The Distribution of the Size of Price Changes*

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—– Preliminary and Incomplete —–

Abstract

Different theories of price stickiness have distinct implications on the properties of the distribution of price changes. One of those characteristics is the number of modes the distribution possess. We formally test for the number of modes in the price change distribution of 32 supermarkets, spanning 23 countries and 5 continents. We present results for three modality tests: the two best-known tests in the statistical literature –Hartigan's Dip and Silverman's Bandwith– and a test designed in this paper, called the *the Proportional Mass* test. Three important results are uncovered. First, when the traditional tests are used, the unimodality around zero is rejected in about 90 percent of the establishments. When we used the Proportional Mass test, which is much more conservative than the first two, we still reject unimodality in two thirds of the supermarkets. Second, if we center our test on the largest mode – as opposed to zero – we have few rejections of unimodality. Finally, the rejection of unimodality changes through time. In countries where there is large inflation the distribution is unimodal around a positive value. In those countries when the inflation drops – which happened almost everywhere during the recent financial recession – unimodality starts to disappear again. These results offer new stylized facts that theoretical models of price stickiness need to match. We perform a simple calibration exercise at the end using the model by Alvarez et al. (2010) and applying our PM test of unimodality to the model's distributions.

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1 Introduction

With the availability of the individual prices underlying the construction of the CPIs from several developed countries, the micro-pricing literature in macroeconomics has become one of the most active areas of research in recent years.[1] One of the main stylized facts uncovered by this literature is that the distribution of price changes (conditional on a change) is centered at zero, it is close to unimodal, and it has a large share of small price changes. Indeed, this finding has also been shown to hold in scanner datasets from retailers in the US. [2]

This result is important because the different theories of price stickiness have direct implications on the form of the distribution of price changes. For example, the standard state-dependent model, such as Golosov and Lucas (2007), predicts that the distribution of price changes should be bimodal, with very little mass near zero. The intuition is that small deviations from the optimal price are less costly than the adjustment cost and therefore those changes should be infrequent. By contrast, time-dependent models of price stickiness – such as the classical Calvo (1983) model – imply that the distribution of price changes should inherit the same properties of the distribution of cost changes, and in low inflation setting such costs will tend to have a unimodal shape centered around zero. In addition, some recent state-dependent models can also imply unimodal distributions. For example, economies of scale in menu costs models, like in Midrigan (2005), or information-constrained models like Woodford (2009) can all produce single-peaked distributions. Finally, Alvarez et al. (2010) recently developed a model with both an observation and adjustment cost in which both state and time-dependent behaviors can appears endogenously. They find that most of the distributions are bimodal when inflation is low.

Surprisingly, even though the shape of the distribution plays a crucial role in distinguishing the different theories of price stickiness, no paper has formally tested for the number of modes. In this paper, we test for unimodality using three different statistical tests and a new dataset that covers many countries and retailers. We go beyond the graphical analyzes in the literature and provide a new test methodology which can be scaled to multiple countries and sectors.[3]

The data include individual product prices in 37 supermarkets across 23 different countries collected at daily frequency. They were collected by the *Billion Prices Project* (BPP) at MIT Sloan using a scraping software that recorded, on a daily basis, the price information for all goods sold by supermarkets with online shopping platforms. The daily frequency of scraped data make it an ideal source of price information to study the distribution of price changes, reducing the sampling biases associated with weekly or monthly prices, as we argue below.[4] Our prices were collected between October 2007 and February 2010. Although there are different starting dates for each supermarket, in all cases we have at least one year of data, with a mean of 571 days, 20 thousand individual products, 5 million daily observations and 100 thousand price changes per retailer. This data set has several advantages: First, we sample every day, as opposed to once a month like most prices to construct the CPI. Hence, we capture sales and other short run phenomena much precisely. Second, we collect the universe of the items and therefore we do not have forced substitutions nor rely on hedonics to compute prices – as it occurs in some of the items underlying the CPI. Finally, we collect posted prices as opposed to unit values. In most scanner's data, prices are unit values, computed as the ration between total sales and total quantity at certain frequency. Unit values can experience small fluctuations due to different intensities in the use of loyalty cards, coupons, and quantity discounts which clearly introduce small price changes that are unrelated to the actual posted price change.[5]

[1] As can be attested by the excellent survey by Klenow and Malin (2009). See Bils and Klenow (2004), Dhyne et al. (2005), Nakamura and Steinsson (2008), Bils et al. (2009), Gagnon (2007), Gopinath and Rigobon (2008), Klenow and Kryvtsov (2008), Wulfsberg (2008).

[2] See Midrigan (2005).

[3] A paper by Cavallo (2010) has found evidence of bi-modality in four Latin American countries: Argentina, Brazil, Chile, and Colombia. The analysis was based on histograms of the distributions in four large supermarkets, one in each country, from October 2007 to October 2008. The same supermarkets are included in this paper with data for a longer time period.

[4] For an introduction to Scraped Data, see Cavallo (2010)

[5] It is important to mention that from the inflation calculation point of view, the scanner data is better than the the data we use. Changes in the use of discounts and in general changes in the consumers demand, is an important part of the welfare calculations of inflation that our data misses. Nevertheless, in this paper we are concern with the firms posting price decision

The first part of our analysis uses the two best-know tests of unimodality available in the statistical literature: Hartigan's Dip test, and Silverman's Bandwidth test. These tests are intuitive, easy to compute, and very powerful. The last aspect is indeed a limitation we see of these tests. Hartigan's Dip rejects unimodality in 36 out of 37 supermarkets, while Silverman's test rejects the null of unimodality in 33 of the supermarkets. Only the most obvious cases of multi-modality are not rejected. These tests exhibit large statistical power, which makes them too sensitive to even tiny bumps in the distribution. Therefore, some of the rejections occur even when the modes are not economically meaningful.[6] Our goal in this paper is to reject unimodality only when the distribution exhibits additional modes that are sufficiently large.

The problem with Hartigan and Silverman's tests is that the null hypothesis is strict unimodality. Hence, any second mode, no matter what small it is, should lead to a rejection. To deal with this limitation, we develop a new test we call the *Proportional Mass* (PM) test. It is designed to find unimodality around specific value of the distribution, like zero percent or the largest mode, and to allow for small modes in the distribution as part of the null-hypothesis. The test is very simple. It computes the mass of price changes smaller than certain bounds in absolute terms (for example, at 1% and 5%). In an unimodal distribution, the mass in the small interval is larger than the proportional (per unit) mass in the larger interval. In the bimodal distribution (with two modes significantly large) the opposite occurs. This is a more conservative test because it requires modes to be of relatively the same importance for a rejection of unimodality to take place. In other words, in the null hypothesis distributions that are not unimodal (but with very small modes) exhibit the same proportional mass than some other distribution that is purely unimodal; and therefore, no rejection occurs. The intuition is that the test is not rejected for a multimodal distribution if the masses of the smaller modes can be rearranged to form a unimodal distribution with the same proportional mass.

One possible source of concern in our test is the fact that badly documented *sales* produce modes in the distribution that would reject unimodality. For example, imagine that the company does temporary sales of 10, 20 and 25 percent discounts for two weeks, then the distribution of price changes will reflect those modes. In order to deal with this problem we concentrated our analysis entirely in the -5 to +5 percent price change window. *Sales* smaller than 5 percent are rare, and therefore, by concentrating in this smaller we made our test even more conservative.[7] When we use this conservative test on our data, we still reject unimodality around zero in about 2/3 of the supermarkets.

Having rejected unimodal distributions, the next step is to understand the reason for this rejection. Instead of centering the PM test around zero, we centered it around the highest mode. The reason is that unimodality around zero could be rejected either because the distribution is indeed bimodal or because the most important mode is away from zero. In low inflationary environments this is rare, but as shown by Alvarez et al. (2010) in a high inflationary environment one mode tends to dominate the distribution even in a state-dependent sticky model. We therefore replicate the PM test centering around the largest mode in the -5 to 5 percent interval. In this exercise, most distributions are indeed unimodal. In other words, our test rejects that the distributions are unimodal around zero, but not around their highest mode. This means that most of the distributions have a major mode that possibly reflects the outcome of an inflationary (or deflationary) process, where firms change their prices according to the average inflation of the country.

Unimodal distributions centered away from zero are consistent with several theories of price stickiness. First, it can be the outcome of a time-dependent model with positive aggregate shocks. For example, if prices are changed at regular intervals and the average inflation is about 5%, the distribution of changes will be unimodal centered at 5%. Second, it can also be the result of a standard adjustment-cost model with aggregate inflation, where adjustment costs are present but there are no negative shocks to create a bimodality. These models have different predictions depending on the level of inflation. When we move from a positive inflation to a zero inflation setting, in a time-dependent model the distribution will remain unimodal around a shifting mode. In a state-dependent model, by contrast, the number of modes will also change as inflation falls, becoming bimodal when the average inflation is near zero. Indeed, when we compute

and therefore our data has advantages because eliminates spurious price changes from the analysis.

[6] In fact, when we apply Silverman's test to a null of bimodality – in favor of more than two modes – it does not reject it in 14 supermarkets.

[7] As we show below unimodality is easily rejected if the whole distribution is used.

the PM score centered at the mode across quarters, we find that the distributions became less unimodal in late 2008 and early 2009 for some countries that were experiencing significant inflation before the crisis.

Overall, the lack of unimodality at zero percent is at odds with the existing literature based on CPI and scanner dataset. We explore possible explanations to reconcile the differences. We find two reasons for why our results may not coincide with the scanner data findings. First, scanner data tend to have unit values and not actual prices. Stores report the total sales and total quantities per item, and prices are computed as the ratio between these two values. Because consumers purchase with or without coupons, or with or without loyalty cards, the unit values change in small proportions due to the randomness in consumer's demand. Second, scanner data is usually reported on a weekly basis, so there is also an averaging that takes place through out the week. Although in our data we do not have prices with loyalty cards, we can simulate a weekly averaging or unit value. When we take our data and average the weekly prices, we cannot reject unimodality in 32 out of 37 supermarkets. In other words, the constant weight weekly average of the prices is enough to create unit values that are sufficiently unimodal so that our test does not reject.

The more challenging task is to reconcile our results with those underlying the CPI data. The CPI data is, at most, a monthly sampling of our daily prices. This could artificially create small changes if there are a large number of temporary price changes within a month. However, when we re-sampled our data to replicate a monthly sampling from statistical offices we find that the results are weaker, but not weak enough to reduce the number of rejections of unimodality. Another possible explanation is the fact that statistical offices sometimes impute missing values with hedonic estimates and average category changes.[8] Unfortunately we do not have access to the CPI data to determine how common these practices are, and therefore we must leave this important question for future research. Nevertheless, it is interesting to highlight that the most unimodal distributions in our sample are from Colombia, Ireland, Uruguay, and the USA. In other words, it is possible that in USA supermarkets exhibit unimodal distributions. Future research should pay special attention to reconciling the results from these different data sets.

Finally, to have a sense of the importance between the state versus time dependent aspect of the data we simulate Alvarez et al. (2010) model for different parameter choices between menu and observation costs. We generate price change distributions from the model and compute our tests for those distributions. We present different levels of inflation and the relative importance of menu costs (vs observation costs) and compare how the tests perform when centered around zero and away from zero. We find that the level of rejection of unimodality around zero increases with the importance of menu costs and inflation.

The paper is organized as follows: Section 2 describes the data. Section 3 introduces three non-parametric statistical tests of unimodality. Section 4 presents the results of these tests, with evidence rejecting unimodality at zero percent. We also discuss some explanations for the difference in our results with the rest of the literature. Section 5 simulates the Alvarez et al. (2010) model for different parameters and computes the three tests for unimodality in the simulated price change distributions. Section6 concludes.

2 Data: The Billion Prices Project

The data was collected by the *Billion Prices Project* (BPP) at MIT Sloan. We used a scraping software to record, on a daily basis, the price information for all goods sold by online supermarkets.

