Inflation and Price Dispersion: New Cross-Sectoral and International Evidence*

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Abstract

This paper investigates the relationship between price dispersion and inflation, shedding light on one major source of the cost of high inflation. By analyzing novel product-level web-scraped data from over 60,000 restaurants and supermarkets across 18 countries facing high and low inflation periods, I uncover new evidence of a significant positive correlation between inflation and price dispersion. My findings reveal that the average weekly inflation, ranging between zero and 11 percentage points across countries within a condensed time frame, is significantly associated with higher price dispersion in both the restaurant and supermarket sectors. The estimates indicate that the marginal effect of suboptimal inflation on product-level distortions is positive, economically significant in all inflation environments and heterogeneous across sectors. Cross-sectionally, I find that an increase of annualized inflation from zero to 10 percent increases inefficient price dispersion for supermarkets by 41% and for restaurants by 61%. Finally, my results suggest that the relation of inflation and price dispersion does not disappear even at high levels of inflation, maintaining a distinct "V" shape around zero inflation inconsistent with standard menu cost models. This indicates a sustained impact of inflation on price dispersion, implying that accommodating higher inflation levels incurs substantial welfare costs.

Keywords: Inflation, price-setting, price distortions.

JEL Codes: E31, E32, E58

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1. Introduction

After interest rates hit the zero lower bound, discussions among central bankers on setting a higher inflation target raised attention on the optimal level of inflation.[1] On the one hand, a higher inflation target would provide more room for monetary policy easing before the zero lower bound is reached. On the other hand, a higher inflation is associated with price distortions that lead to costly misallocations.

In the presence of price rigidities, price distortions appear when inflation does not align with the evolution of the desired relative price. When prices are not fully flexible, an inflation rate that depreciates the relative price of a product too rapidly will create a gap between the product's desired relative price (as it would be in the absence of price stickiness) and its actual price. This product-level distortion leads to in cross-sectional inefficient price dispersion, distorting the allocative role of relative prices and causing costly misallocations in the economy.[2]

Assessing the costs of accommodating higher inflation necessitates a comprehensive understanding of the relationship between inflation and inefficient price dispersion. However, a robust examination of this relationship requires rich micro-level data containing periods of both high and low inflation to observe potential changes in price dispersion. Such data, however, is to acquire, particularly for countries other than the United States. In this study, I bridge this gap by analyzing an extensive dataset of AI-categorized, web-scraped product-level information on prices in over 60,000 restaurants and supermarkets across 18 countries, providing new empirical evidence on the distortionary effects of inflation.

In canonical New Keynesian models typically used to infer the optimal level of inflation, the co-movement of inflation and inefficient price dispersion is strongly sensitive to the assumed price rigidities. In these models, price rigidities are normally assumed to be time- or state-dependent. Under time-dependent rigidities the probabilities of adjusting the price are given by a fixed probability that does not depend on the state of relative prices. This results in some products having a significant gap between their desired and actual relative prices, which firms cannot close endogenously by paying an adjustment cost. Under state-dependent pricing, firms can pay a menu cost in order to adjust the price, which is why we typically do not observe price gaps rising significantly with inflation in this setting.

As shown in Nakamura et al. (2018), when assuming time-dependent pricing à la Calvo, the wel-

[1] See for example the IMF interview with Olivier Blanchard on February 12th, 2010: "*The crisis has shown that interest rates can actually hit the zero level, and when this happens it is a severe constraint on monetary policy that ties your hands during times of trouble. [...] What we need to think about now is whether this could justify setting a higher inflation target in the future*".

[2] Ropele et al. (2024) find a causal effect of the dispersion of inflation expectations, which subsequently leads to inefficient price dispersion, on the misallocation of resources. They argue that while this misallocation is moderate in times of low inflation, it is likely that it becomes significant in times of high inflation.

fare loss associated with an inflation surge similar to the one currently observed could be comparable in magnitude to the welfare loss from business cycle fluctuations in output. When menu costs are assumed instead, these costs are relatively small and barely change with the level of inflation. Thus, from a theoretical point of view, it is not clear how this key relationship should be modeled, creating a new need for good micro foundations on the relation between inflation and inefficient price dispersion.

Despite the importance of obtaining a good estimate of this relationship, limited research has been conducted on the connection between inefficient price dispersion and inflation. This lack of research can be attributed to two key challenges: acquiring the necessary disaggregated data covering periods of elevated inflation and accurately measuring inefficient dispersion. As highlighted in Golosov and Lucas (2007) and Nakamura et al. (2018), variations in desired real prices over time pose a critical challenge when measuring changes in price dispersion because the two main sources of price dispersion, product heterogeneity and inefficient price dispersion, may be lumped together.

The unique dataset utilized in the analysis effectively overcomes the first challenge of limited (global) data availability covering periods of significant inflation. This novel dataset contains weekly web-scraped prices from 60,000 restaurants and supermarkets across 18 countries and covers the recent global high-inflation episode. Notably, the dataset covers diverse levels of inflation across the 18 countries, with (annualized) average weekly inflation rates ranging across countries from 2.39 percent to values as high as 11 percent for restaurants, and from 0.20 percent to around 5.8 percent for supermarkets.[3]

I mitigate the second challenge in two ways. First, by identifying the marginal effects of suboptimal inflation on individual product-level price distortions following the novel approach in Adam et al. (2023). In this paper they show that while the level price gap cannot be precisely estimated, it can still be tested if inflation has a distortionary effect. Second, by measuring price dispersion within extremely narrow categories and within cities after adjusting prices for desired price dispersion. This is done by correcting for product specifics or by using (short-term) product-retailer fixed effects and high frequency data. Assuming that, in the short run, the desired relative prices of products within a category and a city exhibit limited variability, product-retailer fixed effects effectively capture these dynamics.

The analysis begins by demonstrating that inflation has distortionary effects on product-level relative prices. Using the novel approach introduced in Adam et al. (2023), I identify a positive effect of suboptimal inflation on product-level relative price distortions (gaps). This approach, derived from sticky price theories, allows me to estimate the marginal effect of suboptimal inflation on product-

[3]The inter-quartile range of country-sector average inflation runs from 2.34 to 5.78 percent for restaurants and from 0.28 to 4.56 percent for supermarkets, leaving in both sectors a large variation of inflation environments to exploit.

level relative price distortions separately for each category and city. The estimated marginal effects are positive in 99% of the estimated category-city combinations, as predicted by the theory, and significantly positive (t-stat> 2) in 89% of the category-city combinations. When focusing on city-categories with more than 100 observations the share of significantly positive estimates increases to 94%. These results hold internationally despite the significant heterogeneity in inflation. Across sectors, the coefficients are of similar magnitude but with much higher explanatory power for restaurants.

Cross-sectionally, I identify a comovement between category-level inflation and price dispersion that is stable at high levels of inflation. For this purpose, I use either price gaps estimated using the aforementioned mentioned approach or adjusting relative prices for products specifics using either product-retailer fixed effects or products characteristics in narrow categories. This comovement is 0.52 in the baseline estimation. The results are similar across countries but I also observe cross-sectoral heterogeneity in the estimates with a stronger comovement for the stickier and less studied sector, restaurants. An increase of annualized month-on-month inflation from zero to 10%, is associated with an increase in price dispersion of 61% for restaurants and only of 41% for supermarkets. This comovement of inflation and price dispersion seems to maintain significant even at high levels of inflation, indicating a more sustained impact of inflation on price dispersion than previously estimated.

Finally, I show that a standard New Keynesian model with menu costs, calibrated to my data, fails to align with key empirical findings. The model shows an almost negligible comovement between inflation and inefficient price dispersion at different levels of inflation, contradicting one of the main results of this paper. By applying my approach for estimating price gaps on simulated data from the model, I reveal that the estimation strategy does not artificially generate this relationship. The model also fails to accurately capture the kurtosis of price adjustments and the strong correlation between the size of price adjustments and inflation. This exercise suggests that a standard New Keynesian menu cost model is inadequate for measuring the costs associated with inflation-driven inefficient price dispersion, as it fails to capture key moments crucial for this type of analysis.

Overall, the results indicate that the welfare costs of inflation are not negligible. An increase from zero to 10% is associated with a loss of around 0.5% of flex price consumption. This estimate, however, is highly sensitive to the time frequency of the data used, the definition of inefficient price dispersion, and its level around zero inflation. Abstracting from the initial level of price dispersion and leveraging the heterogeneity across countries, I find that the costs associated with inefficient price dispersion nearly triple as inflation rises from zero to 10 percent.

Recent empirical research on the relationship between price dispersion and inflation typically finds a positive but rather weak comovement, with considerable heterogeneity regarding the inflation levels at which this relationship is stronger or weaker. Importantly, most studies focus on periods of low inflation or countries with exceptional inflation, such as Argentina. Among related literature looking at the cost of inflation, three papers focus on the cross-sectional dispersion of prices: Alvarez et al. (2019), Sheremirov (2020) and Sara-Zaror (2021). Alvarez et al. (2019) employing Argentine CPI microdata at biweekly frequency, found that for low inflation, below 10%, the cross-sectional price dispersion varies very little with inflation but its significantly varies for higher levels. Both Sheremirov (2020) and Sara-Zaror (2021) examined price dispersion across various stores for identical products identified in US scanner data, affirming a positive correlation. While both find a positive comovement, Sara-Zaror (2021) extends the approach and, partially contradicting Alvarez et al. (2019), finds that cross-sectional price dispersion strongly rises with the absolute deviation of inflation from zero but this relation flattens out for inflation rates above two percent.[4].

I contribute to this growing literature by providing unique insights into how price distortions behave under a wide range of inflation levels, varying levels of stickiness, and across countries. Previous related empirical research has focused on periods of suboptimally low inflation (Adam et al., 2023) or in sectors with low price stickiness (Sheremirov, 2020; Sara-Zaror, 2021). Given that both the level of inflation and the level of price stickiness are key determinants of the relation of inflation and inefficient price dispersion, the results in this paper are essential for informing models used to assess the optimal level of inflation. Three main contributions can be identified. First, this is the first paper to investigate the marginal effect of inflation on price distortions covering high inflation environments. Second, this paper highlights the importance of including the stickier sectors of the economy in the analysis, where inflation appears to be more distortive. Third, I uncover a new positive relationship between (absolute) inflation and price dispersion, which holds strongly at both low and high inflation levels, and also internationally, but is absent in standard New Keynesian models with menu costs.

Two main reasons could explain that I obtain a more sustained relationship of inflation and inefficient price dispersion than the one observed in previous literature. First, I leverage high-frequency weekly price data while previous research often relied on averaged data over time. As shown in Cavallo (2018), measurement bias can arise when using time averages in scanner data.[5] Moreover, lower frequency also makes it more difficult to distinguish between desired and inefficient price dispersion. Second, recent research underscores the synchronized pricing strategies adopted not only by retail-

[4]This paper also contributes to the broader literature on the cost of inflation that focuses on a wide range of welfare loses due to inflation. While this paper focuses on price distortions, other paper focus on other sources, such as mental burden and perceived costs (e.g. Shiller, 1997; Stantcheva, 2024; Binetti et al., 2024); tax distortions (e.g. Feldstein et al., 1978; Altig et al., 2024); uncertainty (e.g. Friedman, 1977); real wage declines (e.g. Del Canto et al., 2023; Blanco et al., 2024b), and costly wage bargaining conflicts (e.g. Afrouzi et al., 2024; Guerreiro et al., 2024).

