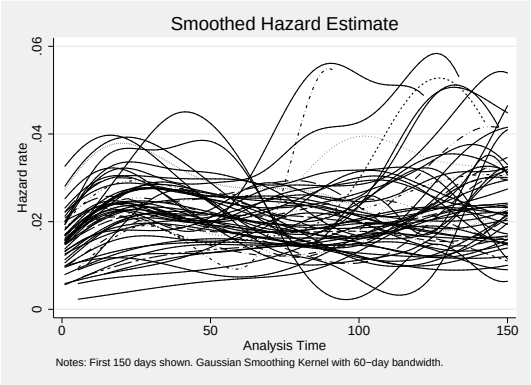
(a) Argentina



(b) Brazil



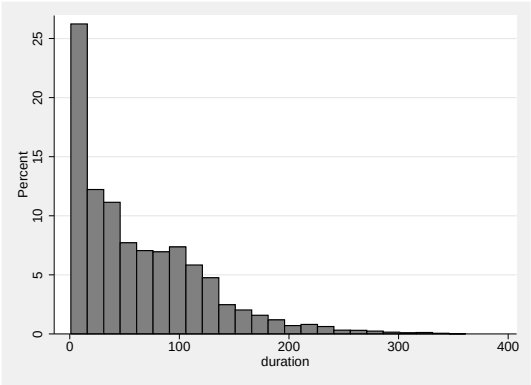
(c) Chile



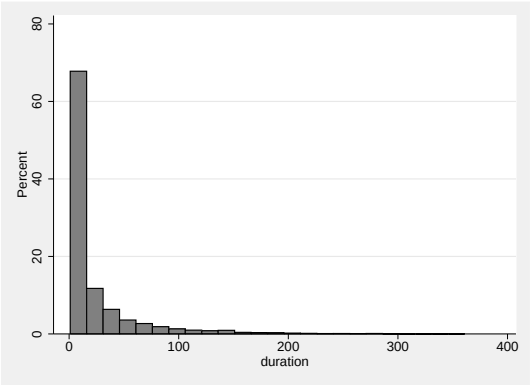
(d) Colombia

Figure 6: Hazard Functions by Category of Goods

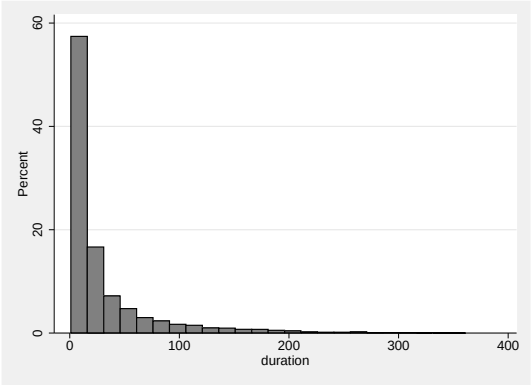
Notes: All uncensored spells are included. Sale events are excluded, with the exception of Chile where sales information is not available. Smoothing function with a Gaussian Kernel and 60-day bandwidth. First 150 days are shown.