The scraping methodology for each retailer works in 3 steps: First, at a given time each day we download all public web-pages where product and price information are shown. These pages are individually retrieved using the same URL or web-address every day. Second, we analyze the underlying code and locate each piece of information that we want to collect. This is done by using custom characters in the code that identify the start and end of each variable, according to the format of that particular page and supermarket. For example, prices are usually shown with a dollar sign in front of them and two decimal digits at the end. This set of characters can be used by the scraping software to identify and record the price every day. Third, we

[8] See BLS (2009)

store the scraped variables in a panel database, containing one record per product-day. Along with the price and product characteristics, retailers show an id for each product in the page's code (typically not visible when the page is displayed to the customer), which allows us to uniquely identify each product over time.[9]

The retailers included in this paper are detailed in Table 1. There are 37 supermarkets in 23 countries and 5 continents. Prices were collected on a daily basis between October 2007 and February 2010, with different starting dates for each supermarket. In all cases, we have at least one year of data, with a mean per retailer of 571 days, 20 thousand individual products, 5 million daily observations and 100 thousand price changes.

[Table 1 about here]

The availability of daily prices and information for every single product sold by each supermarket greatly expands the number of data points available. At the same time, such high-frequency data collection causes frequent gaps in individual price series. These gaps are mostly caused by failures in the scraping procedure and lack of stock in seasonal items. Scraping-related failures are typically resolved in a few days by the BPP scraping team (for example, when the format of a website changes or one of our server machines crashes), so in these cases gaps tend to last a short period of time. By contrast, gaps caused by seasonal and other out-of-stock items can last several months. The standard treatment of gaps in the literature, which fills them with the last recorded price before calculating price changes, can change the distribution of the size of price changes considerably. The effect depends on the macroeconomic context. For example, in cases of high inflation, price changes would appear larger, because prices are accumulated over time. In a context with volatile temporary shocks, two large price changes of opposite magnitudes could appear as one small change. Therefore, in this paper we focus on "consecutive" price changes for which information is directly observed at days t and t-1.

3 Tests for Unimodality

The standard analysis of unimodality in the the micro-price literature relies on histograms and cummulative frequency plots.[10] Although this is adequate to examine the shape of few distributions, it is sometimes hard to determine when particular modes are large enough to grant a rejection. Additionally, it is difficult to compare across a large number of retailers and countries like those included in this paper, particularly if we want to look at differences in modality across categories and over time.

Our contribution is to formally test for unimodality using three non-parametric statistical tests: Hartigan's Dip (or Excess Mass) Test, Silverman's Bump (or Bandwidth) Test, and a test we develop in this paper called the *Proportional Mass Test*.[11]

Hartigan's and Silverman's tests are common in the the statistics literature, but have rarely been used in economic applications. One recent exception is Henderson et al. (2008), who use both tests to analyze the distribution of income per capita across countries. These tests are intuitively appealing and simple to compute. They are also statistically powerful, minimizing the probability of making a false acceptance. Unfortunately, this means that they tend to reject unimodality very easily.[12]

To address these concerns, we developed a more conservative test, called the *Proportional Mass Test* (PM), which also makes an explicit assessment of the multi-modality of the distribution centered around a

[9] For more on the scraping methodology, see Cavallo (2010) and www.billionpricesproject.org

[10] See Kashyap (1995), Klenow and Kryvtsov (2008), Kackmeister (2007), Midrigan (2005) and Cavallo (2010)

[11] Parametric tests of multi-modality are more common in economics. For example see Paapaa and van Dijk (1998) and Anderson (2004) for methods involving mixing normal distributions and mass overlaps. However, these tests require the *ex-ante* assumption of a number of clusters or groups and they may reject the null hypothesis of normality, but not necessarily unimodality

[12] Another minor drawback, for our purposes, is that in micro-price setting applications we want to know whether the unimodality is centered around zero.

specific value of price changes. Using this test, we can explore the shape of distribution both around zero or at any other point of interest of the distribution – such as the largest mode. This is important to test some of the predictions of time-dependent and state-dependent sticky-price models.

In this section we discuss the three tests and later present the results in section 4.

3.1 Hartigan's Dip Test

Hartigan's dip test relies on the fact that the cumulative distribution function of a density function f with a single mode at m_f is convex on the interval $(-\infty, m_f)$ and concave on the interval (m_f, ∞).[13] The intuition of this property is very simple. At the right hand side of the mode, the density is non increasing – meaning that its derivate is non-positive. The opposite occurs at the left of the mode.

The Dip statistic measures the departure of an empirical distribution from the best fitting unimodal distibution. The intuition behind the computation of the dip statistic is straightforward. If the empirical distribution has multiple modes, with a cumulative distribution that has several regions of convexity and concavity, then it will be "stretched" until it takes the shape of an unimodal distribution. The larger the stretch needed, the larger the departure from unimodality. If the empirical distribution has a single mode, then the dip statistic will be zero.

In Hartigan's method, positive dip values provide evidence to reject the null hypothesis of unimodality. To determine the statistical significance of a positive dip, Hartigan and Hartigan (1985) sets the null hypothesis equal to the uniform distribution, for which, asymptotically, the dip value is stochastically largest among all unimodal distributions.[14] This increases the power of the test, making it more likely to reject the null hypothesis of unimodality.

3.2 Silverman's Bandwidth Test

Silverman's Bandwidth or "Bump" test uses kernel smoothing functions to evaluate modality. Given a sample $X = (x_1, x_2, ..., x_n)$, a non-parametric kernel estimate of the unknown density function f is given by

$$\hat{f}\left(x, h\right) = (nh)^{-1} \sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{1}$$

where h is the smoothing parameter (or "bandwidth") and K is the Gaussian kernel function. Silverman (1981) showed that the larger smoothing h, the fewer the number of modes in $\hat{f}\left(x, h\right)$. Therefore, for the null hypothesis of unimodality, he proposed the test statistic

$$\hat{h}^1_{crit} = \inf\left\{h : \hat{f}\left(x, h\right) \text{ has 1 mode}\right\} \tag{2}$$

This is the minimum smoothing required for the smoothed kernel density to have one mode. Large values of $\hat{h}^1_{crit}$ are evidence against the null hypothesis, because larger degrees of smoothing are needed to eliminate additional modes in the density estimate.

The statistical significance of $\hat{h}^1_{crit}$ is evaluated using a smoothed bootstrap test.[15] For each bootstrapped

[13]See Hartigan and Hartigan (1985)

[14]Hartigan and Hartigan (1985) also show that this is not always the case with small samples. To address this concern, we use a calibration of the dip test proposed by Cheng and Hall (1998), also used by Henderson et al. (2008).

[15]The bootstraps are drawn from an smoothed conditional function re-scaled to have a variance equal to the sample variance. Henderson et al. (2008) for details.

sample, we compute the minimum bandwidth $\hat{h}_{crit}^{m*}$ required to have one mode and estimate the probability $\hat{P}$, given by

$$\hat{P} = P\left(\hat{h}_{crit}^{1*} \geq \hat{h}_{crit}^{1}\right) \tag{3}$$

Given that we expect to see higher values of $\hat{h}_{crit}^{1}$ if H_o is false, the smaller $\hat{P}$, the stronger the evidence against the null.[16]

This methods can be used to test for m modes, and is usually carried out in sequence, starting with one mode, until the test fails to reject the null hypothesis. This is a major advantage of Silverman's approach, because it allows us to test explicitly for bi-modality in the size of price changes. In addition, this test is intuitively appealing and easy to compute.

Unfortunately, it also has some weaknesses. First, it is easily affected by outliers in the tails of the distribution. Second, it is sensitive to tiny bumps in the distribution which leads to frequent rejections of the null hypothesis, especially with large samples.[17]

3.3 Proportional Mass Test

We now propose a more conservative "Proportional Mass Test" that compares the relative mass of the distribution between bounds to determine the degree of unimodality around a centered value.

The test relies on the fact that unimodal distributions have a high proportion of their mass close to the mode. If we take an interval around the mode and make it progressively larger, the mass increases by *smaller* increments each time. By contrast, in a bimodal distribution the mass increases by *larger* increments each time. Therefore, the relative size of these additional increments of mass can be used to determine the degree of unimodality in the distribution.

Consider the case where the distribution is unimodal centered at zero percent, as illustrated in Figure 1. The mass between -1% and 1% should be larger than the mass between -5 and 5 per unit, that is,

$$P\left(|\Delta p| \leq 1\right) \geq P\left(|\Delta p| \leq 5\right)/5 \tag{4}$$

The *proportional mass* between $i = 1$ and $j = 5$ is thus given by

$$PM_{1,5}^{0} = \ln \frac{P\left(|\Delta p| \leq 1\right)}{P\left(|\Delta p| \leq 5\right)/5} \tag{5}$$

This ratio is positive when the distribution is unimodal around zero.[18] By contrast, when the distribution is strictly bimodal around zero, $PM_{1,5}^{0}$ is negative. Both cases are illustrated in Figures 1(a) and 1(b). Finally, if the distribution is bimodal but the modes are not significantly large, as seen in Figures 1(c) and 1(d), then the PM will be positive. This ensures that minor bumps in the distribution will not cause a rejection of unimodality.

This ratios is generalized to incorporate information from different intervals and compute the *Proportional Mass Score* around zero, given by

[16] Because the number of modes is non-increasing with h, $\hat{P}$ is equivalent to the share of bootstraps that have more than one mode when evaluated with bandwidth $\hat{h}_{crit}^{1}$. We use this approach to estimate $\hat{P}$, also called the *achieved significance level* in the bootstrap literature, because it is easier to compute.

[17] These problems are derived from the use of a single bandwidth in the kernel smoothing estimates.

[18] If the distribution is uniform, $PM_{1,5}^{0} = 0$ when the domain of the distribution is wider than 5, otherwise $PM_{1,5}^{0}$ is positive

$$PM^0 = \frac{1}{|Z|} \sum_{ij \in Z} PM_{ij} \tag{6}$$

where Z is the set of all combination ij such that $i < j$.

The null hypothesis is that the PM score is positive (i.e. unimodal distribution), and the statistical significance is evaluated using bootstrapped samples from the data. The same logic applies when we want to test the degree of unimodality around a mode m, with PM^m given by

$$PM^m = \frac{1}{|Z|} \sum_{ij \in Z} \ln \frac{P\left(|\Delta p - m| \leq i\right)}{P\left(|\Delta p - m| \leq j\right) / (j/i)} \tag{7}$$

In our computations, we consider the intervals $i, j \in \{1, 2.5, 5\}$, but we also test the robustness of our results to changes in these intervals. Future research should solve the optimal bandwidth in the proportional mass test. This is beyond the scope of the present paper and is left for future research.

4 Results

4.1 Rejection of Unimodality at 0%

We first run Hartigan's Dip test in all supermarkets. The first two columns in Table 3 show the dip statistics and p-values for the null hypothesis of unimodality. The dip statistics are consistent with a simple graphical analysis of the histograms in Figures A4 to A6. For example, the lowest dips belong to AU_WOOLWORTH, NL_ALBERT, TESCO, UK_OCADO, UK_SALINSBURY, and VIRTUALEXITO. These are distributions either have a large dominating mode or seem to be uniformly distributed. However, as a statistical test, Hartigan's method is too powerful. At the 1% significance level, unimodality is rejected in 36 out of 37 supermarkets. This test rejects the null hypothesis even for distributions with only minor departures from unimodality. Unfortunately, there is no way to reduce its power with large samples.

[Table 3 about here]

Next, we consider Silverman's bandwidth test. The results are shown in columns 3 to 5 of Table 3. The critical bandwidth values, which measure the degree of "smoothing" needed to obtain a single-mode kernel estimate, are also consistent with a simple graphical analysis. Some of the lowest critical values are, once again, in AU_WOOLWORTH, TESCO, UK_OCADO, UK_SALINSBURY and VIRTUALEXITO. However, although slightly more conservative, Silverman's test still rejects the null of unimodality in 33 out of 37 supermarkets. The rejection level is high even when we consider the null hypothesis of 2 or less modes. In fact, in 22 supermarkets we find evidence supporting *more* than 2 modes. The test appears to be too sensitive to tiny bumps in the distribution. This is especially true in those retailers with the largest number of observations, such as DEVOTO, CN_LINHUA, JUMBO, RU_UTKANOS, TESCOIRELAND, US_WEBVAN and WOOLWORTH. In these cases, we reject both unimodality and bimodality around zero. This is a major limitation for us. The test detects small bumps caused by the aggregation across categories or types of products, which are are not relevant for our main objective. We are looking for modes that are sufficiently large and can provide insights into the importance of menu costs and other pricing behaviors.