[5]This was also discussed in Campbell and Eden (2014). They suggest that even weekly averages can obscure a single price change, making it appear as two consecutive minor adjustments. Averaging unit prices within a month can also distort the dispersion of prices within a month. For example, two products could have different prices in every week of a month, but still have the same average price.

ers but also by firms, resulting in a convergence of prices for specific products even across retailers (Bhattarai and Schoenle, 2014). When focusing on specific products, if these are highly synchronized by the producing firm even across retailers, only a small fraction of the variation in prices is left for the analysis, while there may still be exist large differences in price dispersion across, for example, brands of still water. At the retailer level, which is usually a very concentrated market, there may also be stronger complementarities in pricing.

This paper is structured as follows. Section 2 presents the data that used in the analysis together with some summary statistics. Section 3 introduces the methodology and identifies the role of suboptimal inflation for product specific price distortions. Section 4 focuses on the relation between inflation and inefficient price dispersion across products. Section 5 relates the results to the predictions of a calibrated standard menu costs and makes an approximation of the implied costs of high inflation. Finally, section 6 draws a conclusion.

2. Data and Summary Statistics

For the empirical analysis, I gathered online prices from one of the world's largest food delivery companies, which operates in 25 countries. Weekly price data was collected from all available restaurants and supermarkets. In addition to prices, I collected information on product names, the retailer-specific category of each product, and the address and rating of each establishment. Daily records of the establishment's opening hours were also obtained to confirm operational status each week. The data collection covered 18 countries, focusing on the city with the highest number of firms in each country, except for four countries for which data were collected for one or two additional major cities. The collection began in March 2023 and the current results include data up to the first week of October 2025. This results in approximately 130 time observations (weeks) for each city.

Table 1 presents the main descriptive statistics of the data used by sector. The countries included in the analysis are, in the order shown in the table: Armenia, Côte d'Ivoire, Spain, Georgia, Ghana, Croatia, Italy, Kenya, Kyrgyzstan, Kazakhstan, Morocco, Poland, Portugal, Romania, Slovenia, Tunisia, Ukraine and Uganda. The data was collected for the city with the most establishments available, except for Italy, Poland, Spain and Portugal where data from two or three major cities as robustness. In Ghana and Slovenia the services were terminated in May 2024; these two countries were replaced by Portugal and Tunisia in the dataset.[6]

[6] The cities included for countries with multiple locations are Warsaw and Krakow (Poland); Porto and Lisbon (Portugal); Madrid, Barcelona, and Valencia (Spain); and Rome, Milan, and Naples (Italy). Data collection for Lisbon began in May 2024, replacing Slovenia in the sample. Data for Valencia, Naples, Krakow, and Porto have been collected since February 2025 onward. For all other countries with multiple cities, data collection of the second city begins at most 4 weeks after the start of the sample period.

Table 1: Descriptive Statistics of the Main Dataset by Sector

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	946	102,153	2.39	32.83	12.61	129	103,584	0.20	16.13	10.30
CI	1,109	43,009	3.48	32.80	17.12	75	114,611	4.14	8.50	9.54
ES	12,772	961,837	2.80	21.16	11.41	968	577,360	3.08	3.72	8.18
GE	2,303	163,176	4.64	14.88	12.11	352	123,981	1.89	7.73	15.54
GH	434	17,357	10.98	13.04	13.67	15	26,592	1.05	7.94	14.95
HR	1,047	94,149	6.43	14.88	11.38	132	77,576	3.25	4.42	13.15
IT	12,259	936,910	2.74	31.42	13.60	654	397,792	1.11	4.48	11.95
KE	1,762	140,445	4.33	21.75	14.04	302	371,700	3.88	10.35	10.28
KG	883	82,392	6.94	10.76	9.84	81	58,162	3.66	5.36	8.45
KZ	1,805	193,215	6.47	13.10	11.43	123	229,617	3.86	3.19	12.91
MA	2,169	151,196	3.23	19.70	13.81	267	392,970	1.65	4.31	9.81
PL	4,542	374,700	5.56	11.37	9.94	241	309,178	2.00	3.20	11.89
PT	6,412	322,356	2.37	26.51	13.45	412	267,050	1.52	4.00	15.70
RO	2,667	290,191	7.39	10.90	12.34	296	240,299	4.36	3.21	10.51
SI	429	25,302	4.95	20.11	9.88	45	13,849	2.23	3.76	18.97
TN	1,545	72,681	4.92	16.68	11.46	65	44,989	2.83	4.47	9.13
UG	1,275	74,271	5.80	22.79	15.60	223	261,176	1.13	11.14	9.55
UA	2,696	298,496	9.42	7.92	10.13	182	348,491	5.79	2.81	12.80
All	57,055	4,343,836	4.48	19.03	12.43	4,562	3,958,977	2.38	6.04	11.87

Notes: the following countries are included (same order): Armenia, Côte d'Ivoire, Spain, Georgia, Ghana, Croatia, Italy, Kenya, Kyrgyzstan, Kazakhstan, Morocco, Poland, Portugal, Romania, Slovenia, Tunisia, Ukraine and Uganda. Inflation computed transforming average weekly inflation in yearly inflation. Mean absolute adjustment only includes adjusting prices. The duration is estimated by first computing the (weekly) frequency of adjustment in products observed more than eight weeks, then taking the unweighted average across products, and finally transforming it to a monthly duration: $(-1/(ln(1-freq)))/4$.

Across the 18 countries and two sectors, I observe approximately 10 million products sold by over 60,000 firms. The number of restaurants is significantly higher, with about 57,000 restaurants compared to roughly 4,500 supermarkets. The original dataset also included over 6800 establishments that were never observed open and were thus excluded from the analysis. The sample is unbalanced, with some products and establishments entering and exiting the sample. This does not pose a problem for the empirical analysis, where I additionally only keep products observed in at least eight weeks in which the selling firm was confirmed to be open.

During the studied period, annualized average inflation was considerably higher for restaurants (4.48%) compared to supermarkets (2.38%), with a substantial variation across countries. As shown previously in the literature, for example in Nakamura and Steinsson (2008) and Nakamura and Steinsson (2010) for the United States, the duration calculated from the weekly frequency is much longer for restaurants than for supermarkets. Notably, this holds true even during a period when restaurants experienced significantly higher inflation. Additionally, I observe that countries with higher inflation for restaurants do not necessarily have shorter price durations. This could indicate that restaurants struggled to increase the frequency of adjustments to keep relative prices stable in response to higher inflation. Appendix C provides additional price setting moments by country and sector, adjusting price changes for product heterogeneity as in Klenow and Kryvtsov (2008). The time period and countries covered in this study offer unique conditions for analyzing price-setting behavior during periods of elevated aggregate inflation. The 75th (25th) percentile of country-sector inflation reached 4.6% (0.28%) for supermarkets and 5.8% (2.4%) for restaurants, providing substantial variation to examine how firms adjust prices when facing broad inflationary pressures across specific product categories.

This dataset primarily includes products from CPI expenditure categories such as "Food and Non-Alcoholic Beverages," "Restaurants, Cafes, and the Like," "Alcoholic Beverages," "Non-Durable Household Goods," and "Articles for Personal Hygiene." Together, these categories represent about 30% of the CPI basket weight in the European Union.

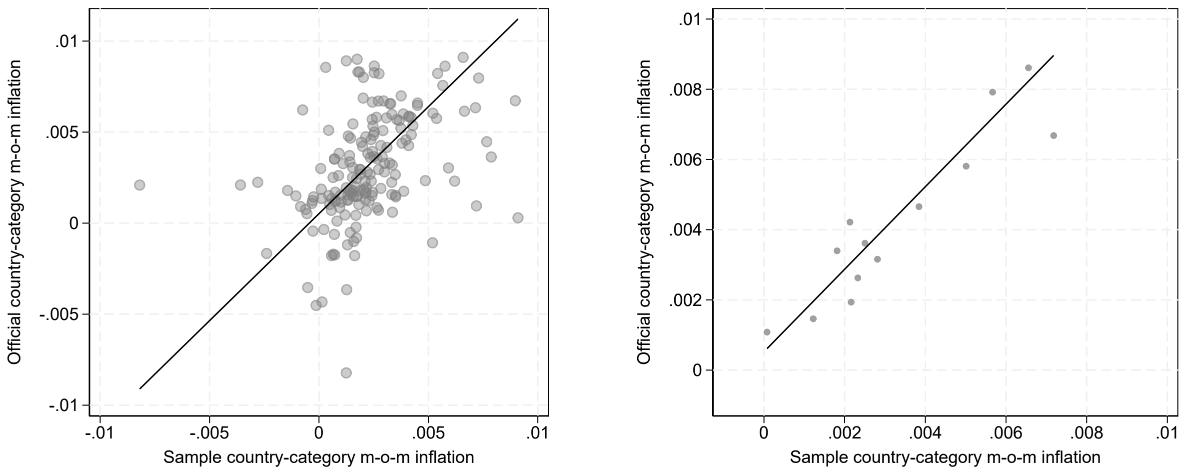
Given the vast scope of the dataset and the need for homogeneous categorization across countries, I utilized machine learning algorithms from Google and OpenAI for the classification of the products in narrow categories. Initially, all product descriptions and online categories were translated into English using Google Translate Cloud services. Subsequently, these translated texts were used to classify the products. For this I employed a custom fine-tuned AI algorithm from OpenAI, which I trained on a manually classified sample of about 50,000 products from all countries in the sample. This specialized algorithm, trained separately for restaurant and supermarket products, categorizes each item and provides a confidence probability. This probability helps in selecting products that are likely to be accurately categorized.[7]

Products were classified into 355 cagories: 81 categories for restaurants products and 274 categories for supermarket items, providing a finer granularity than the COICOP classification commonly used by statistical offices. For instance, restaurant categories used include "Coke," "Burger with fries," and "Sushi," while supermarket categories feature items like "Microfiber towel" and "Apples". The complete list of categories considered and their corresponding COICOP codes is available in Appendix A. This innovative approach to classifying products opens new possibilities for research using automatically and homogeneously categorized online international price data.

The data used in this paper offers five main advantages. First, it is exceptionally difficult to find datasets that track the price setting of hundreds of firms within a narrow location, which arguably face similar local demand shocks. According to the delivery company, firms on their platform can freely set their prices and pay a fixed fee. This fee is usually 30% if the delivery company delivers the

[7] Building on subsequent improvements to the OpenAI classification model, a second fine-tuned version was trained directly on the original product descriptions, removing the need for a prior translation to English.