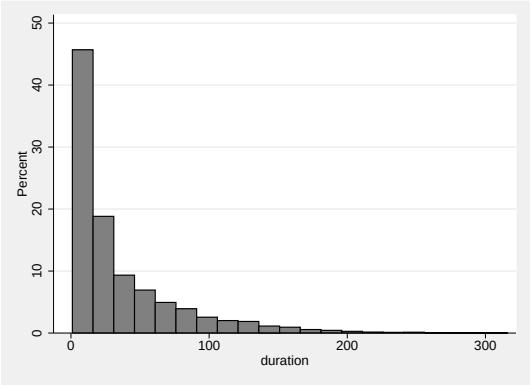
(a) Argentina



(b) Brazil



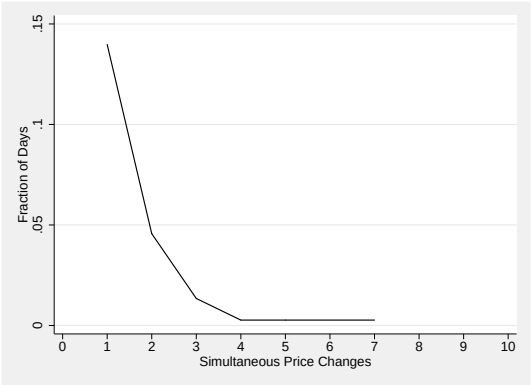
(c) Chile



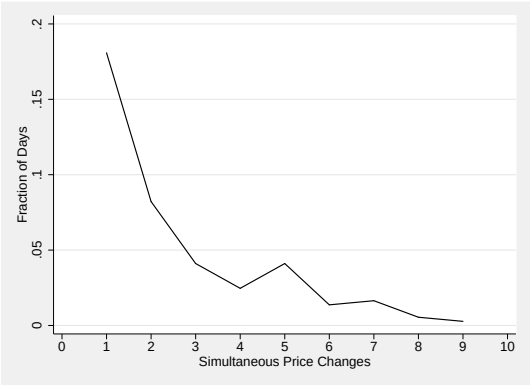
(d) Colombia

Figure 7: Histogram of Duration Spells

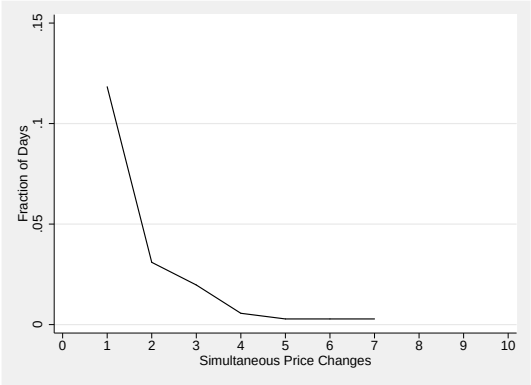
Notes: All uncensored spells are included. Sale events are excluded, with the exception of Chile where sales information is not available.



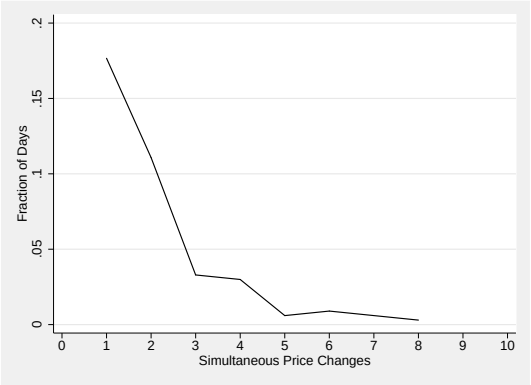
(a) Argentina



(b) Brazil

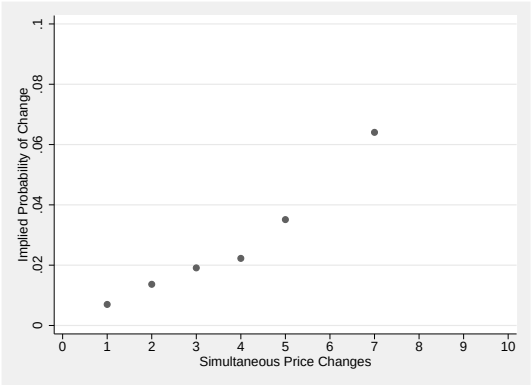


(c) Chile

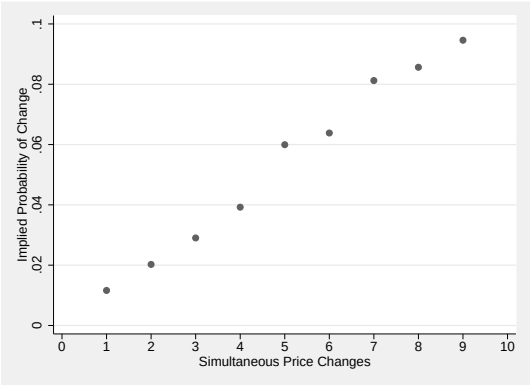


(d) Colombia

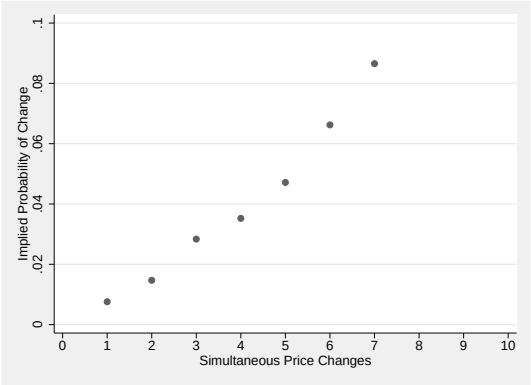
Figure 8: Distribution of Synchronized Changes - Example with "Rice" Aisles



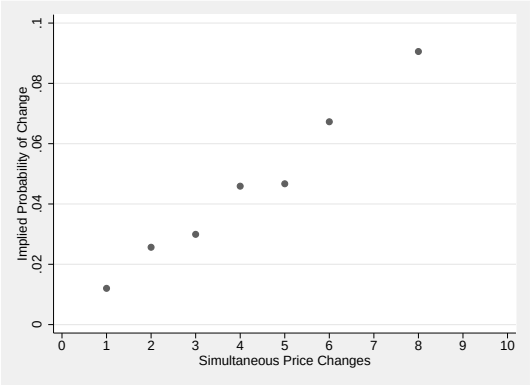
(a) Argentina



(b) Brazil



(c) Chile



(d) Colombia

Figure 9: Implied Probabilities - Example with "Rice" Aisles