Finally, the estimates for the PM test centered at 0% are presented in Table 4. Column 3 shows the PM score point estimate, columns 4 and 5 show the mean and the standard deviation in 500 bootstrapped samples, and column 6 shows the share of bootstrapped estimates that have a negative PM score (bimodality).

[Table 4 about here]

As expected, the PM test is far more conservative. We fail to reject unimodality in 13 supermarkets, or 1/3 of the total. This test does a better job at ignoring small bumps in the distribution, because it spreads their additional mass in relatively wide intervals used to calculate the proportional mass ratios. Still, even though we have been stacking the odds to find unimodality, the PM test continues to rejects the null hypothesis in 24 supermarkets, or 2/3 of the total. The evidence against unimodality at zero percent is simply overwhelming.

The PM score computed at quarterly intervals provides similar results. In Table 5 we show quarterly PM scores for every retailer. The negative scores (bimodality) are common thought the table for most retailers. This can also be seen in Table 6, which shows the share of bootstrapped sampled with PM scores below 0. In this case, the 1's in the table provide evidence of bimodality.

[Table 5 and Table 6 about here]

Overall, our three statistical tests strongly reject the hypothesis of unimodality around zero percent. We have shown results within the interval of -5% to 5%, but these findings are robust to extensions with distributions at the +/- 10% and +/- 50% intervals. In fact, the wider the range of the distribution, the lower the evidence of unimodality around zero.[19]

4.2 Unimodality away from 0%

There may be no unimodality around zero percent, but the size distributions can still have large modes away from zero. This can be explored using the PM test centered on the mode (i.e. the highest "mode" in the distribution), rather than zero. Positive PM scores in this case would indicate the presence of modes that are large enough to dominate the mass of price changes within a +/-5% interval. These modes could reflect the outcome of an inflationary (or deflationary) macroeconomic context.

In Table 7, we center the PM test around the highest mode in each supermarket, which is negative in 13 and positive in 21 supermarkets. With this new test, 34 out of 37 supermarkets have a *positive* PM score, which is consistent with the existence of a major mode *away* from zero percent. The share of bootstrapped samples with negative PM scores, shown in the last column, confirms that there is little evidence of bimodality away from zero.

[Table 7 about here]

The PM scores away from zero can be use to explore the changes in modality with different levels of inflation. Indeed, changes in the pattern of modality can have important implications for some theoretical models. For example, standard state-dependent models would predict that an economy that moves gradually from a peak of inflation to a peak of deflation will have a distribution that looks initially unimodal with a positive mode, then bimodal at zero, and finally unimodal with a negative mode. Table 8 shows the estimates of the PM test centered around the largest mode for each quarter. We find that the distributions became less unimodal (away from zero) in late 2008 and early 2009. The last row in Table 9 shows that the share of retailers with evidence of bimodality starts to rise in the fourth quarter of 2008 and peaks in the second quarter of 2009. This is a time when recession was affecting many of these countries. Although the shift in modality is not as stylized as standard models predict, they suggest that modality and inflation are closely linked over time.

[Table 8 and Table 9 about here]

[19]See the Appendix for details

4.3 Reconciling differences with the Literature

Our main finding, the lack of unimodality of price changes around zero percent, is at odds with the existing literature that uses Scanner and CPI data. In this section, we consider possible explanations for these differences by replicating some of the sampling methodologies in these two types of data.

4.3.1 Differences with Scanner Data

Scanner datasets have two important differences with our data. First, prices are constructed as "unit values", with the ratio of total sales over total quantity sold for each product. Because consumers can sometimes purchase products with or without coupons, with or without loyalty cards, or even at different prices within the same day, this unit value will change in small percentages with the randomness in consumer demand. Second, scanner data are reported on a weekly basis, so there is also an averaging that takes place along the week. The effect of this averaging is discussed by Campbell and Eden (2005). Their focus was not on the size of changes, but they described some complications caused by weekly averages using a simple example. Consider a three week period with a single price change on the middle of the second week. If average weekly prices are used, each week would have a different price and two –smaller– price changes would be observed.

Although we do not have information on the use of loyalty cards and coupons, we can replicate the weekly averaging in our data and see how it affects our results. We do so by first computing the weekly average price per individual product, and then re-calculating price changes only when consecutive weekly prices are available.

Our results in Table 10 show that the evidence of unimodality increases dramatically with weekly averaged prices. This table compares the effect of weekly averaging on the three measures of modality embedded in our tests: the dip statistic, the critical bandwidth and the PM score (centered at 0%). A drop in Hartigan's dip means that, on average, the distribution is now closer to being unimodal. A drop in Silverman's critical bandwidth means that less smoothing is needed to obtain an unimodal kernel estimate. An increase in PM scores means that the distribution becomes unimodal around zero. In all three cases, the evidence for unimodality increases dramatically with weekly prices. Furthermore, the PM test centered at zero also fails to reject unimodality in 32 out of 37 supermarkets.

[Table 10 about here]

4.3.2 Differences with CPI Data

Reconciling our results with CPI studies is harder because the differences in the data go far beyond simple sampling methodologies. Nevertheless, the monthly sampling of prices could lead to artificially small price changes when there frequent temporary shocks lasting less than a month. For example, if a price were to fall from \$10 to \$9, and then move back to \$10.1 within a few days, monthly sampling would detect a +1% price change instead of two changes of -10% and +12%. Cavallo (2010) showed that these type of temporary changes can occur frequently in supermarket data, and it can be particularly relevant in low-inflation settings like the US, where most of the literature's CPI findings come from.[20]

To approximate the CPI sampling methods, we randomly picked one day of the month for each individual product and recorded the price. If we chose a day where no price information is available, the price is missing for that month. Next, we re-calculated price changes only when consecutive monthly price observations were available.

[20] In a setting with high inflation, monthly sampling can have the opposite effect, accumulating several small price changes that occur within a month.

In contrast to weekly averages, monthly sampling of the data has no effect on the degree of unimodality. The average dip statistic, critical bandwidth and PM score in Table 10 are similar with daily and monthly data (even though the number of observations drops significantly once monthly data is used).

An alternative explanation for our differences with the CPI literature it related to individual price corrections in the US CPI series. The BLS makes several adjustments in individual prices that can potentially affect the distribution of the size of changes. First, changes in a price spell can be cause by *forced item substitutions* that occur when an item is no longer available. In these cases, the BLS estimates a price change using hedonic quality adjustments or the average price change for that category of products. Second, even when no product substitutions occur, the BLS sometimes imputes prices that are considered temporarily missing. Seasonal products –including Fresh Food– are the typical case when this happens. Third, individual prices can also be adjusted for coupons, rebates, loyalty cards, bonus merchandize, and quantity discounts, depending on the share of sales volume that had these discounts during the collection period. Fourth, some food items that are sold on a unit basis –like apples– are sometimes weighted in pairs to calculate an average-weight price. These and other price adjustments are described in the BLS Handbook of Methods.[21] Unfortunately, we do not know how frequent these changes are in practice, or whether they can explain most of the small price adjustments previously found by the literature. Without access to the US CPI data, we must leave this important questions for future research.

5 Simulation and Calibration

[to be completed]

6 Conclusions

The shape of the distribution of the size of prices changes is an important implication of the different theories behind price stickiness. One of the key characteristics of this shape is the number of modes around –and away– zero percent. We formally tested for this modality in a large set of supermarkets, spanning 23 countries and 5 continents, using the two best-known tests in the statistical literature –Hartigan's Dip and Silverman's Bandwith– and a test designed in this paper –the Proportional Mass test–. Three important results are uncovered. First, when the traditional tests are used, the unimodality around zero is rejected in about 90 percent of the establishments. When we used the Proportional Mass test, which is much more conservative than the first two, we reject unimodality in two thirds of the supermarkets. Second, if we center the test on the largest mode – as opposed to zero – we have few rejections of unimodality. Finally, the rejection of unimodality changes through time. In countries where there is large inflation the distribution is unimodal around a high inflation mode. In those countries when the inflation drops – which happened almost everywhere during the recent financial recession – bimodality starts to appear.

The results presented in this paper are not conclusive evidence in favor or against particular theories of price stickiness. Certainly further research is needed to understand which theories are more likely to explain certain behaviors, and how those behaviors change through time and across product categories.

In this paper we have shown that modality, once formally tested, exists mostly away from zero percent, and varies with the level of inflation and other country characteristics. Future theoretical work in the are of price stickiness must account for these variation.

[21] See , Chapter 17, pages 30 to 33.

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Tables

Table 1: Supermarket Data

Database	Country	Started	Days	Obs.	Products	# Pr P/day	Pr. Ch. (cc)		Sales
COTO	Argentina	10/7/2007	876	13117K	26K	12K	155K	1.2%	YES
LESHOP	Argentina	23/7/2007	861	5294K	11K	6K	103K	2.0%	YES
AU_BANANABLUE	Australia	8/4/2008	574	232K	3K	1K	147K	63.4%	NO
AU_EFRESH	Australia	8/7/2008	571	202K	1K	0K	2K	1.0%	NO
AU_GROCERIES4U	Australia	8/4/2009	209	3292K	7K	6K	2K	0.1%	NO
AU_WOOLWORTH	Australia	5/3/2008	667	1967K	18K	4K	46K	2.3%	YES
PAO	Brasil	10/10/2007	873	10780K	22K	11K	260K	2.4%	YES
JUMBO	Chile	10/24/2007	859	12102K	35K	12K	120K	1.0%	NO
CN_CARREFOUR_BEIJING	China	12/5/2008	451	1101K	7K	3K	6K	0.5%	NO
CN_LIANHUA	China	3/19/2008	712	6644K	46K	10K	22K	0.3%	NO
VIRTUALEXITO	Colombia	11/13/2007	839	4186K	9K	5K	77K	1.8%	YES
EC_TIA	Ecuador	3/19/2009	347	667K	3K	2K	6K	0.9%	NO
FR_AUCHANDIRECT	France	10/29/2008	488	2806K	10K	5K	11K	0.4%	NO
FR_HOURA	France	11/18/2008	468	4878K	17K	10K	18K	0.4%	NO
FR_TELEMARKET	France	11/5/2008	481	3102K	21K	6K	33K	1.1%	NO
DE_KAISER	Germany	10/22/2008	495	453K	3K	3K	1K	0.2%	NO
HK_PARKNSHOP	Hong Kong	5/24/2008	646	1229K	10K	6K	3K	0.3%	YES
TESCOIRELAND	Ireland	5/28/2008	642	11660K	35K	18K	94K	0.8%	YES
IT_ONLINEMARKET	Italy	11/19/2008	467	1076K	4K	3K	2K	0.2%	NO
IT_PRONTOSPESA	Italy	12/5/2008	451	1622K	5K	4K	7K	0.4%	YES
MX_SORIANA	Mexico	5/15/2009	290	600K	4K	2K	39K	6.5%	YES
NL_ALBERT	Netherlands	5/2/2009	303	1485K	10K	8K	4K	0.3%	YES
WOOLWORTHS	New Zealand	6/17/2008	622	9528K	39K	12K	295K	3.1%	NO
RU_UTKANOS	Russia	2/11/2009	383	13765K	120K	30K	308K	2.2%	NO
SG_GROCERYSTORE	Singapore	3/20/2009	346	514K	2K	2K	1K	0.1%	YES
ES_CARREFOUR	Spain	6/27/2008	612	3017K	11K	5K	28K	0.9%	YES
TR_MIGROS	Turkey	6/4/2008	635	8889K	30K	13K	55K	0.6%	YES
UK_BRITISHCORNERSHOP	UK	10/5/2008	512	2774K	7K	6K	20K	0.7%	NO
TESCO	UK	5/7/2008	663	8124K	24K	13K	152K	1.9%	YES
UK_OCADO	UK	6/27/2008	612	3442K	16K	5K	25K	0.7%	NO
UK_SALINSBURY	UK	2/17/2009	377	494K	6K	4K	5K	1.0%	YES
WAITROSE	UK	6/18/2008	621	433K	4K	3K	1K	0.3%	NO
DEVOTO	Uruguay	10/23/2007	860	12297K	46K	10K	79K	0.6%	YES
US_WEBVAN	US	4/11/2009	324	13484K	57K	35K	486K	3.6%	NO
LOWES	US	5/6/2008	664	6309K	14K	10K	35K	0.6%	YES
SAFEWAY	US	5/8/2008	662	11868K	29K	15K	262K	2.2%	YES
EXCELSIOR	Venezuela	5/16/2008	654	10292K	20K	13K	49K	0.5%	NO
Mean			571	5236K	20K	8K	80K	2.9%	
Median			612	3292K	11K	6K	33K	0.8%	