Figure 1: Official vs Online Data Inflation



(a) Scatter

(b) Bincatter

Notes: These figures display the average month-on-month inflation between March 2023 and October 2025 for a specific country-COICOP calculated from online data against the official value. Eight observations with an average absolute inflation larger than one percent monthly deleted. Binscatter weighted by number of observations included in each county-COICOP. Linear weighted fitted line in sub-figure (a) has a significant slope of 1.175, a R^2 of 0.63 and includes 174 country-COICOPs combinations. The weighted correlation of these observations is 0.79.

order, and 15% for in-store pickup or if the delivery is performed by the retailer or restaurant.[8] Second, weekly web-scraped data requires no time aggregation and arguably minimizes measurement error (Alvarez et al., 2022). These points are especially relevant when analyzing price dispersion, which can be strongly affected by time and location aggregation or collection frequency. Third, this approach enables the detailed analysis of pricing decisions within the services sector, an area that has been largely overlooked in related literature. Previous studies have predominantly concentrated on the retail sector, owing to the accessibility of scanner or web-scraped data. However, the retail sector is often considered to be more flexible in its pricing strategies compared to services. Fourth, the automated categorization of products, tailored for this specific international dataset, facilitates cross-country comparisons while minimizing composition effects. Finally, the findings in this study are replicable, as the data can be shared for replication purposes.

To demonstrate that the data tracks official inflation statistics, I next compare the inflation rates in my dataset with official inflation rates for similar product categories, finding a comovement of the two series. For this the 355 categories were first matched to "Classification of Individual Consumption" (COICOP) codes and then to official consumer price statistics. For each week-COICOP-country

[8]See for example "Spain pricing", "Kenya pricing" or the following press article "Glovo and its Restaurants - Is It Good For Restaurants?". All websites visited in January 2024

combination, a month-on-month inflation rate was calculated by averaging product-level month-on-month inflation rates for all products available in a specific week, COICOP category, and country. The average month-on-month inflation over all periods available for a specific country-COICOP was then compared with the same average from official statistics. This comparison provides an indication of how well the country-COICOP tracks official inflation over the studied period. Due to the unavailability of monthly consumer price index data in a disaggregated form for all countries, this analysis only covers eight countries: Spain, Georgia, Croatia, Italy, Kazakhstan, Poland, Portugal, Romania and Slovenia. Inflation rates between April 2023 and October 2025 were considered.[9]

Figure 1 plots the average month-on-month (m-on-m) country-COICOP inflation from the online data against inflation for the same country and category from official sources, for all countries and categories. The linear fitted line in subfigure 1(a) has a slope of 1.175, a R^2 of 0.63 and includes 174 country-COICOPs. The correlation weighted by number of products is 0.79. Sub-figure (b) in the constructs a binscatter from the same observations included in Sub-figure (a). Appendix A compares the COICOP-country monthly averages instead of the averages over the full sample, and provides more detailed information on the matched samples and sources. Considering that the COICOP categories could not always be accurately matched and that the online data is only collected from one or two cities in each country, the results are surprisingly good.[10]

For the estimations in the following sections, I will employ all observed products that fulfill the following criteria. First, they must be assigned to a narrow category g according to the algorithm categorizing the products. Second, the firm selling the product needs to be observed open in the last four weeks. Note that in addition to collecting prices on a weekly basis, my codes also check which retailers are open on a daily basis. Third, I only keep products observed for at least eight weeks when the retailer was flagged as open. Fourth, for each category-city, I exclude the products with prices in the top and bottom one percent.

3. Suboptimal Inflation and Product Level Price Distortions

Does inflation distort relative prices? Can we construct a measure of capturing these distortions? When actual inflation deviates from the rate that is optimal for a given product, the product's relative price is eroded at the wrong speed. Because adjusting prices is costly or otherwise constrained, this suboptimal erosion generates a wedge—a price gap—between the desired relative price and the actual

[9] Official data for Spain, Croatia, Italy, Poland, Portugal, Romania, and Slovenia was downloaded from Eurostat; for Kazakhstan from the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan Bureau of National Statistics; and for Georgia from the National Statistics Office of Georgia (GEOSTAT).

[10] Other papers showing that online prices can be informative on the dynamics of official CPI and offline prices are, for example, Alvarez and Lein (2020), Cavallo (2013), Cavallo (2017) and Cavallo and Rigobon (2016). In particular, Cavallo (2017) shows that online prices are very similar to offline ones, even identical in 72% of the cases.

one. These gaps misallocate resources across products and sectors and constitute one of the primary welfare costs of non-optimal inflation. Quantifying this mechanism, however, requires confronting two distinct challenges. The first is data: observing the very similar products across many firms, countries, and inflation environments simultaneously is exceptional. The novel web-scraped dataset described in Section 2 addresses this directly. The second is identification: even with rich micro-data, measuring actual price gaps caused by inflation is difficult because observed price dispersion at any point in time conflates genuine distortions with desired differences in relative prices arising from product heterogeneity and idiosyncratic shocks. Separating these two components requires a disciplined empirical strategy.

This section addresses both challenges. I begin in Section 3.1 with illustrative evidence from two specific product-market pairs in Madrid that builds intuition for the mechanism and motivates the formal approach. Section 3.2 then implements the identification strategy proposed by **?**, which recovers the marginal effect of suboptimal inflation on product-level distortions without requiring a precise estimate of the gap level. The results in Section 3.4 document the cross-sectoral and cross-country heterogeneity in these effects.

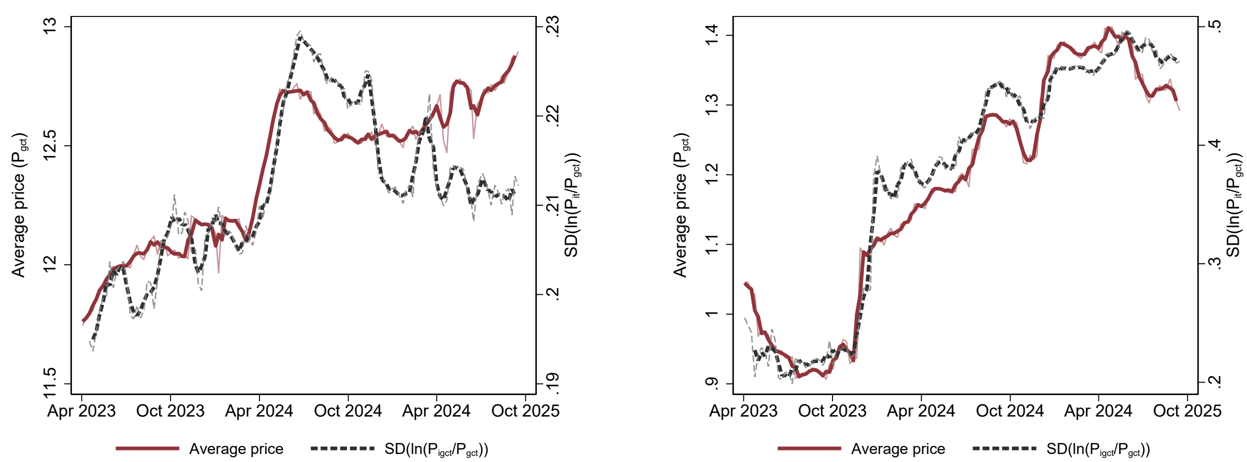
3.1 Illustrative Evidence: Prices, Dispersion, and Inflation

Figure 2 presents the dynamics of average prices and cross-sectional price dispersion for two very narrowly defined products in Madrid: a Pizza Margherita sold by restaurants, and a 330 ml Coca-Cola sold by supermarkets, over the period April 2023 to October 2025. For each product, the left axis shows the geometric average price P_{gct}—the category price index—and the right axis shows the standard deviation of log relative prices, SD($\ln P_{igct}/P_{gct}$), where P_{igct} is the price of product i in category g, city c, and week t. This measure captures the percentage spread of individual prices around the category mean in each week. Note that these products definitions are narrower than the 355 categories in which I classify all products using the fine-tunned model.[11]

Prices rose substantially over the sample: in less than three years the average Pizza Margherita price increased from 11.50 to 12.90 Euros, and the Coke from 1.04 to 1.29 Euros. More importantly, cross-sectional dispersion tracked the price level closely throughout. Dispersion rose in episodes of rapid price increase and only began to fall once prices stabilized—exactly the pattern predicted by sticky-price theory. For the Coke, dispersion nearly doubled, from approximately 0.25 to 0.45. A simple regression of log dispersion on log average price confirms a strong and statistically significant relationship: a coefficient of 1.24 (robust standard error 0.10, $R^2 = 0.56$) for the pizza and 2.05 (robust

[11] This further classification was performed using regular expressions (e.g, "margh" or "330 ml") on product names and descriptions within the baseline categories. Within each week-city-product definition the bottom and top 5 percentile of prices were dropped for the calculations. Additional products shown in Figure B.2.

Figure 2: Prices and Price Dispersion for Specific Products



(a) Pizza Margherita Restaurants (Madrid, ES) (b) Coke Can 330 ML Supermarkets (Madrid, ES)

Notes: These figures display the dynamics of average prices and dispersion of relative prices for two very narrowly defined products in Madrid: a Pizza Margherita sold by restaurants, and a 330,ml Coca-Cola sold by supermarkets. Over time, on average 400 products are included in the category Pizza Margherita and 200 products in the category Coke 330 ml. Additional products shown in Figure B.2.

standard error 0.04, $R^2 = 0.93$) for the Coke.

These patterns could be seen as suggestive evidence that inflation distorts prices and generates price dispersion across products. However, this type of analysis has different caveats. First, even within the narrow categories "Pizza Margherita" and "330 ml Coke", some residual product heterogeneity remains—in size, ingredients, or packaging—and the observed dispersion partly reflects these efficient differences. Moving from the broader "restaurant pizza" category to "restaurant pizza margherita" already reduces measured dispersion substantially from 0.32 to 0.21, but it is not clear that the remaining variation is entirely inefficient or due to desired dispersion in relative prices. This issue gets amplified by products entering and exiting the sample over time. In addition, finding very specific product categories for which we have sufficient products in one city, would strongly restrict the sample to a few categories and cities. For example, I observe over 8,000 products per week in the category "restaurant pizza" on average in Madrid, while I only observe around 400 for the more specific "restaurant pizza margherita". Second, the optimal inflation rate for each product need not be zero. A product whose relative price should depreciate over time—because its quality-adjusted cost is falling—is optimally associated with a positive inflation rate, and the relevant distortion is deviation from this product-specific optimum rather than from zero. Third, the correlations in Figure 2 are not necessarily causal. Even after cleaning relative prices using, for example, product-specific fixed effects and time trends, the remaining residual could result from distortive inflation or desired product-time specific idiosyncratic shocks. These limitations motivate the use of the identification strategy proposed in Adam et al. (2023), which I describe in the remainder of this section. This methodology allows me to isolate a component of relative price dispersion and establish that it is, to a large extent, causally driven by suboptimal inflation.