Table 2: Share of Small Changes

Database	**Country**	**Percent of Price Changes with Size**		
		< |**10%**|	< |**5%**|	< |**1%**|
AU_BANANABLUE	Australia	13.6	6.2	0.7
AU_EFRESH	Australia	13.3	1.9	0.4
AU_GROCERIES4U	Australia	50.4	23.9	2.2
CN_LIANHUA	China	73.9	37.7	2.6
COTO	Argentina	54.6	28.7	4.2
DEVOTO	Uruguay	69.5	59.5	41.6
EC_TIA	Ecuador	43.1	22.2	3.9
ES_CARREFOUR	Spain	66.8	35.4	5.2
EXCELSIOR	Venezuela	45.9	29.1	3.2
FR_AUCHANDIRECT	France	79.5	53.9	8.3
FR_HOURA	France	42.9	23.4	4.6
FR_TELEMARKET	France	70.9	57.7	13.2
HK_PARKNSHOP	Hong Kong	51.7	27.7	4.0
IT_PRONTOSPESA	Italy	27.4	14.0	1.1
JUMBO	Chile	48.3	25.8	3.6
LOWES	US	39.0	20.3	0.9
MX_SORIANA	Mexico	21.3	13.8	3.1
NL_ALBERT	Netherlands	80.2	60.2	6.2
PAO	Brasil	55.3	35.1	4.3
RU_UTKANOS	Russia	40.0	23.7	8.6
SAFEWAY	US	14.5	4.4	1.0
SG_GROCERYSTORE	Singapore	66.7	27.8	1.1
TESCO	UK	58.8	47.7	23.6
TESCOIRELAND	Ireland	38.3	18.9	4.2
TR_MIGROS	Turkey	22.2	8.9	1.0
UK_BRITISHCORNERSHOP	UK	16.8	6.8	0.1
UK_OCADO	UK	66.1	53.7	26.5
VIRTUALEXITO	Colombia	59.9	37.9	7.6
WAITROSE	UK	29.3	14.3	1.7
WOOLWORTHS	New Zealand	35.8	16.2	2.1
Mean		**46.5**	**27.9**	**6.4**
Median		**47.1**	**24.9**	**3.8**

Table 3: Estimation of Hartigan's Dip and Silverman's Tests

	DIP Test (calibrated)		Silverman's Test		
	Dip Stat. (lower is unimodal)	Null = 1 mode P-values	Critical Band. (lower is unimodal)	Null = 1 mode P-values	Null $\leq$ 2 modes P-values
AU_BANANABLUE	0.04	0.00	2.21	0.00	0.03
AU_EFRESH	0.07	0.04	1.79	0.25	0.24
AU_GROCERIES4U	0.02	0.00	1.27	0.00	0.33
AU_WOOLWORTHS	0.01	0.00	0.65	0.00	0.00
CN_CARREFOUR	0.02	0.00	1.34	0.00	0.13
CN_LIANHUA	0.02	0.00	1.61	0.00	0.00
COTO	0.07	0.00	1.92	0.00	0.00
DEVOTO	0.10	0.00	0.49	0.00	0.00
EC_TIA	0.02	0.00	1.60	0.00	0.20
ES_CARREFOUR	0.03	0.00	1.72	0.00	0.00
EXCELSIOR	0.04	0.00	0.77	0.00	0.00
FR_AUCHANDIRECT	0.02	0.00	1.40	0.00	0.00
FR_HOURA	0.02	0.00	1.10	0.00	0.01
FR_TELEMARKET	0.04	0.00	0.59	0.00	0.00
HK_PARKNSHOP	0.04	0.00	1.22	0.00	0.00
IT_ONLINEMARKET	0.02	0.00	0.92	0.03	0.10
IT_PRONTOSPESA	0.03	0.00	1.57	0.00	0.15
JUMBO	0.02	0.00	1.74	0.00	0.00
LESHOP	0.03	0.00	1.47	0.00	0.00
LOWES	0.07	0.00	2.42	0.00	0.01
MX_SORIANA	0.03	0.00	0.81	0.00	0.00
NL_ALBERT	0.01	0.00	1.06	0.00	0.07
PAO	0.03	0.00	1.12	0.00	0.00
RU_UTKANOS	0.02	0.00	0.95	0.00	0.00
SAFEWAY	0.04	0.00	1.56	0.00	0.00
SG_GROCERYSTORE	0.09	0.00	2.48	0.00	0.33
TESCO	0.01	0.00	0.68	0.00	0.00
TESCOIRELAND	0.05	0.00	1.70	0.00	0.00
TR_MIGROS	0.02	0.00	1.62	0.00	0.03
UK_BRITISHCORNERSHOP	0.08	0.00	2.47	0.00	0.00
UK_OCADO	0.01	0.00	0.54	0.00	0.17
UK_SALINSBURY	0.01	0.00	0.83	0.00	0.00
US_WEBVAN	0.06	0.00	1.05	0.00	0.00
VIRTUALEXITO	0.01	0.00	0.66	0.03	0.97
WAITROSE	0.03	0.00	0.95	0.06	0.12
WOOLWORTH	0.05	0.00	2.35	0.00	0.00

Table 4: Estimation of the Proportional Mass Test
(Distribution centered at 0%)

Establishment	Observations	Centered Centered	Point Estimate	Mean of Bootstrap	Standard Deviation	Mass below zero
AU_BANANABLUE	9140	0.000	-0.345	-0.344	0.020	1.000
AU_EFRESH	35	0.000	-0.000	-0.087	0.260	0.593
AU_GROCERIES4U	585	0.000	-0.503	-0.501	0.083	1.000
AU_WOOLWORTH	19332	0.000	0.216	0.216	0.008	0.000
CN_CARREFOUR_BEIJING	1730	0.000	-0.241	-0.241	0.039	1.000
CN_LIANHUA	10669	0.000	-0.620	-0.621	0.021	1.000
COTO	45946	0.000	-0.150	-0.150	0.007	1.000
DE_KAISER	9	0.000	0.341	0.352	0.323	0.086
DEVOTO	52454	0.000	0.959	0.959	0.001	0.000
EC_TIA	1450	0.000	-0.081	-0.079	0.037	0.992
ES_CARREFOUR	10084	0.000	-0.196	-0.196	0.016	1.000
EXCELSIOR	15779	0.000	-0.463	-0.463	0.016	1.000
FR_AUCHANDIRECT	6121	0.000	-0.171	-0.173	0.019	1.000
FR_HOURA	5309	0.000	-0.089	-0.088	0.020	1.000
FR_TELEMARKET	20355	0.000	0.103	0.103	0.008	0.000
HK_PARKNSHOP	933	0.000	-0.111	-0.113	0.049	0.996
IT_ONLINEMARKET	635	0.000	0.060	0.061	0.052	0.110
IT_PRONTOSPESA	910	0.000	-0.548	-0.553	0.069	1.000
JUMBO	31936	0.000	-0.236	-0.235	0.010	1.000
LESHOP	20283	0.000	-0.132	-0.133	0.011	1.000
LOWES	5261	0.000	-1.192	-1.192	0.050	1.000
MX_SORIANA	5131	0.000	0.095	0.094	0.016	0.000
NL_ALBERT	2473	0.000	-0.416	-0.416	0.039	1.000
PAO	88811	0.000	-0.092	-0.092	0.005	1.000
RU_UTKANOS	70016	0.000	0.393	0.393	0.004	0.000
SAFEWAY	10466	0.000	0.156	0.156	0.011	0.000
SG_GROCERYSTORE	100	0.000	-1.073	-1.133	0.349	1.000
TESCO	71788	0.000	0.582	0.582	0.003	0.000
TESCOIRELAND	18353	0.000	0.109	0.109	0.008	0.000
TR_MIGROS	4597	0.000	-0.435	-0.435	0.028	1.000
UK_BRITISHCORNERSHOP	1423	0.000	-1.919	-1.922	0.167	1.000
UK_OCADO	13597	0.000	0.638	0.638	0.005	0.000
UK_SALINSBURY	1776	0.000	0.167	0.168	0.026	0.000
US_WEBVAN	210698	0.000	0.487	0.487	0.002	0.000
VIRTUALEXITO	29012	0.000	-0.011	-0.012	0.007	0.940
WAITROSE	312	0.000	-0.264	-0.274	0.098	1.000
WOOLWORTHS	42557	0.000	-0.293	-0.294	0.008	1.000

Note: Bootstrap derived from 500 replications.

Table 5: Estimation of the Proportional Mass Test for each quarter
(Distribution centered at 0%)

Estimates through time	Q4.2007	Q1.2008	Q2.2008	Q3.2008	Q4.2008	Q1.2009	Q2.2009	Q3.2009	Q4.2009
AU_BANANABLUE					-0.295	-0.274	-0.106	-0.587	-0.697
AU_EFRESH							0.108	0.270	
AU_GROCERIES4U					-0.920	-1.403	-0.588	-0.015	-0.134
AU_WOOLWORTH			0.234	0.192	0.277				
CN_CARREFOUR_BEIJING									-0.222
CN_LIANHUA							-1.221		-0.331
COTO	-0.784	-0.641	-0.704	-0.750	-0.675	-0.865	-0.199	0.454	-0.264
DE_KAISER									
DEVOTO	1.055	1.012	0.906	0.939	0.798	0.907	0.935	0.914	-1.555
EC_TIA						-0.495	-0.094	-0.347	0.245
ES_CARREFOUR				0.217	0.040	-0.388	-0.392	-0.292	-0.259
EXCELSIOR			0.508	0.114	0.030	-0.054	-0.901	-0.095	-0.132
FR_AUCHANDIRECT					0.044	-0.338	-0.690	-0.106	-0.219
FR_HOURA					-0.769	-0.235	0.277	-0.358	-0.198
FR_TELEMARKET					-0.600	-0.322	-0.446	0.444	0.357
HK_PARKNSHOP			-0.816	0.029	-1.042	-1.268	-1.316		
IT_ONLINEMARKET					-1.195	-0.462	-0.584	0.085	0.009
IT_PRONTOSPESA					0.238	-0.522	-0.470	-1.032	-0.579
JUMBO	-0.591	-0.174	-0.263	-0.267	-0.335	-0.222	-0.072	-0.064	0.012
LESHOP	-0.301	-0.239	-0.239	-0.015	-0.010	-0.102	0.103	-0.391	-0.171
LOWES			-1.479	-1.238	-1.800		-1.151	-1.179	-1.114
MX_SORIANA							0.719	-0.529	-0.305
NL_ALBERT							-0.740	-0.388	-0.419
PAO	-1.430	-0.684	-0.459	-0.518	-0.242	-0.513	-0.120	-0.330	0.531
RU_UTKANOS						-0.190	-0.121	0.624	0.031
SAFEWAY			-0.487	0.106	-0.190	0.212	0.332	0.491	0.160
SG_GROCERYSTORE							-0.866	-1.238	
TESCO			0.686	0.689	0.393	0.510	0.658	0.660	0.674
TESCOIRELAND			0.007	0.202	-0.711	-0.117	-0.039	-0.207	-0.549
TR_MIGROS			-0.430	-0.591	-0.438	-0.686	-0.415	-0.247	-0.689
UK_BRITISHCORNERSHOP						-2.429	-1.132		
UK_OCADO				0.707	0.605	0.581	0.561	0.374	
UK_SALINSBURY							0.107	0.346	
US_WEBVAN							0.479	0.574	0.376
VIRTUALEXITO	-0.017	0.056	0.003	0.110	-0.019	0.017	-0.077	-0.061	0.055
WAITROSE			-0.775	-0.450	-0.379	0.280	0.046		
WOOLWORTHS			-0.035	-0.016	-0.315	-0.497	0.012	-0.501	-0.549