3.2 Methodology for Identifying the Distortionary Effects of Inflation

For intuition, consider a unique product i sold in a specific location by a particular supermarket or restaurant in a period t. Under flexible pricing, the firm's desired optimal relative price $p^*_{it} = P^*_{it}/P_t$ the firm wants to charge for product i evolves according to

$$\ln p^*_{it} = \ln p^*_i - \ln \Pi^*_i \mathrm{t}, \tag{3.1}$$

where p^*_i is the optimal product introduction price and Π^*_i is a product-specific time trend, accounting for factors such as relative changes in marginal costs over time. Under this setting, the optimal gross inflation rate $\ln \Pi$ for product i is $\ln \Pi = \ln \Pi^*_i$ because this automatically erodes the relative price at the desired rate, eliminating the need for nominal price adjustments over time. If the gross inflation rate exceeds this value, the relative price will be eroded too rapidly, necessitating nominal price adjustments. Conversely, if the gross inflation rate is below this value, the product will appreciate too fast, also necessitating nominal price adjustments. One could then say that there is a gross inflation rate that is optimal for product i, and any deviation from this value will be suboptimal. For example, computers with different technologies may require different rates of depreciation over time. Similarly, cheap and expensive goods within a narrow category might have different trends as reported in Cavallo and Kryvtsov (2024) for the recent period.

Under flexible prices, suboptimal inflation is not problematic since prices consistently readjust to the optimal relative level. In contrast, when some degree of price stickiness exists, these adjustments are costly or not possible in a given period, leading to a product- and time-specific gap_{it} between the flexible and sticky prices. This gap between the desired and actual price, caused by suboptimal inflation and price stickiness, distorts the allocative properties of relative prices and generates costs due to misallocation.

Several papers attempt to measure the relationship between inflation and price distortions by estimating this gap_{it} directly from micro-data. For example, one could argue that the dispersion in relative prices of a category as narrow as "restaurant pizza margherita", stems from price distortions. However, accurately determining the level of distortion is highly complex. Once we move beyond the simplistic process of optimal relative prices described by Equation (3.1) and consider potential product-specific idiosyncratic shocks ε_{it}, the situation becomes more challenging.

We could categorize the products into narrow categories g facing similar idiosyncratic shocks and estimate

$$\ln p_{igt} = \ln a_{ig} - (\ln b_{ig})\mathrm{t} + u_{igt}, \tag{3.2}$$

where $\ln p_{igt}$ is the log relative price of product i belonging to category g, $\ln a_{ig}$ represents a product fixed effect capturing the optimal introduction price $\ln p_i^*$, and $(\ln b_{ig})$ represents the time trend capturing $\ln\Pi_i^*$. However, even if the estimated $\ln p_{igt}$ and $(\ln b_{ig})$ converge to the true introduction price and time trend, the resulting residual u_{igt} could still contain both, a true distortion (gap_{it}) and variation induced by product idiosyncratic shocks (ε_{it}).

While accurately determining the level of price distortions right is challenging in the presence of product idiosyncratic shocks, Adam et al. (2023) demonstrate that one can still identify the marginal effect of inflation suboptimal inflation to price distortions from relative prices. This is because, while the product-level variance of the *desired* relative price (over time) is independent of inflation, the variance of the *actual* relative price contains information about price distortions and should correlate with inflation if inflation is distortionary.

More precisely, it can be shown in a theoretical framework that the variance of the residual from Equation (3.2) is equal to

$$\mathrm{Var}_i(u_{igt}) = v_g + c_g(\ln\Pi_g - \ln\Pi_{ig}^*)^2. \tag{3.3}$$

with the intercept is a function of the idiosyncratic shock process $\ln\varepsilon_{igt}$ and the Calvo price stickiness parameter α_g for category g,

$$v_g \equiv \mathrm{Var}_g\left((1-\alpha_g)E_t\sum_{j=0}^{\infty}\alpha_g^j \ln\varepsilon_{igt+j}\right), \tag{3.4}$$

and the slope

$$c_g \equiv \frac{\alpha_g}{(1-\alpha_g)^2}, \tag{3.5}$$

depending only on the Calvo stickiness parameter under time-dependent pricing.[12]

From equation (3.4) it becomes clear that it is difficult to infer the level of price dispersion from $\text{Var}_i(u_{igt})$, since the intercept also contains efficient price components arising from idiosyncratic fundamental shocks. However, the second term in (3.3) captures how, according to the theory, an increase in the suboptimal inflation affects price distortions. Estimating the term c_g, which measures the marginal effect of suboptimal inflation on price distortions, will be the main goal of this section. Equation 3.5 shows how this term is related to the stickiness parameter under time-dependent price setting, indicating that greater stickiness should lead to a more pronounced effect of suboptimal inflation on relative price distortions.

The exact estimation will consist of two unrelated first-stage regressions and one second-stage regression. I start by estimating one regression 3.2 for each product. From this regression, one can construct an estimate of the left-hand side of (3.3) by taking the variance over time of the residuals u_{igt} for each product. Next, we need an estimate of the suboptimal level of inflation $\ln\Pi_g - \ln\Pi^*_{ig}$. A separate first stage regression can be used to estimate this right hand side variable:

$$\ln P_{igt} = \ln\tilde{a}_{ig} + (\ln\Pi_g/\Pi^*_{ig})\mathrm{t} + \tilde{u}_{igt}, \tag{3.6}$$

where P_{igt} is the nominal price of product i. Intuitively, the adjustments in the nominal price over time reflect the changes made to return to the desired optimal price, and are thus informative about the level of suboptimal inflation for each product. The city subscript c is ignored for now to improve readability, but all regressions are conducted within a city and category combination.

Finally, the second stage consists in estimating the marginal effect of suboptimal category inflation on price distortions for each category g. For this I estimate the following OLS regression:

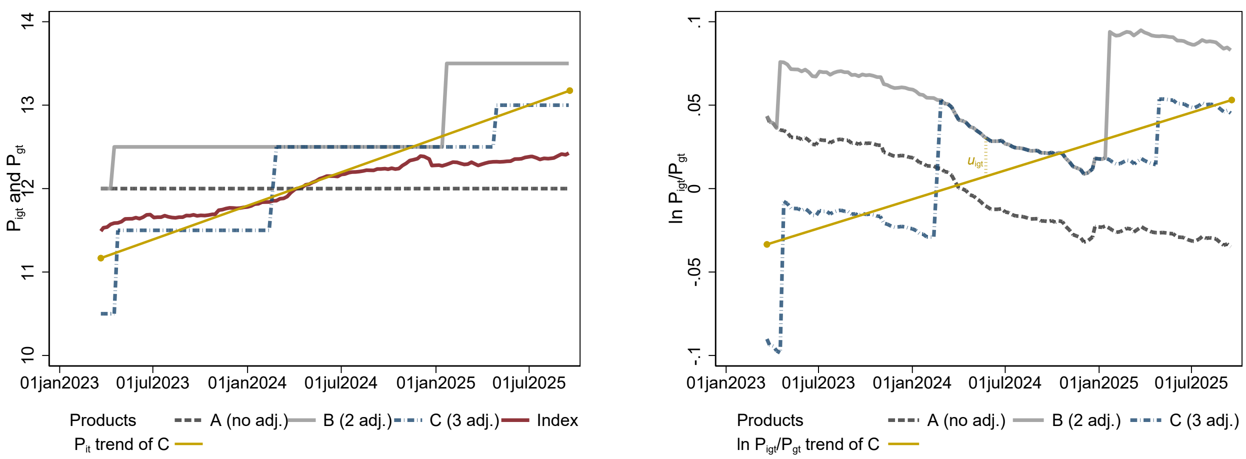
$$\widehat{\text{Var}}_i(u_{igt}) = v_g + c_g(\widehat{\ln\Pi_g/\Pi^*_{ig}})^2 + \varepsilon_{ig} \tag{3.7}$$

where $\widehat{\text{Var}}_i(u_{igt})$ is the variance of the "first" first-stage residuals for product i belonging to category g, and $\widehat{\Pi_g/\Pi^*_{ig}}$ is the estimate of the gap between the optimal inflation of product i and the category-specific inflation from the "second" first stage. To improve readability, I have also omitted the subscript c here.

The intuition behind both first stages is transparent from Figures 3, which displays the dynamics of nominal and relative prices for three Pizza Margherita products in Madrid. Figure 3(a) shows the

[12]For a detailed derivation and a derivation under state-dependent pricing, see Adam et al. (2023).

Figure 3: Example of Prices, Relative Prices, and Price Gaps



(a) Nominal Prices and Price Index

(b) Relative Prices and Price Gaps

Notes: ...

nominal price series P_{igt} for each product alongside the category price index P_{gt}. Also in the Figure, the slope of product C nominal price trend, estimated in logs via equation (3.6), directly encodes the rate at which that product must adjust nominally to keep pace with inflation — this is the suboptimal inflation term recovered by the "second" first-stage regression. Products whose nominal prices trend steeply upward are those for which actual inflation most exceeds their optimal rate. Figure 3(b), displays the dynamics of relative prices $\ln p_{igt} \ln(P^*_{igt}/P_{gt})$. One can see how inflation shifts the relative prices of the different products over time and how nominal adjustments seem to bring prices back to their optimal relative price. Using this relative price, I construct for each product and week a residual u_{igt} using 3.2. From these residuals, I compute for each product the variance over time $\widehat{\mathrm{Var}}_i(u_{igt})$. With these two moments together, we can recover the marginal effect of suboptimal inflation on price distortions, for each category. For intuition, if the products whose relative prices fluctuate most around their trend are precisely those facing the largest wedge between actual and optimal inflation, this is because inflation distorts relative prices. After showing that this residual u_{igt} is caused, at least to a large extent, by inflation, Section 4 will use the dispersion of these as a measure of "inefficient" price dispersion and analyze the relation with inflation over time.

The methodology used is useful for rejecting the hypothesis that inflation distorts prices, although the level of c_g may be biased downward. Adam et al. (2023) demonstrate that the first-stage error biases the coefficient c_g toward zero. This bias will be especially pronounced in category-cities with a small number of products, making comparisons across sectors and countries more difficult. It is important to note that this bias does not work in my favor.

For the estimation, I will employ all observed products that fulfill the following criteria. First, they must be assigned to a narrow category g according to the algorithm categorizing the products. Second, the firm selling the product needs to be observed open in the last four weeks. Note that in addition to collecting prices on a weekly basis, my codes also check which retailers are open on a daily basis. Third, I only keep products observed for at least eight weeks when the retailer was flagged as open. Fourth, for each category-city, I exclude the products with prices in the top and bottom one percent. This leaves 5,765,701 unique products and over 274 million product-weeks for the estimation of the first stage estimations. In addition, following Adam et al. (2023), I do not include the products with the highest 5% values of $\widehat{\text{Var}}(u_{igt})$ and $\widehat{\Pi_g/\Pi^*_{ig}}$. On average, there are 684 products i in a category-city combination entering the second stage regression.

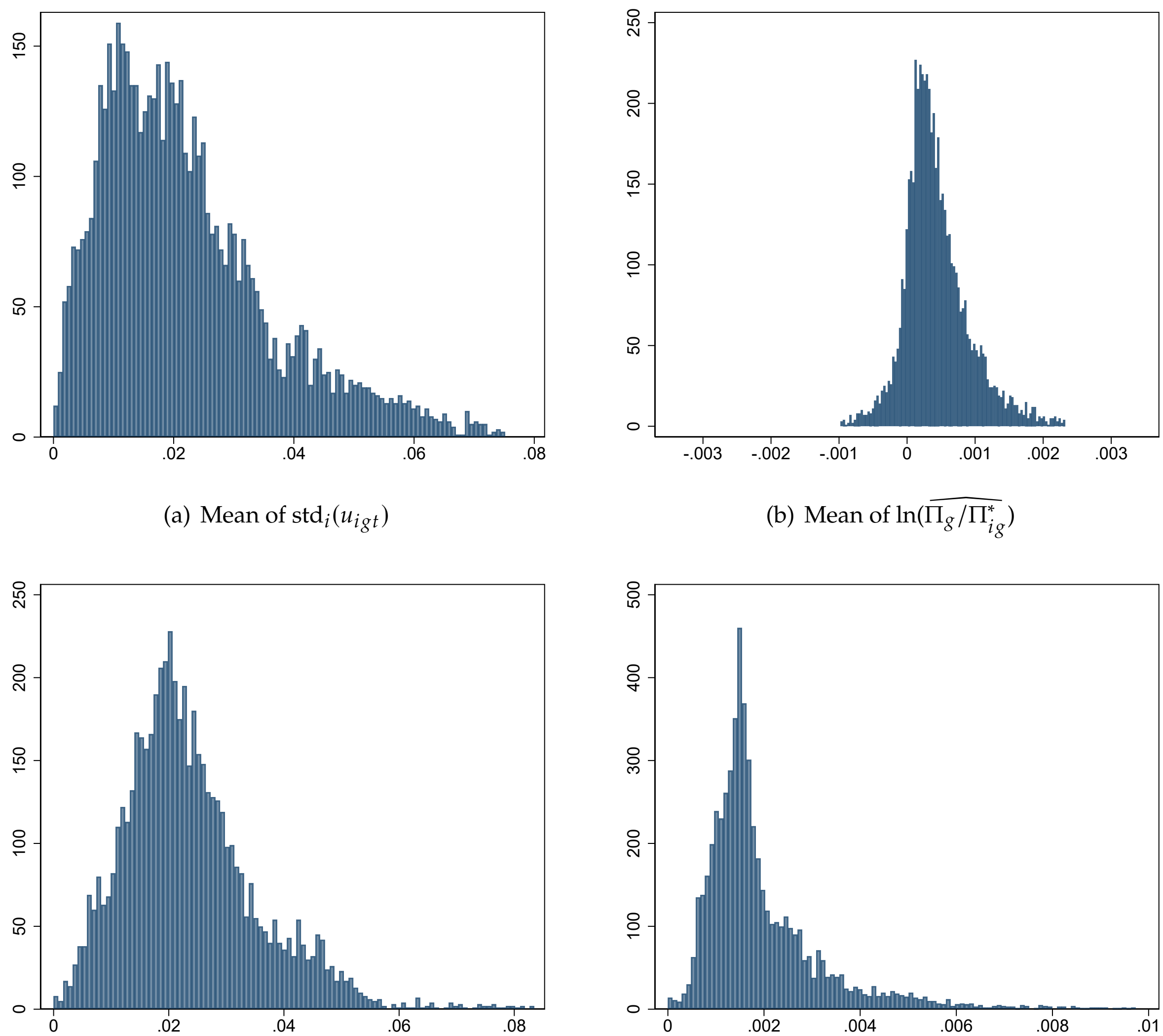
3.3 Main Results on Product-Level Price Distortions

The city-category averages and standard deviations of the product-level $\text{std}_i(u_{igt})$ and $\ln(\widehat{\Pi_g/\Pi^*_{ig}})$ resulting from the first-stage regressions are shown in Figure 4. The top figures show the category-city mean non-squared variables entering the second-stage while the bottom figures show their standard deviation in order to give an overview of the variation available for the second stage. To avoid small sample bias, category-city combinations with less than 50 products are excluded from the second stage and from the figure. This leaves me with a total of 5,661 city-category combinations out of 7,272. In addition, the figures do not include the top percentile of these observations for better visualization.

Particularly noteworthy is the figure in the upper right-hand corner, panel (b), which shows the distribution of mean suboptimal inflation rates at the product level. For most category-city combinations (87%), the average annualized suboptimal inflation rate across all category-cities was positive with a median of 1.8% – 0.04 % week-on-week. Focusing on categories from restaurants, this number is slightly higher with 99% of the category-cities presenting a positive suboptimal inflation rate and a median suboptimal inflation of 1.9%.

This is a very different context than the one analyzed in Adam et al. (2023), where a large proportion of categories were in the negative region. At the same time, it is not surprising given the period of high inflation studied in this paper. Having a sample containing countries and periods with high inflation, is crucial for giving an understanding on how the relation looks like during periods of high inflation. For example, in a classical New Keynesian model with menu costs, during periods of high inflation, firms may bear the cost of price adjustment more frequently during periods of high inflation, thus preventing the perpetuation of inefficient dispersion. Empirically, Sara-Zaror (2021) find

Figure 4: Price dispersion and Sub-optimal Inflation from First-stage Regressions



(a) Mean of $\text{std}_i(u_{igt})$

(b) Mean of $\ln(\widehat{\Pi_g/\Pi^*_{ig}})$

(c) Std of $\text{std}_i(u_{igt})$

(d) Std of $\ln(\widehat{\Pi_g/\Pi^*_{ig}})$

Notes: This figure shows the distribution of some statistics resulting from the first-stage regressions. The means and standard deviations (std) were computed using the product-level first-stage results of $\text{std}_i(u_{igt})$ and $\ln(\widehat{\Pi_g/\Pi^*_{ig}})$ for products included in one city-category. A total of 5,661 city-categories for which with at least 50 products are included. All figures exclude the top percentile of the variable for better visualization. Panel (b) also excludes the bottom percentile.

that the comovement of price dispersion and inflation becomes flatter for higher inflation rates. This paper rationalizes this with a model with search costs.

The top left figure (a) shows the distribution of the category-city averages of the product-specific standard deviations of the residuals from the first-stage regression (3.2). This is the the same as the average of the square root of the dependent variable in the second-stage regression (3.7). The key takeaway from the figure is that on average relative prices vary significantly over the life of a product around a linear path for the desired relative price – captured by the intercept and time trend in the first stage (3.2). Note that this variation could include both, product-idiosyncratic shocks that move the desired relative price, and inefficient price gaps.

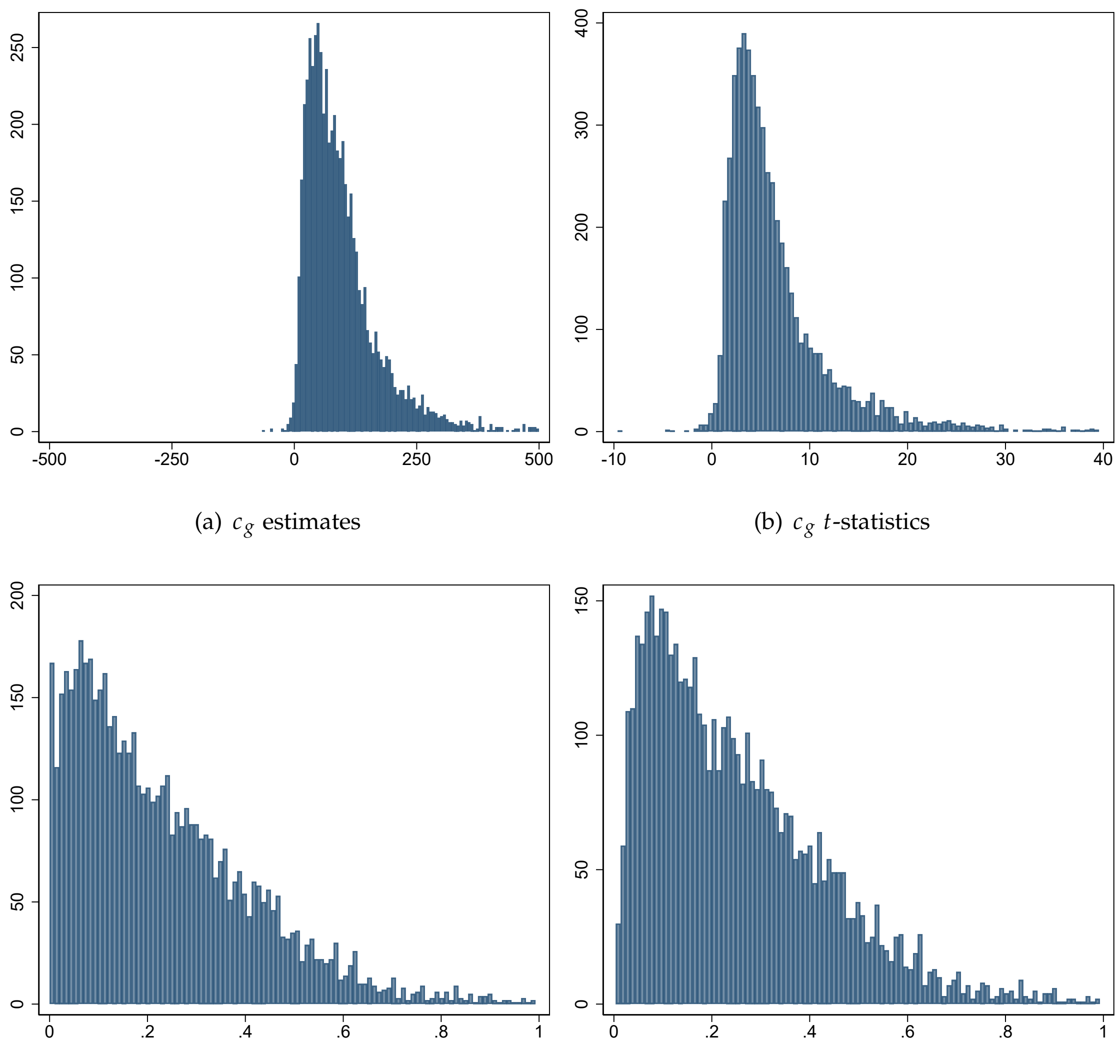
The bottom figures show that there is a significant amount of variation across products within a city and category. This is important for estimating the second-stage regression. Interestingly, panels (a), (c), and (d) show a very similar distribution to that reported in Adam et al. (2023), making the level of suboptimal inflation the only input to the second stage that strongly diverges from theirs.

Next, I discuss the main results on the marginal effect of inflation on product-level price distortions. Figure 5 presents the distribution of my estimates from estimating the second-stage regression (3.7) separately for each category-city combination. Category-cities with an absolute c_g greater than 500 or an absolute $t-$statistic of c_g greater than 40 are excluded from all figures to improve readability. This affects less than 2,5% of the sample. The figures then include 5,585 city-category combinations out of the estimated 5,661.