Table 6: Estimation of the Mass bellow zero for each quarter
(Distribution centered at 0%)

Estimates through time	Q4.2007	Q1.2008	Q2.2008	Q3.2008	Q4.2008	Q1.2009	Q2.2009	Q3.2009	Q4.2009
AU_BANANABLUE					1.000	1.000	1.000	1.000	1.000
AU_EFRESH							0.478	0.148	
AU_GROCERIES4U					1.000	1.000	1.000	0.629	0.741
AU_WOOLWORTH			0.000	0.000	0.000				
CN_CARREFOUR_BEIJING									1.000
CN_LIANHUA							1.000		1.000
COTO	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	1.000
DE_KAISER									
DEVOTO	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000
EC_TIA						0.938	0.900	1.000	0.000
ES_CARREFOUR				0.000	0.146	1.000	1.000	1.000	1.000
EXCELSIOR			0.000	0.002	0.250	0.884	1.000	0.984	0.988
FR_AUCHANDIRECT					0.122	1.000	1.000	1.000	0.988
FR_HOURA					1.000	1.000	0.000	1.000	1.000
FR_TELEMARKET					1.000	1.000	1.000	0.000	0.000
HK_PARKNSHOP			1.000	0.307	1.000	1.000	1.000	0.000	0.000
IT_ONLINEMARKET					0.994	0.982	0.986	0.381	0.473
IT_PRONTOSPESA					0.372	1.000	1.000	1.000	1.000
JUMBO	1.000	1.000	1.000	1.000	1.000	1.000	0.980	0.994	0.319
LESHOP	1.000	1.000	1.000	0.731	0.665	1.000	0.000	1.000	1.000
LOWES			1.000	1.000	1.000		1.000	1.000	1.000
MX_SORIANA							0.000	1.000	1.000
NL_ALBERT							1.000	1.000	1.000
PAO	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000
RU_UTKANOS						1.000	1.000	0.000	0.000
SAFEWAY			1.000	0.000	1.000	0.000	0.000	0.000	0.000
SG_GROCERYSTORE							1.000	1.000	0.000
TESCO			0.000	0.000	0.000	0.000	0.000	0.000	0.000
TESCOIRELAND			0.505	0.000	1.000	1.000	0.786	1.000	1.000
TR_MIGROS			1.000	1.000	1.000	0.874	1.000	1.000	1.000
UK_BRITISHCORNERSHOP					0.000	1.000	1.000	0.000	0.000
UK_OCADO			0.000	0.000	0.000	0.000	0.000	0.000	
UK_SALINSBURY							0.000	0.000	
US_WEBVAN							0.000	0.000	0.000
VIRTUALEXITO	0.667	0.026	0.447	0.000	0.796	0.250	1.000	0.994	0.000
WAITROSE			1.000	0.998	0.972	0.050	0.617		
WOOLWORTHS			0.802	0.828	1.000	1.000	0.271	1.000	1.000

Table 7: Estimation of the Proportional Mass Test
(Distribution centered at the Mode)

Establishment	Observations	Centered Centered	Point Estimate	Mean of Bootstrap	Standard Deviation	Mass below zero
AU_BANANABLUE	9606	-2.900	0.109	0.109	0.012	0.000
AU_EFRESH	105	-3.700	-0.565	-0.597	0.232	1.000
AU_GROCERIES4U	1078	4.900	0.225	0.221	0.031	0.000
AU_WOOLWORTH	19330	-0.300	0.213	0.213	0.008	0.000
CN_CARREFOUR_BEIJING	1804	-2.100	0.285	0.284	0.023	0.000
CN_LIANHUA	12691	4.100	0.432	0.432	0.008	0.000
COTO	50598	0.900	0.178	0.178	0.005	0.000
DE_KAISER	13	1.400	00nan	00nan	00nan	0.000
DEVOTO	52651	0.300	0.908	0.908	0.001	0.000
EC_TIA	1552	4.100	0.115	0.114	0.033	0.000
ES_CARREFOUR	9791	2.100	0.177	0.177	0.012	0.000
EXCELSIOR	18146	2.700	0.735	0.735	0.004	0.000
FR_AUCHANDIRECT	5486	3.100	0.313	0.313	0.013	0.000
FR_HOURA	6314	4.500	0.305	0.303	0.013	0.000
FR_TELEMARKET	20869	1.100	0.725	0.725	0.004	0.000
HK_PARKNSHOP	1086	1.900	0.220	0.217	0.033	0.000
IT_ONLINEMARKET	594	-2.100	-0.095	-0.091	0.058	0.946
IT_PRONTOSPESA	1020	1.500	0.077	0.075	0.039	0.026
JUMBO	32092	4.100	0.129	0.128	0.007	0.000
LESHOP	36321	4.900	0.287	0.287	0.005	0.000
LOWES	4684	-3.300	0.261	0.261	0.016	0.000
MX_SORIANA	5021	-1.700	0.342	0.341	0.013	0.000
NL_ALBERT	2603	-1.100	0.381	0.381	0.017	0.000
PAO	90226	1.900	0.380	0.380	0.003	0.000
RU_UTKANOS	70366	0.100	0.406	0.406	0.003	0.000
SAFEWAY	10780	-0.300	0.159	0.160	0.011	0.000
SG_GROCERYSTORE	83	1.300	0.090	0.085	0.129	0.259
TESCO	71839	-0.500	0.711	0.711	0.002	0.000
TESCOIRELAND	17991	-0.500	0.152	0.153	0.008	0.000
TR_MIGROS	6437	3.100	0.118	0.118	0.014	0.000
UK_BRITISHCORNERSHOP	2132	4.100	0.310	0.310	0.021	0.000
UK_OCADO	13554	-0.500	0.695	0.695	0.005	0.000
UK_SALINSBURY	1769	-0.700	0.460	0.459	0.019	0.000
US_WEBVAN	230505	-0.100	0.423	0.423	0.002	0.000
VIRTUALEXITO	29651	1.100	0.159	0.159	0.007	0.000
WAITROSE	425	2.900	0.153	0.153	0.058	0.006
WOOLWORTHS	46034	3.100	0.127	0.127	0.005	0.000

Note: Bootstrap derived from 500 replications.

Table 8: Estimation of the Proportional Mass Test
(Distribution centered at the Mode)

Estimates through time	Q4.2007	Q1.2008	Q2.2008	Q3.2008	Q4.2008	Q1.2009	Q2.2009	Q3.2009	Q4.2009
AU_BANANABLUE					0.048	0.125	-0.056	0.174	0.171
AU_EFRESH							-0.313	0.270	
AU_GROCERIES4U					0.320	0.382	0.116	-0.036	0.000
AU_WOOLWORTH			0.215	0.178	0.291				
CN_CARREFOUR_BEIJING									0.245
CN_LIANHUA							0.553		0.288
COTO	0.335	0.356	0.425	0.627	0.525	0.906	0.189	0.745	0.136
DE_KAISER									
DEVOTO	1.024	0.868	0.914	0.895	0.835	0.853	0.931	0.882	0.323
EC_TIA						0.369	0.109	0.221	0.243
ES_CARREFOUR				0.453	0.088	-0.041	0.448	0.285	0.233
EXCELSIOR			0.520	0.165	0.004	0.108	0.970	0.138	0.071
FR_AUCHANDIRECT					0.401	0.295	0.294	0.444	0.087
FR_HOURA					0.632	0.379	0.242	0.464	-0.127
FR_TELEMARKET					0.328	0.410	0.881	0.892	0.528
HK_PARKNSHOP			0.620	0.321	0.635	0.180	0.122		
IT_ONLINEMARKET					0.103	0.200	0.474	0.207	0.160
IT_PRONTOSPESA					0.341	0.208	0.217	0.107	0.167
JUMBO	0.170	0.169	0.160	0.157	0.139	0.205	-0.040	-0.050	0.201
LESHOP	0.177	0.200	0.163	0.175	0.307	0.048	0.027	0.461	0.018
LOWES			0.254	0.110	0.472		0.583	0.465	0.161
MX_SORIANA							0.716	0.672	0.238
NL_ALBERT							0.603	0.371	0.545
PAO	0.894	0.270	0.327	0.401	0.245	0.777	0.367	0.103	0.641
RU_UTKANOS						0.161	0.170	0.627	0.387
SAFEWAY			0.107	0.085	-0.169	0.240	0.324	0.494	0.127
SG_GROCERYSTORE							0.143	0.432	0.581
TESCO			0.778	0.823	0.483	0.661	0.803	0.816	0.794
TESCOIRELAND			0.138	0.175	0.032	0.119	0.081	0.251	0.348
TR_MIGROS			0.057	0.230	0.133	0.570	0.174	0.222	0.152
UK_BRITISHCORNERSHOP					0.401	0.090	0.334	0.413	0.162
UK_OCADO				0.780	0.651	0.645	0.586	0.401	
UK_SALINSBURY							0.411	0.667	
US_WEBVAN							0.388	0.495	0.189
VIRTUALEXITO	0.080	0.042	0.217	-0.069	0.183	0.110	0.181	0.113	0.443
WAITROSE			0.230	0.293	0.290	0.196	0.207		
WOOLWORTHS			0.138	-0.007	0.276	0.173	0.013	0.221	0.128

Table 9: Estimation of the Mass below zero for each quarter
(Distribution centered at the Mode)

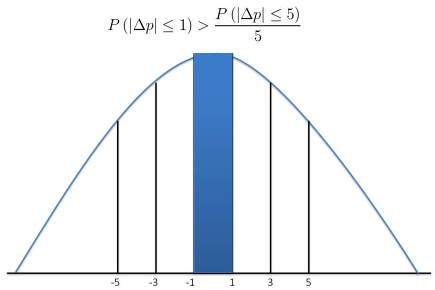
Estimates through time	Q4.2007	Q1.2008	Q2.2008	Q3.2008	Q4.2008	Q1.2009	Q2.2009	Q3.2009	Q4.2009
AU_BANANABLUE					0.076	0.000	0.982	0.000	0.000
AU_EFRESH							0.902	0.142	
AU_GROCERIES4U					0.000	0.000	0.052	0.595	0.491
AU_WOOLWORTH			0.000	0.000	0.000				
CN_CARREFOUR_BEIJING									0.000
CN_LIANHUA							0.000		0.000
COTO	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DE_KAISER									
DEVOTO	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
EC_TIA						0.054	0.048	0.000	0.000
ES_CARREFOUR				0.000	0.010	0.802	0.000	0.000	0.000
EXCELSIOR			0.000	0.000	0.481	0.002	0.000	0.000	0.118
FR_AUCHANDIRECT					0.000	0.000	0.000	0.000	0.124
FR_HOURA					0.000	0.000	0.000	0.000	0.988
FR_TELEMARKET					0.000	0.000	0.000	0.000	0.000
HK_PARKNSHOP			0.000	0.000	0.000	0.068	0.253	0.000	0.000
IT_ONLINEMARKET					0.349	0.058	0.006	0.112	0.014
IT_PRONTOSPESA					0.192	0.004	0.018	0.118	0.006
JUMBO	0.000	0.000	0.000	0.000	0.000	0.000	0.930	0.958	0.000
LESHOP	0.000	0.000	0.000	0.000	0.000	0.022	0.196	0.000	0.220
LOWES			0.002	0.002	0.000		0.000	0.000	0.000
MX_SORIANA							0.000	0.000	0.000
NL_ALBERT							0.000	0.000	0.000
PAO	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
RU_UTKANOS						0.000	0.000	0.000	0.000
SAFEWAY			0.000	0.000	1.000	0.000	0.000	0.000	0.000
SG_GROCERYSTORE							0.124	0.016	0.014
TESCO			0.000	0.000	0.000	0.000	0.000	0.000	0.000
TESCOIRELAND			0.034	0.000	0.018	0.000	0.042	0.000	0.000
TR_MIGROS			0.210	0.000	0.000	0.006	0.004	0.000	0.000
UK_BRITISHCORNERSHOP					0.000	0.092	0.000	0.000	0.008
UK_OCADO			0.000	0.000	0.000	0.000	0.000	0.000	
UK_SALINSBURY							0.000	0.000	
US_WEBVAN							0.000	0.000	0.000
VIRTUALEXITO	0.016	0.066	0.000	0.988	0.000	0.000	0.000	0.000	0.000
WAITROSE			0.150	0.000	0.022	0.178	0.188		
WOOLWORTHS			0.000	0.689	0.000	0.000	0.291	0.000	0.000
# $Mass > 0$	1	1	4	3	8	10	14	6	9
# Supermarkets	6	6	17	18	26	26	34	32	31
Ratio Bimodal	0.17	0.17	0.24	0.17	0.31	0.38	0.41	0.19	0.29