I find that 99% of the estimated coefficients are positive supporting sticky price theories and indicating that inflation has distortionary effects on prices. According to the distribution of t-statistics: 89% of the coefficients have a t-statistic above 2, 50% above 5 and less than 0.1% of the coefficients have a t-statistic below minus two. The numbers improve substantially when focusing on city-categories with more than 100 products instead of 50, then 94% of the city-categories have a t-statistic > 2 and 57% have a t-statistic >5. This is consistent with the finding that the methodology introduces a downward bias which is especially accentuated for categories with a small number of products. Overall, the results provide strong support for the distorting effects of suboptimal inflation on product-level relative prices during periods of high positive suboptimal inflation.

In addition, the average R^2 of the second-stage regressions is 24%. Indicating that suboptimal inflation explains a substantial portion of the cross-product variance of the first-stage residuals. The average R^2 is higher, with a value of 26%, when focusing on categories with a positive significant coefficient (t-stat$>$ 2) and lower, with a value of 6% when focusing on categories with a negative significant coefficient (t-stat$<$ 2). This can also be observed in the distribution of the second-stage R^2 of observations with a t-statistic of c_g >2, displayed in panel (e) of Figure 5. The square of suboptimal inflation explains then a sizeable share of the cross-product variance of first-stage residuals, especially when the coefficient has the expected sign and is significant. This indicates that these residuals capture to a large extent distortions caused by suboptimal inflation, and can be used for the cross-sectional analysis in Section 4.

Figure 5: Marginal Effects of Sub-optimal Inflation on Price Distortions



(a) c_g estimates

(b) c_g t-statistics

(c) Second-stage R^2

(d) Second-stage R^2 when t-statistic of c_g >2

Notes: This figure shows the descriptive statistics of the second-stage regression. Observations with an absolute c_g larger than than 500 or absolute $t-$statistic of c_g larger 40 excluded from all figures to increase readability, this is less than 2% of the sample, leaving 5,585 city-category combinations in panels (a)-(c). Panel (d) additionally drops observations with a t-statistic of c_g <2.

3.4 Cross-Sectoral and Cross-Country Heterogeneity on Product Level Price Distortions

Next, I analyze the heterogeneity of the estimated c_g across countries and across sectors. Table 2 presents some summary statistics on the estimated c_g separately for each country. The median c_g is also reported separately for restaurants and supermarkets. Figure 6, shows the distributions of the c_g estimates, their $t-$statistics, and the second-stage R^2s, separately for the two sectors.

Overall, inflation seems to have a much more pronounced effect on product-level price distortions in restaurants. The median c_g for restaurants is slightly higher at a value of 90.88 and with bell-shaped distribution of the coefficients. The distribution in Figure 6 panel (b) also indicates larger $t-$statistics

Table 2: Suboptimal Inflation and Product Inefficient Price Distortions

	$c_g > 0$	t-stat < -2	t-stat > 2	t-stat > 5	Median c_g	Restaurants Median c_g	Supermarkets Median c_g
AM	97.51%	1.49%	88%	54%	48.48	123.37	32.76
CI	100.00%	0.00%	86%	40%	106.44	107.27	106.44
ES (Madrid)	99.03%	0.00%	91%	57%	102.96	141.65	92.14
ES (Barcelona)	100.00%	0.00%	93%	59%	105.00	201.29	90.81
ES (Valencia)	100.00%	0.00%	96%	55%	20.86	46.02	17.09
GE	99.58%	0.42%	84%	42%	129.49	99.06	173.95
GH	100.00%	0.00%	88%	39%	42.08	43.08	41.42
HR	99.07%	0.00%	84%	36%	104.95	106.94	104.41
IT (Rome)	99.68%	0.00%	90%	52%	162.28	266.07	139.13
IT (Milan)	99.34%	0.00%	83%	48%	139.68	237.42	119.05
IT (Naples)	100.00%	0.00%	98%	80%	26.34	26.34	.
KE	100.00%	0.00%	97%	67%	111.84	177.50	96.50
KG	99.46%	0.00%	93%	49%	85.79	79.78	91.14
KZ	99.61%	0.00%	89%	44%	80.12	76.62	81.46
MA	98.67%	0.00%	88%	51%	52.59	93.38	48.14
PL (Warsaw)	99.33%	0.00%	87%	50%	45.89	60.19	41.12
PL (Krakow)	100.00%	0.00%	97%	51%	29.67	31.47	27.70
PT (Lisbon)	99.22%	0.00%	84%	45%	126.89	104.84	148.84
PT (Porto)	100.00%	0.00%	93%	51%	49.54	47.44	49.64
RO	98.36%	0.00%	79%	40%	60.44	108.25	50.24
SI	99.01%	0.00%	94%	46%	112.97	85.72	196.65
TN	99.42%	0.58%	92%	46%	50.07	59.62	39.22
UA	98.96%	0.00%	92%	59%	36.69	42.79	34.42
UG	100.00%	0.00%	91%	49%	73.01	88.82	68.38
Pooled	99.40%	0.09%	89%	50%	77.42	90.88	71.35

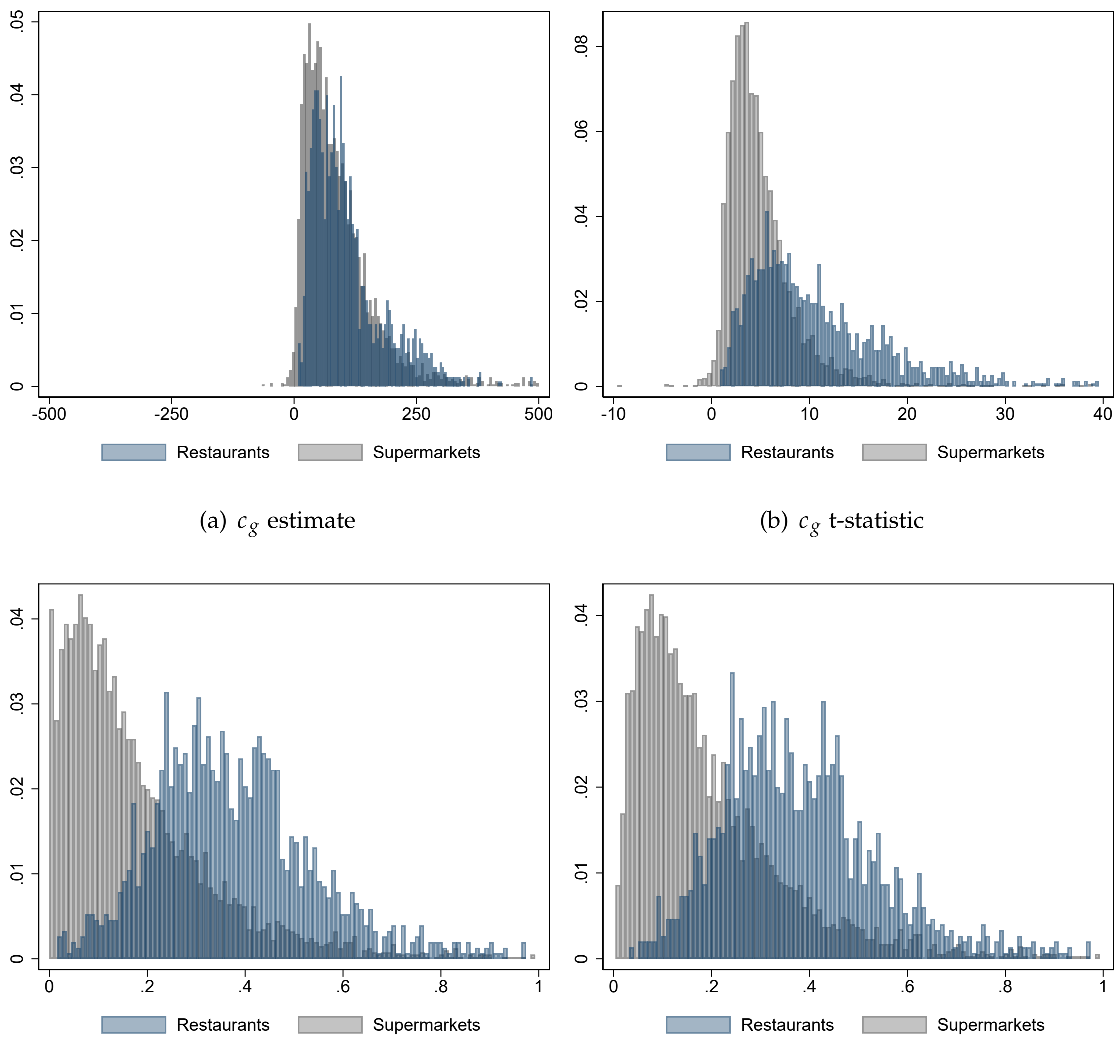
Notes: This table reports statistics on the estimated c_gs by country and sector. The columns t-stat < -2, t-stat > 2 and t-stat > 5 report the fraction of estimated c_gs with a t-stat smaller than -2 and greater than 2 and 5, respectively. The last three columns show the median c_g over all sectors, for restaurants and for supermarkets, respectively. The following countries (cities) are included (in the same order): Armenia, Côte d'Ivoire, Spain (Madrid and Barcelona), Georgia, Ghana, Croatia, Italy (Rome and Milan), Kenya, Kyrgyzstan, Kazakhstan, Morocco, Poland, Romania, Slovenia, Ukraine, and Uganda.

for the restaurant categories. Due to the downward bias affecting especially small categories, the results should be taken with a grain of salt. On average, restaurant categories have 1,860 products while supermarket categories only 525, so that one possibility behind the lower c_g for supermarkets could be a larger bias toward zero.

The distribution of R^2 of restaurant categories appears to the right of that of supermarkets, indicating that the share of price distortions that can be explained by suboptimal inflation is also larger on average for restaurants. The median R^2 across category-city combinations stands at 35% for restaurants while it stands at 17% for supermarkets. The heterogeneity across sectors suggests that it is important not to focus only on the retail sector when analyzing price distortions.

Across countries and cities, I find similar results despite very heterogeneous average inflation rates. All countries present a share of positive c_g above 95%, except Armenia, and most of the countries have a share of positive significant c_g ($t-$statistic$>$ 2) above 80 percent. Again the very different

Figure 6: Second-stage Descriptive Statistics by Sector



(a) c_g estimate

(b) c_g t-statistic

(c) Second-stage R^2

(d) Second-stage R^2 with $|c_g$ t-statistic$| > 2$

Notes: This figure shows the descriptive statistics of the second-stage regression separately by sector. Observations with an absolute c_g larger than than 500 or an absolute t−statistic of c_g greater than 40 are excluded from all figures to improve legibility. This is less than 5% of the sample, leaving 4,247 city-category combinations in panels (a)-(c). Panel (d) additionally drops observations with a t-statistic of c_g <2.

sample sizes make comparisons of the level of the estimates difficult, but even cities with a large number of observations and very heterogeneous average inflation rates, like Ukraine (Kyiv) and Italy (Rome), have a similar share of significant coefficients. This is evidence that even in high inflation environments, inflation continues to have distorting effects on relative prices.