Table 10: Comparison with Scanner and CPI sampling methods

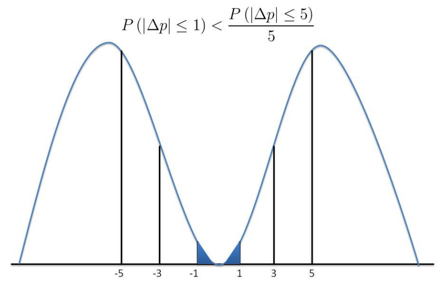
	Daily Data	Weekly Average	Monthly Sampling
Mean Dip (Hartigan)	0.035	0.019	0.046
Mean Critical Bandwidth (Silverman)	1.351	0.799	1.471
Mean PM Score	-0.143	0.145	-0.203

Note: Unimodal distributions have lower Dips, lower CBs and positive PMs.

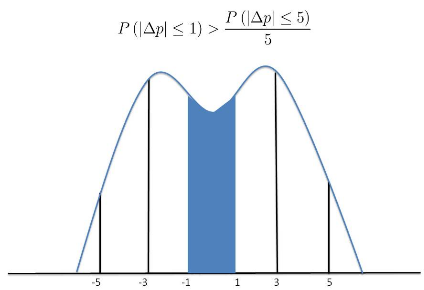
Figures



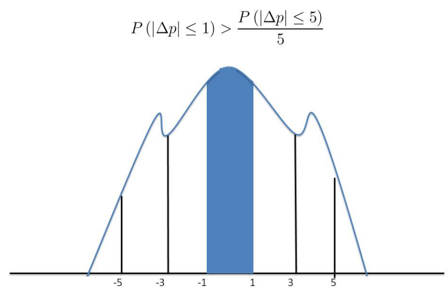
(a) Unimodal PM > 0



(b) Bimodal PM < 0

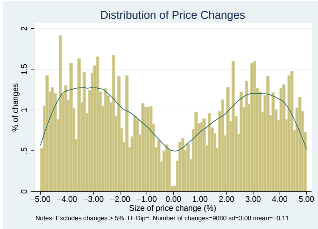


(c) PM > 0

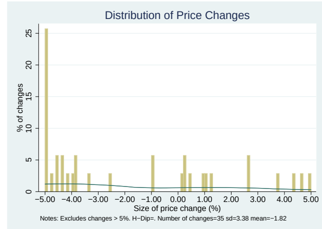


(d) PM > 0

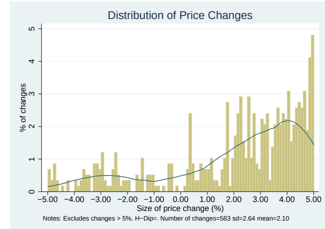
Figure 1: Example of PM values



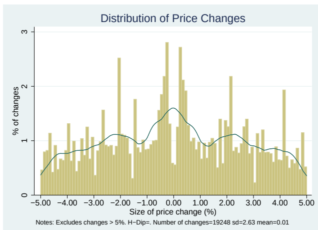
(a) AU_BANANABLUE



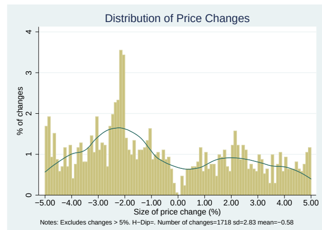
(b) AU_EFRESH



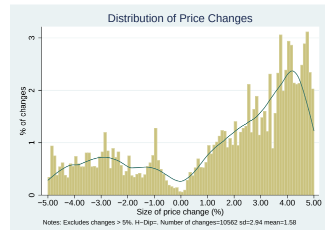
(c) AU_GROCERIES4U



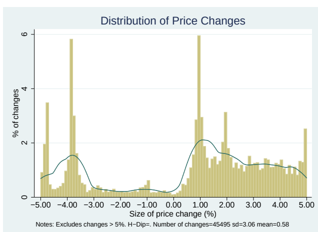
(d) AU_WOOLWORTH



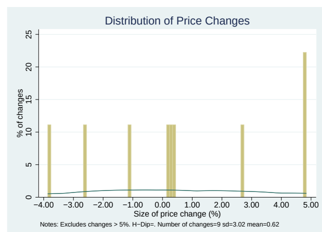
(e) CN_CARREFOUR_BEIJING



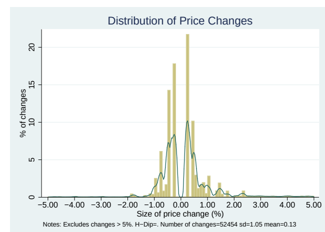
(f) CN_LIANHUA



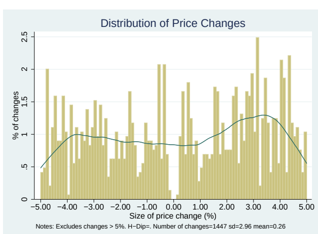
(g) COTO



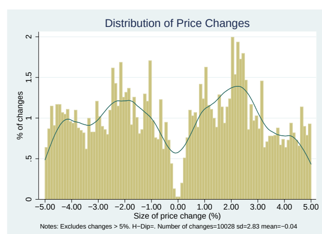
(h) DE_KAISER



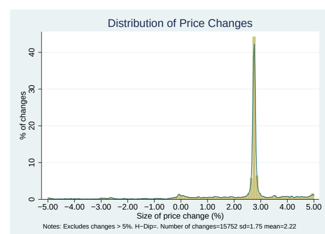
(i) DEVOTO



(j) EC_TIA

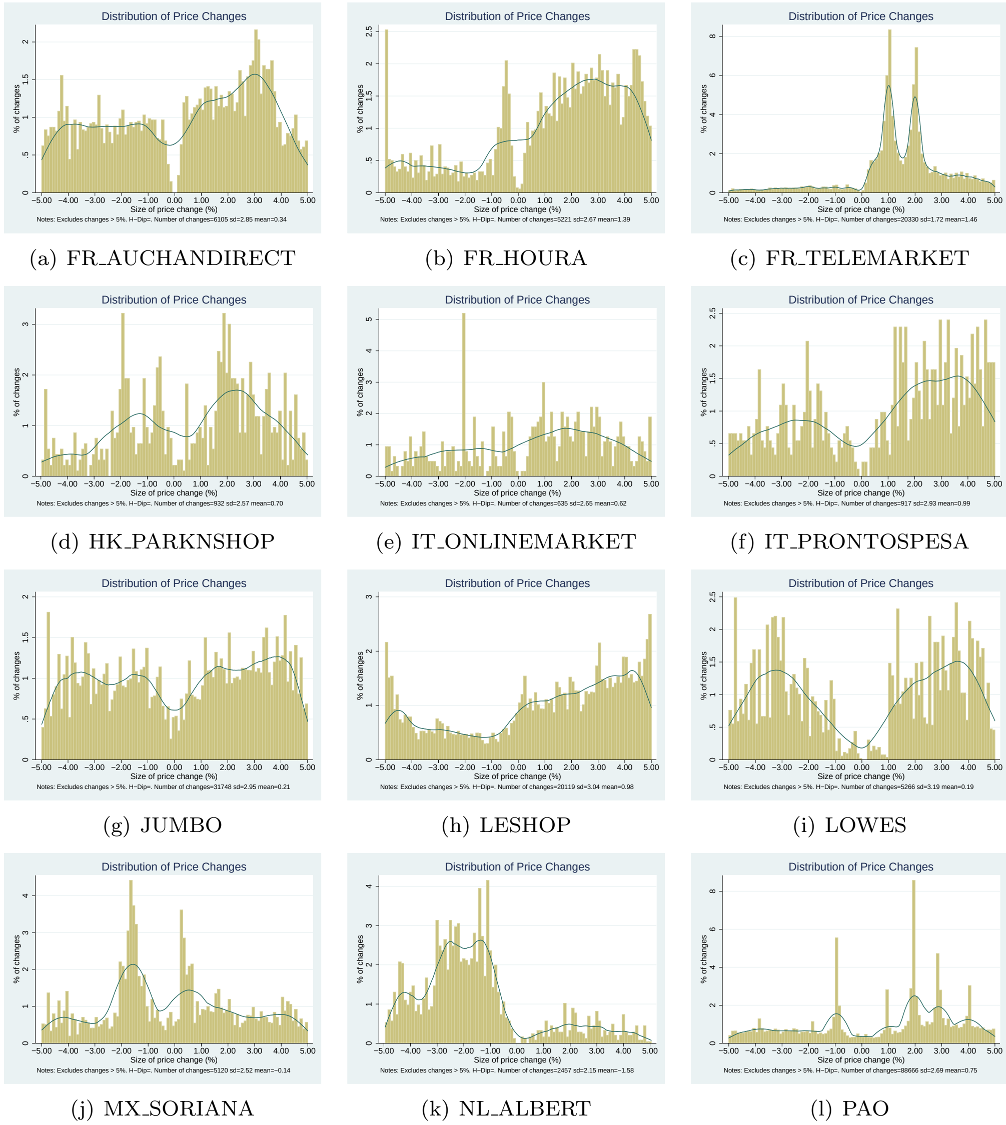


(k) ES_CARREFOUR



(l) EXCELSIOR

Figure 2: Histogram of Changes - Range -5% to 5%



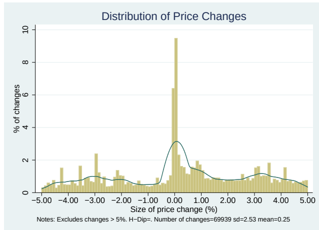
(a) FR_AUCHANDIRECT (b) FR_HOURA (c) FR_TELEMARKET

(d) HK_PARKNSHOP (e) IT_ONLINEMARKET (f) IT_PRONTOSPESA

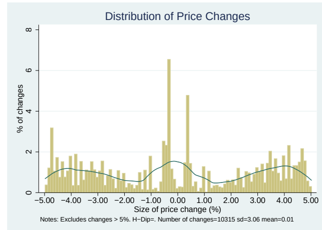
(g) JUMBO (h) LESHOP (i) LOWES

(j) MX_SORIANA (k) NL_ALBERT (l) PAO

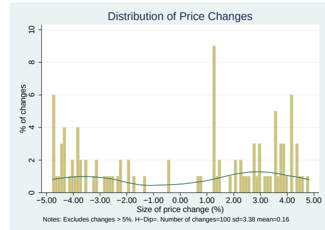
Figure 3: Histogram of Changes - Range -5% to 5%