4. From Product-Level Distortions to Cross-Sectional Price Dispersion

In the previous section, I showed how inflation induces price distortions at the product level. This section now examines the comovement of inflation with price dispersion across sectors.

4.1 Introducing Cross-Sectional Price Dispersion and Methodology

We know that the log relative price of product i in period t is

$$\ln p_{irgct} = \ln p^*_{irgct} - t\ln \Pi^*_{irgct} + u_{irgct}, \tag{4.1}$$

where g is the category assigned to the product, r is the retailer selling the product and c is the city in which we observe this product. I introduce the subscripts c and r in this section, but these characteristics were also present in a product in previous sections.

While I have shown so far that the variance of u_{irgct} over time for a given product depends on the level of suboptimal inflation, I have not yet analyzed in detail the cross-sectional price dispersion. This is, the variance of relative prices within a narrow category, city and week $\text{Var}_{gct}(\ln p_{irgct})$. It can be shown that the term can be decomposed as follows

$$\text{Var}_{gct}(\ln p_{irgct}) = \text{Var}_{gct}(\ln p^*_{irgc} - t\ln \Pi^*_{irgc}) + \text{Var}_{gct}(u_{irgct}). \tag{4.2}$$

The first component on the right-hand side captures the price dispersion that results from flexible prices and that would exist even in the absence of price stickiness. It includes the optimal (relative) introduction price and the time trend so that it can be computed from the first stage (3.2).

The second term,

$$\text{Var}_{gct}(u_{irgct}) = v_{cg} + c_{cg} E^{gc}[(\ln \Pi_{gc} - \ln \Pi^*_{igc})^2] \tag{4.3}$$

captures variation from the stochastic components (v_g, see equation 3.4) and price distortions caused by suboptimal inflation.

When pooling all category-city-week combinations, the medians of $\text{Var}_{gct}(\ln p_{irgct})$, $\text{Var}_{gct}(\ln p^*_{irgct} - t\ln \Pi^*_{irgct})$ and $\text{Var}_{gct}(u_{irgct})$ are 0.3398, 0.3363 and .0019, respectively. This indicates that most of the price dispersion, about 99%, comes from product heterogeneity in the product entry price and trend while only a small fraction, about 0.6%, comes from the estimated residuals. Indicating that the product-specific time trends play a minor role, from the flexible price heterogeneity the largest share of the variance comes from the introduction price or constant term, $\text{Var}_{gct}(\ln p^*_{irgc})$, with a variance of 0.3332.

The value of the cross-sectional price dispersion may seem small, but it is in concordance with previous research measuring it from relative prices adjusted for product characteristics. The average $\text{SD}_{gct}(u_{irgct})$ across all countries, categories, and time periods is about 0.038 in my sample. Sheremirov (2020) finds a standard deviation of log prices, after controlling for store, good and store-time fixed effects, of 0.06 for regular prices and of 0.088 in posted prices. Alvarez et al. (2019) finds a standard deviation of log prices of narrow CPI expenditure items of 0.09 for inflation rates below 10%, after controlling for store, store time, and store category fixed effects. Sara-Zaror (2021) finds an average standard deviation of log prices (including sales) of 0.087 for the same product across retailers. Some reasons for the slightly lower $\text{SD}_{gct}(u_{irgct})$ analyzed in my data could be the inclusion of product-specific time trends and that I measure price dispersion within very narrow time windows (weekly) and locations (cities).

As equation (4.3) indicates, one can expect a relationship between price dispersion and inflation. However, the effect of an increase in inflation $\ln \Pi_g$ depends on the average level of optimal inflation of that category. Suppose that the average optimal inflation rate is zero, then an *increase* of $\ln \Pi_g$ from -2% to -1% will *decrease* the absolute level of suboptimal inflation and thus the inefficient price dispersion. In contrast, an *increase* of $\ln \Pi_g$ from 1% to 2% is expected to *increase* price dispersion because it moves inflation further away from the optimal level of zero. For this reason we need to take into account the absolute deviation of inflation, not its level, when estimating the comovement of inflation with price dispersion.

To asses the average comovement of inflation with price dispersion, my baseline specification regresses the standard deviation of u_{irgct} in a given category, week and city on a category fixed effect and the absolute city-category (annualized) month-on-month inflation. This is a simplification to make my results comparable to previous research analyzing cross-sectional price dispersion.

Setting optimal inflation at the value of zero instead of the estimated optimal level, should be a fair approximation for several reasons. First, my estimates of optimal relative inflation from the first stage (3.2) are zero or very close to zero for most of the products. Second, I am mostly analyzing food and beverages in restaurants, food and beverages at supermarkets, and other household goods, which probably do not optimally need a positive inflation depreciating their relative price. This would be different if I included products such as clothing, computers or cars, all of which depend heavily on either of seasonal or technological depreciation. Finally, I use week-on-week or month-on-month inflation in the analysis, so that the rates are expected to be close to zero in any case. Including inflation in absolute terms allows me to have lower inflation in negative territory have a similar effect as higher inflation in positive territory, consistent with the expectation that any deviation from optimal inflation should increase inefficient price dispersion.

The estimated regression is then:

$$\mathrm{SD}_{gct}(u_{irgct}) = \gamma_g + \beta|\Delta p^{Annual}_{gct-4}| + \varepsilon_{gct}. \tag{4.4}$$

As measures of inflation I use either the absolute annualized weekly week-on-week inflation rate ($|\Delta p^{Annual}_{gct}|$) or the absolute weekly annualized month-or-month inflation rate ($|\Delta p^{Annual}_{gct-4}|$), both computed by averaging the product-specific week-on-week or month-on-month inflation rates within each category, city, and week. In the baseline regressions I include category fixed effects γ_g and report in the Appendix B the results when including instead category-city fixed effects (γ_{gc}) or including additional date-city fixed effects. The baseline specification does not include squared monthly inflation and thus does not allow for a stronger or weaker comovement for different inflation rates, the linearity of the relationship will be analyzed in detail in Subsection 4.3.

I also examine the comovement of inflation with other measures of price dispersion. One option often used in the literature is to control for retailer or restaurant and product specific heterogeneity (Sheremirov, 2020; Alvarez et al., 2019). This is achieved by estimating in a first steep the regression

$$\ln P_{irgct} = \alpha_{gc} + \delta_{ct} + \gamma_{rct} + \eta_{irgc} + \varepsilon_{irgct}, \tag{4.5}$$

where $\ln P_{irgct}$ is the log price of product i sold by restaurant or retailer r, belonging to category g in city c and period t. In the regression, α_{gc}, δ_{ct}, γ_{rct} and η_{irgc} are category×city, city×time, retailer×city×time and product fixed effects, respectively. Then, I estimate for each category-city-week combination the standard deviation of the residual ε_{irgct}, $\mathrm{SD}_{gct}(\varepsilon_{irgct})$. This specification removes the variation due to retailer products having a consistently higher price within a category and the variation from specific retailers charging a higher price for all products in a given week.

In addition, I control for product specifics using product information contained in the product name or description instead of using the fixed effects approach. For this purpose, I focus on the the beverage categories in both sectors because they usually contain product size information in the name. This includes the following categories: beer, cider, energy drinks, fruit juices, ice tea, sodas and water bottles. Using regular expressions, I subtract the product volume from the product description. In these specifications, I estimate inflation ($\Delta p^{Annual}_{vgct-4}$) and price dispersion at the ML volume-category-city-week.

Especially when analyzing the heterogeneity between the two sectors in my sample, the estimation (4.4) could yield misleading results. The average $\text{SD}_{gt}(u_{irgct})$ may be different across sectors, so that even under very similar estimated coefficients β in the regression (4.4), the marginal effect in one sector may be larger. Since the methods used cannot identify the level of the true gap with u_{irgct}, I also use the log of $\text{SD}_{gct}(u_{irgct})$ as the dependent variable when analyzing the sectors separately. The slope indicates then the percentage marginal effect of an increase in inflation in these specifications, which also helps with interpretation.

For the estimation I only include in $\text{SD}_{gct}(\varepsilon_{irgct})$ and $\text{SD}_{gct}(u_{irgct})$ products which were not dropped in the previous section and keep in the baseline estimations city-categories-weeks with more than 50 products included in the calculation of the standard deviation in a specific period. I only include category-city-week combinations with an annualized inflation below 20%. The results when keeping city-categories-week combinations with more than 100 or 20 observations or including also periods with annualized inflation above 20% are reported in the Appendix B.

Table 3: Price Dispersion and Inflation Comovement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\text{SD}_{gct}(u_{irgct})$	$\text{SD}_{gct}(u_{irgct})$	$\text{SD}_{gct}(u_{irgct})$	$\text{SD}_{gct}(u_{irgct})$	$\text{SD}_{gct}(u_{irgct})$	$\log(\text{SD}_{gct}(u_{irgct}))$	$\log(\text{SD}_{gct}(u_{irgct}))$	$\text{SD}_{gct}(\varepsilon_{irgct})$	$\text{SD}_{vgct}(\ln p_{irgct})$	$\Delta\text{SD}_{gct}(p_{irgct})$
$\lvert\Delta p^{Annual}_{gct-4}\rvert$	0.124***	0.061***		0.122***	0.132***	4.061***	6.118***	0.119***		0.033***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.15)	(0.17)	(0.00)		(0.00)
$\lvert\Delta p^{Annual}_{gct}\rvert$			0.074***							
			(0.00)							
$\lvert\Delta p^{Annual}_{vgct-4}\rvert$									0.239***	
									(0.05)	
Sector	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants	Both	Both	Both
Cat. FEs	Y	N	Y	Y	Y	Y	Y	Y	N	N
Cat.× City FEs	N	Y	N	N	N	N	N	N	N	N
Cat.× Vol FEs	N	N	N	N	N	N	N	N	Y	N
N	374,233	374,216	323,362	244,996	129,237	244,992	129,237	374,233	39,167	381,788
R^2	0.35	0.69	0.29	0.23	0.30	0.12	0.14	0.39	0.44	0.01
Within R^2	0.13	0.06	0.07	0.11	0.24	0.03	0.08	0.09	0.01	0.01

Notes: This table shows the relationship between different weekly measures of cross-sectional price dispersion and inflation at the category-(product volume)-city level. The measures of price price dispersion considered are the category-city-week standard deviation of product level residuals u_{irgct} from equation (3.2), $\text{SD}_{gct}(u_{irgct})$, the category-city-week standard deviation of product-level residualized log-prices, $\text{SD}_{gct}(\varepsilon_{irgct})$, the category-product volume-city-week standard deviation of log prices ($\text{SD}_{vgct}(\ln p_{irgct})$) computed for homogeneous beverage categories and the change in the category-city-week standard deviation of log prices based on a balanced sample of products available in t and $t-1$ ($\Delta\text{SD}_{gct}(p_{irgct})$). The explanatory variables are either the category-city annualized weekly month-on-month or week-on-week inflation, $\lvert\Delta p_{gct-4}\rvert$ and $\lvert\Delta p_{gct}\rvert$ respectively, and the category-volume-city annualized weekly month-on-month inflation ($\lvert\Delta p_{vgct-4}\rvert$). Standard errors clustered at the category-city level in parethesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2 Main Results on the Comovement of Inflation and Price Dispersion

Table 3 reports various estimated coefficients of comovement between cross-sectional price dispersion and inflation. In general, the estimated coefficients are larger than previously estimated and seem to be closer to models mix time- and state-dependent pricing with high implied costs of inflation. All coefficients are significant and the coefficient in the baseline estimate in column (1) is 0.124.