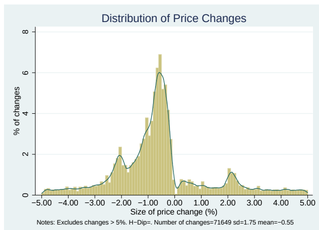
(a) RU_UTKANOS



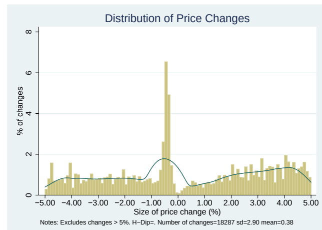
(b) SAFEWAY



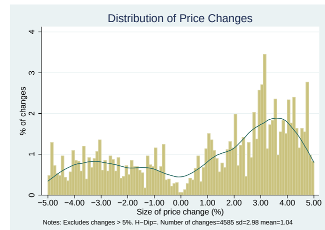
(c) SG_GROCERYSTORE



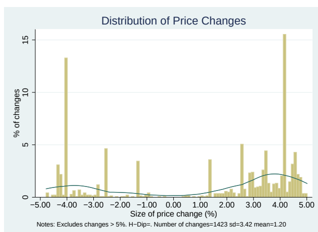
(d) TESCO



(e) TESCOIRELAND



(f) TR_MIGROS



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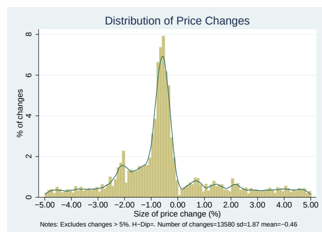

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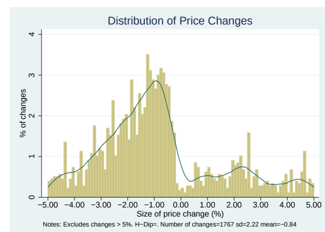

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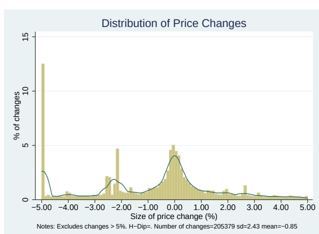

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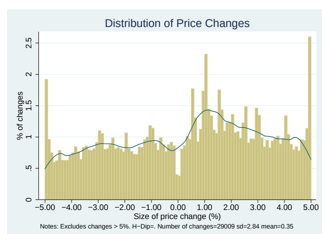

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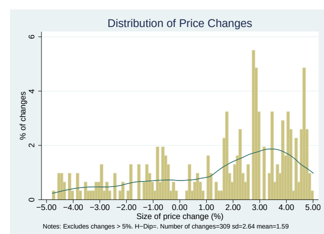

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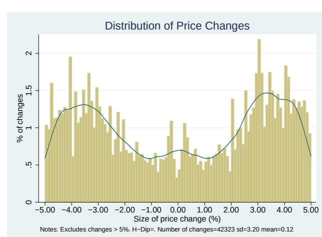


(m) WOOLWORTHS

Figure 4: Histogram of Changes - Range -5% to 5%

–APPENDIX–

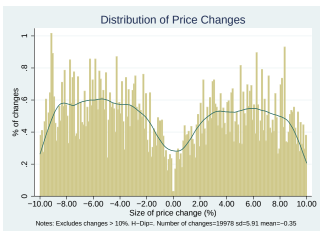
The Distribution of the Size of Price Changes

Alberto Cavallo Roberto Rigobon
Harvard University MIT & NBER

August 20, 2010

A Appendix

A.1 Additional Figures



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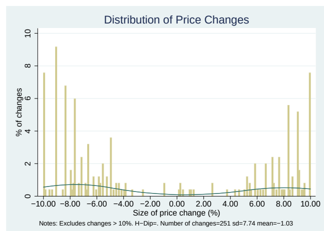

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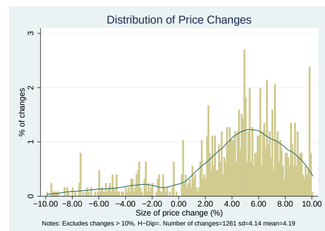

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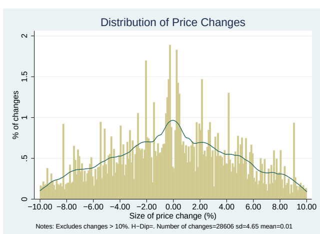

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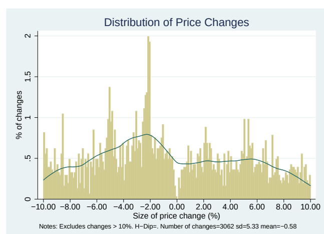

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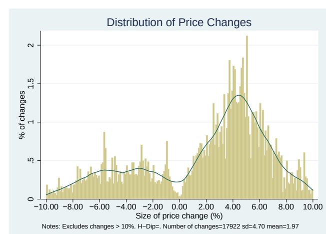

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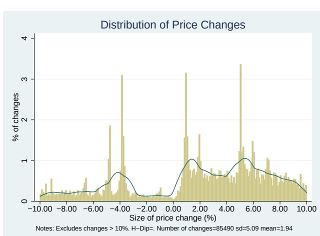

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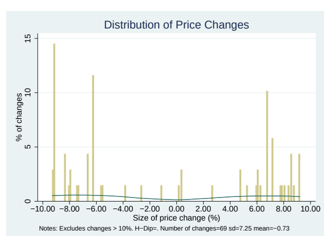

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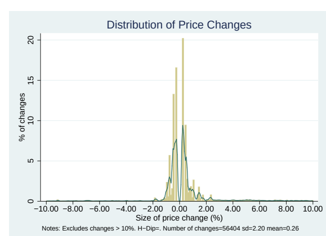

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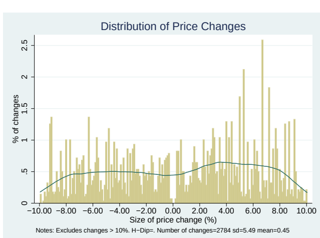

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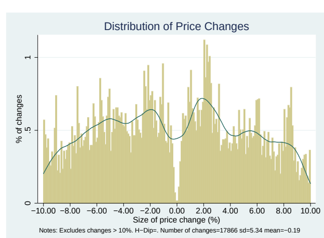

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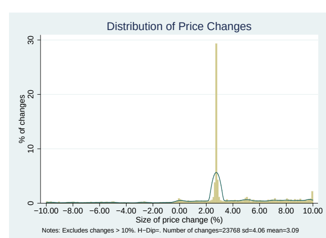
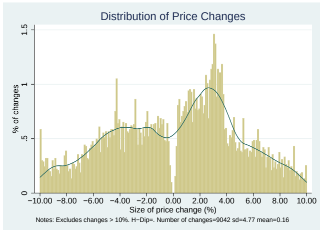


(l) EXCELSIOR

Figure A1: Histogram of Changes - Range -10% to 10%



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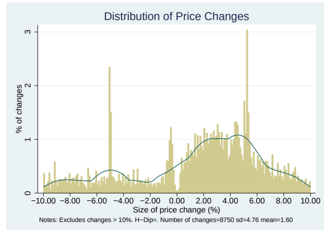

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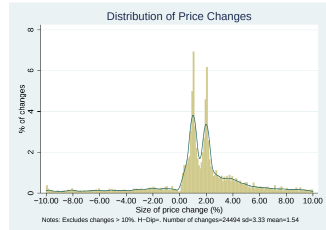

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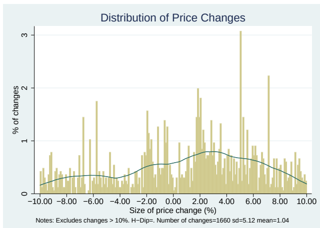

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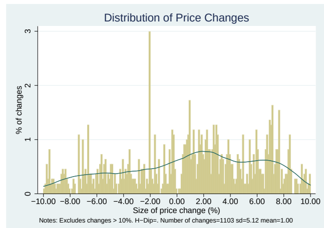

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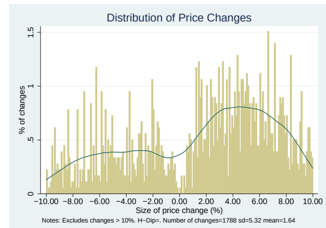

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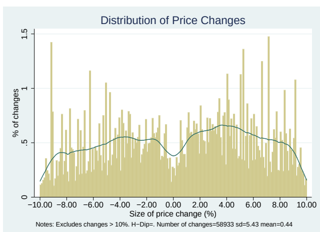

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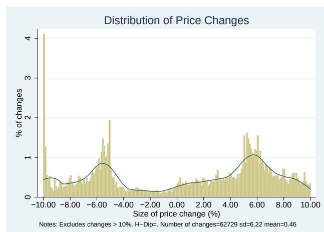

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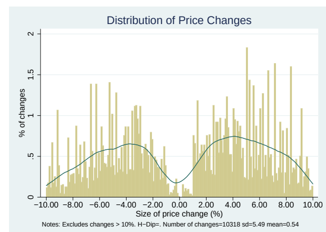

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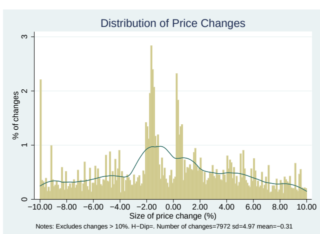

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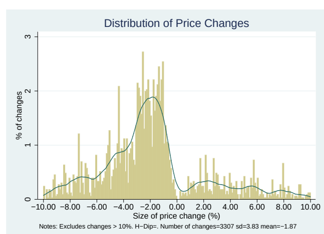

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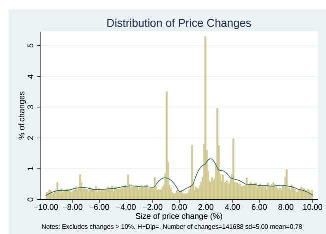
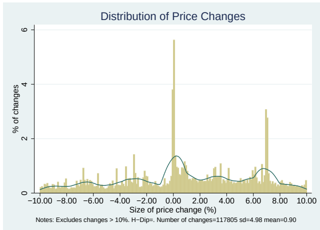


(l) PAO

Figure A2: Histogram of Changes - Range -10% to 10%



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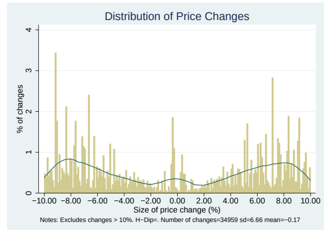

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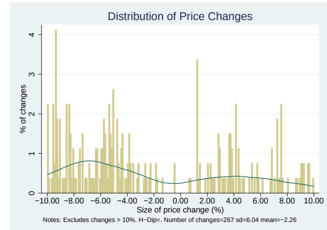

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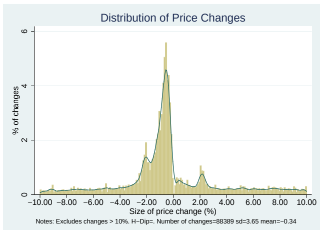

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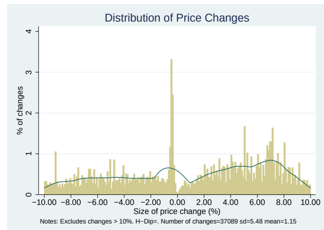

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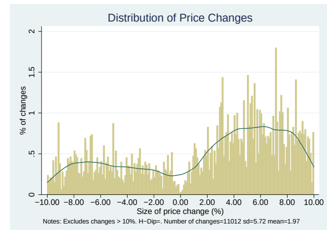

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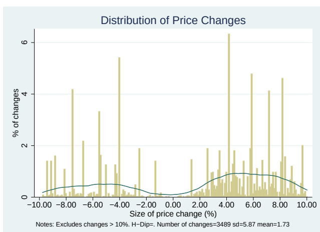

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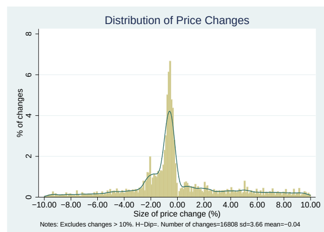

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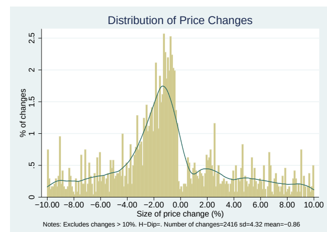

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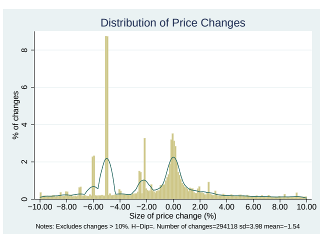

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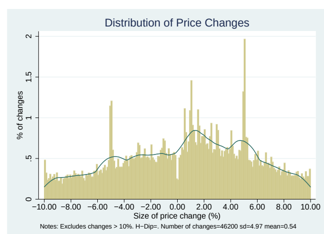

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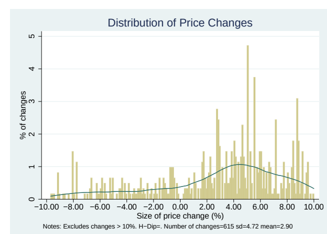

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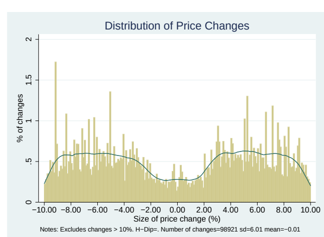
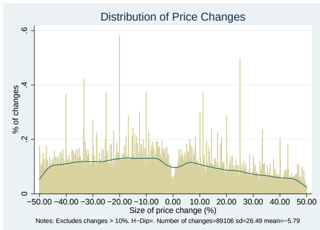


(m) WOOLWORTHS

Figure A3: Histogram of Changes - Range -10% to 10%



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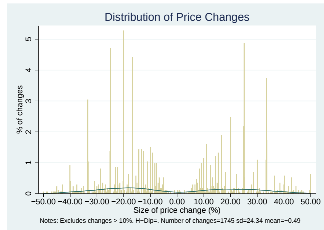

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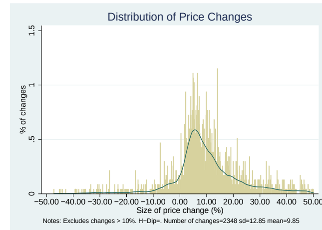
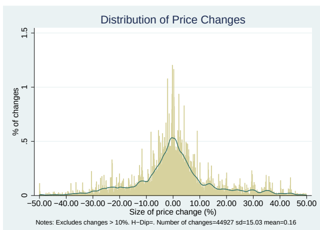
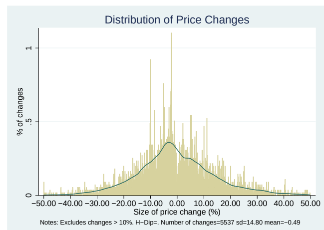


(c) AU_GROCERIES4U



(d) AU_WOOLWORTH



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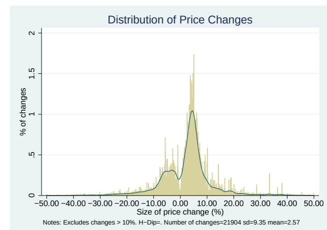
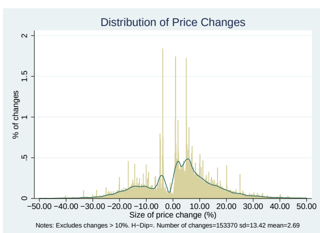


(f) CN_LIANHUA



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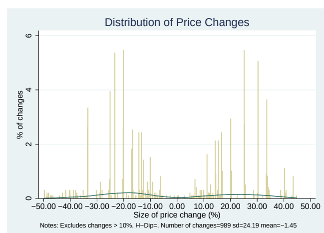

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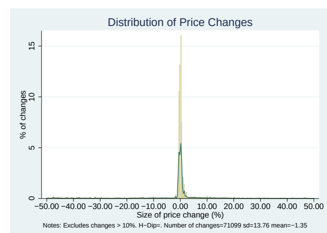

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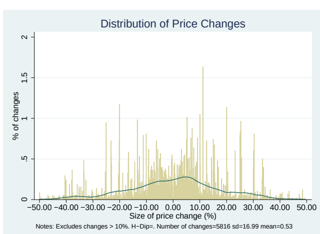

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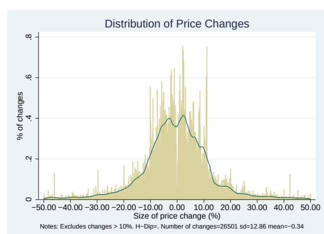

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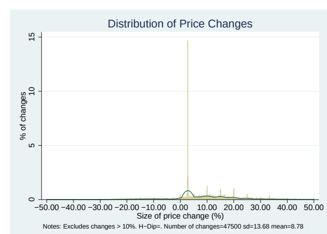
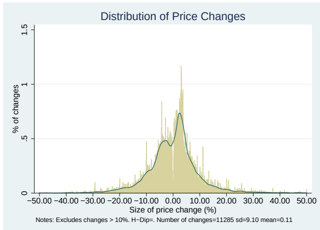
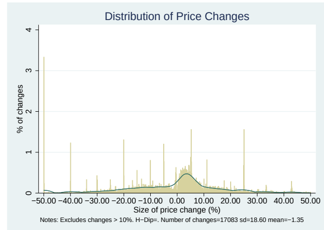


(l) EXCELSIOR

Figure A4: Histogram of Changes - Range -50% to 50%



(a) FR_AUCHANDIRECT



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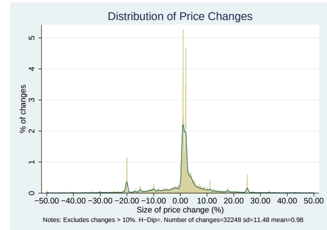

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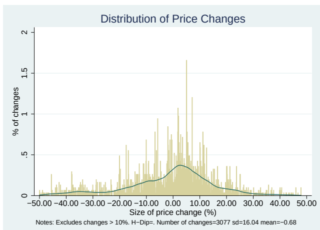

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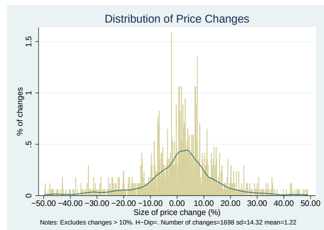

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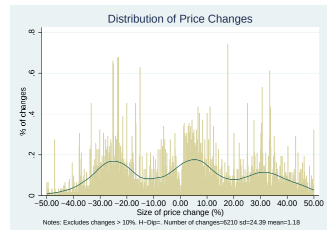

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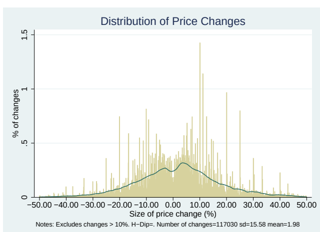
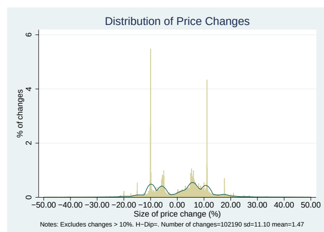
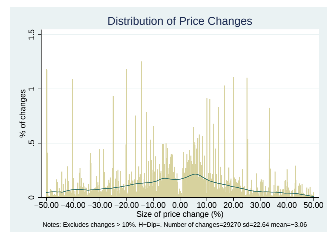


(g) JUMBO



(h) LESHOP



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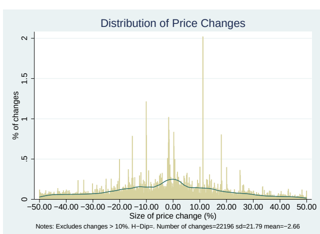

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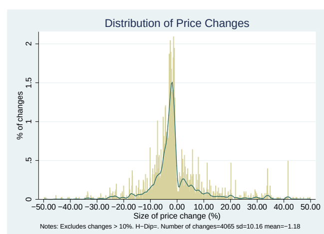

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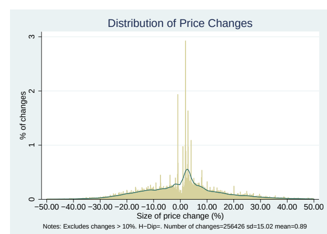
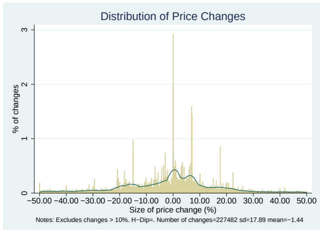
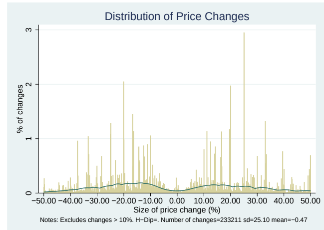


(l) PAO

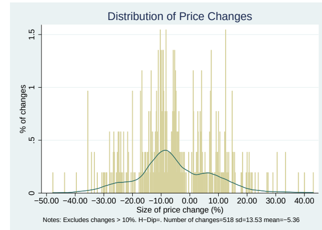
Figure A5: Histogram of Changes - Range -50% to 50%



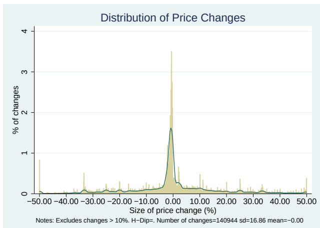
(a) RU_UTKANOS



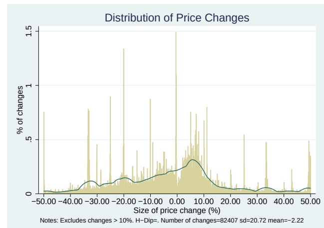
(b) SAFEWAY



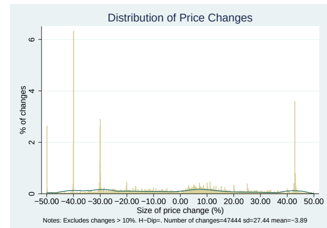
(c) SG_GROCERYSTORE



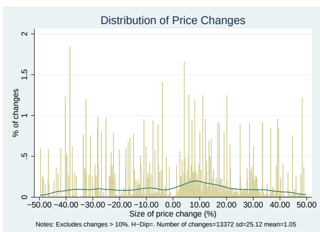
(d) TESCO



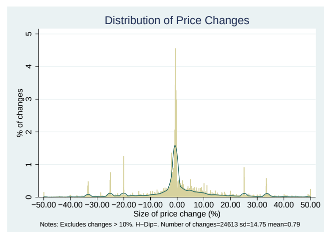
(e) TESCOIRELAND



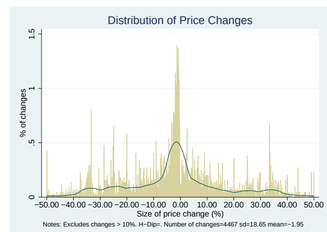
(f) TR_MIGROS



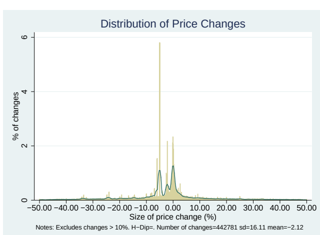
(g) UK_BRITISHCORNERSHOP



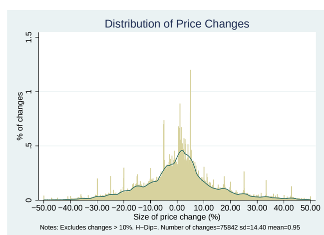
(h) UK_OCADO



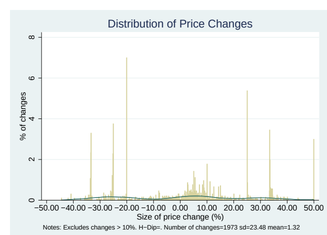
(i) UK_SALINSBURY



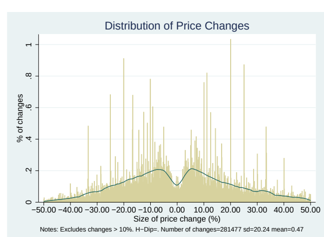
(j) US_WEBVAN



(k) VIRTUALEXITO



(l) WAITROSE



(m) WOOLWORTHS

Figure A6: Histogram of Changes - Range -50% to 50%