Including the more restrictive category-city fixed effects in column (2), the relationship appears to be less strong but still large and significant, with a value of 0.061. This restrictive setting absorbs the cross-country variation within the (similar) narrow categories, which is why it is not the baseline specification. This variation is key and a contribution of the paper because if inflation and price dispersion are persistent, the cross-country variation help us understand how also how different average levels of inflation influence price dispersion. The coefficient is lower when using the week-on-week average category inflation rate in column (3) instead of the month-on-month inflation rate. The coefficients are also remarkably close to the baseline estimate when price dispersion is estimated using the dispersion of the residuals from the fixed effects regression, see column (8).

The regression analyzing the relationship of log prices without fixed effects and focusing instead on the dispersion of relative (log) prices directly within a product volume-category-city also yields a significant coefficient. The variance decomposition shown earlier indicates that a large part of the price dispersion comes from price dispersion at the time of product introduction. To capture this product heterogeneity, in column (10), I additionally estimate the effect of category inflation on the change in the standard deviation of log prices of a balanced panel of products available in periods t and $t-1$. This also yields a positive and significant coefficient. This specification assumes no product-specific time trend in the flexible relative price.

Across sectors columns (4) and (5) report a significantly larger coefficient for restaurant categories. However, I observe that the average dispersion is significantly lower for restaurants so that the difference in the marginal effect is even larger. This can be observed in columns (6) and (7), where we observe how an increase of annualized inflation from zero to 10%, is associated with an increase in $\mathrm{SD}_t^g(u_{irgct})$ of 61.2% for restaurants and only of 40.6% for supermarkets. These numbers indicate a strong heterogeneity on how inflation might affect inefficient price dispersion across sectors. This again points again to the importance of looking beyond the retail sector, a widely analyzed sector using scanner data, where the effects are significantly smaller.

As reported in the Appendix Table B.5, all cities and countries in the sample have an estimated coefficient which is positive with the coefficients ranging from 0.034 for Porto to 0.098 for Georgia (Tbilisi). The magnitude of the coefficients should to be compared to the coefficient when including category-city fixed effects, in Table 3 column (2), which is 0.061. All countries have a similar coefficient, which is close to the specification including category-city fixed effects, indicating that the slope estimated pooling all cities are not driven by one specific city, but rather is a relationship that holds internationally in very different economies facing different inflation rates. The heterogeneity in the coefficients can be partially explained by the heterogeneous average inflation faced in each country. Regressing the 24 city-specific estimates on the median category inflation in that city yields a coefficient of -0.654 with a standard error of 0.236, with a R^2 of 0.26.

The results are significant for a number of additional specifications reported in Appendix B. Including additional city × week fixed effects, Table B.3, only has a small effect on the estimates. Absorbing city-categories having a higher or lower price dispersion over the sample by including city × category fixed effects, slightly diminishes the size of the coefficients, as reported in Appendix Table B.4. Including only city-category-weeks with more than 100 or more than 20 observations has no effect on the estimates, as reported in Table B.2. The same table also reports the predicted values with inflation at 0 and at 10%. The results are also robust to trimming the top percentile of inflation and of $\mathrm{SD}_{gct}(u_{irgct})$ (Table B.2).

4.3 Comovement of Inflation and Price Dispersion at Different Levels of Inflation

In addition to questioning whether price dispersion moves together with inflation, it is crucial to determine the specific levels of inflation at which this relationship becomes evident and whether there are some levels of inflation at which this relationship flattens out. Empirical results so far provide mixed results on this question. Sara-Zaror (2021) finds a strong comovement between inflation and price dispersion that flattens out for inflation rates above 2%. While in Alvarez et al. (2019), empirical results suggest that price dispersion barely changes with inflation for annualized inflation rates below 10%, and then it starts to increase with inflation. In this context, my data will provide unique insights as it covers a wide range of inflation environments across categories and countries.

To contribute to this key question for determining the optimal inflation target, I plot the relationship between inflation and price dispersion in a binned scatterplot. For this purpose, I follow the approach in Sara-Zaror (2021) and divide the available category-city-week inflation rates into 100 equally sized bins and obtain an average price dispersion within each inflation bin. I do this for the two measures of price dispersion $\mathrm{SD}_{gct}(u_{irgct})$ and $\mathrm{SD}_{gct}(\varepsilon_{irgct})$ and using annualized month-on-month (m-on-m, $\Delta p_{gct-4}^{Annual}$) and week-on-week (w-on-w, Δp_{gct}^{Annual}) weekly inflation rates. To limit the heterogeneity in the lower and upper bins, in this analysis I exclude observations with an absolute annualized inflation rate larger than 20% – m-on-m or w-on-w depending on the underlying inflation rate used.

As before, one could argue that some categories have consistently higher dispersion on average, for example, due to a stronger idiosyncratic component in equations (3.3) and (3.4) or because a larger number of products are included in the category. For this reason, I also construct a binscatter after subtracting the category fixed effect and the number of observations effect from the two dispersion measures.

More specifically, when examining the residuals u_{irgct} and the m-on-m inflation rate, I estimate the following regression:

$$\widetilde{\mathrm{SD}}_{gct}(u_{irgct}) = \delta_g + \delta|\Pi_{gct-4}| + \delta_2 N^i_{gct} + \varepsilon_{gct}, \tag{4.6}$$

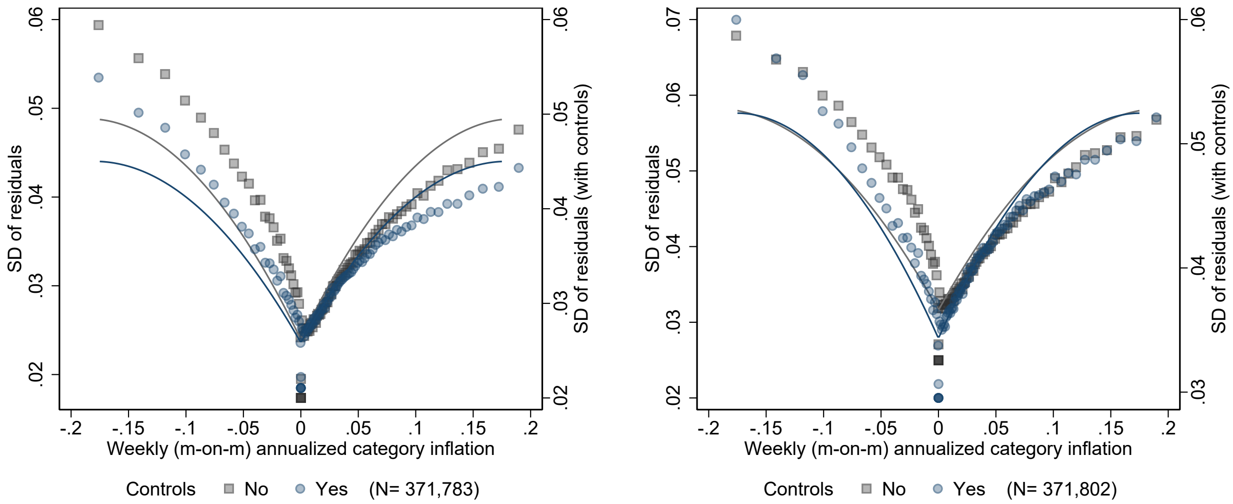
where $\widetilde{\mathrm{SD}}_{gct}(u_{irgct})$ is the demeaned price dispersion measure, using the average price dispersion across all city-category-weeks combinations, δ_g is a category fixed effect, $|\Pi_{gct-4}|$ is the category-city-week m-on-m inflation and N^i_{gct} are the number of products included in a specific category-city-week combination. Then I construct the binscattter out of the price dispersions controlling for category and category-size effects: $\widehat{\mathrm{SD}}_{gct}(u_{irgct}) = \mathrm{SD}_{gct}(u_{irgct}) - \hat{\delta}_1|\Pi_{gct-4}| - \hat{\delta}_2 N^i_{gct}$.

I find that the relationship of cross-sectional price dispersion persists at high levels of inflation. Figure 7 shows the resulting figures separately for the two measures and two inflation rates. The figures include more than 370,000 category × city × week combinations, divided in 100 bins so that each bin contains more than 3,700 observations. For both dispersion measures, for both inflation measures (m-on-m or w-on-w), and controlling for category-city FEs or not, one can observe that price dispersion is at its lowest close to zero and increases as inflation deviates from zero towards the positive and negative regions.

From my preferred scatterplot, in Figure 7 Panel (a), it does not appear the case that the effect flattens out much even at very high levels of month-on-month inflation. Even at annualized inflation rates of of 20% the relationship persists. That is, one cannot observe the almost complete flattening observed in Sara-Zaror (2021) and the "Υ" relation of the two measures, where at inflation levels of 2% year-on-year the increase of price dispersion flattened out significantly. The link seems to depict rather a "V" shape during in this sample covering countries and periods with a large range of inflation levels. The result also does not seem to be generated by having a small sample for the extreme cases, since in each figure each point is based on more than 3,700 observations.

This finding is reinforced by the results in Appendix Table B.2. In this table, I report the estimates of (4.4) for a subsample of city-category-weeks with annualized month-on-month inflation rates above 5% and for the results when the squared inflation rate is added as an additional independent variable. The coefficient for the high inflation subsample is positive and significant (0.084) and close to that for the full sample (0.124). The squared term does significantly alter the linear effect (0.221), but the

Figure 7: Price Dispersion and Inflation



(a) $\text{SD}_{gct}(u_{irgct})$ and m-on-m inflation

(b) $\text{SD}_{gct}(\varepsilon_{irgct})$ and m-on-m inflation

Notes: These binscatters display the relation of inflation and different measures of price dispersion. Each dot corresponds to the average price dispersion for 100 equally sized inflation bins. The unit of observation is a category × city × week. The number of category × city × week included in panels (a) and (b) are 371,783 and 371,802, respectively. One bin represents around over 3,700 category × city × week combinations. Both panels are based on weekly annualized month-on-month average category-city inflation rates ($\Delta p^{Annual}_{gct-4}$).

predicted increase in $\text{SD}_{gct}(u_{irgct})$ after going from an inflation rate of 0 to 10 percent only changes from 37.2 percent to 46.8 percent.

5. Theory Meets Data and The Costs of Inflation

In this section, I start by providing different approximations on the costs of (high) inflation. These numbers should be seen as a rough approximations, suggesting that inflation induces sizable costs associated with inefficient price dispersion. I then link my empirical results and methodology to a standard menu cost model. This makes two contributions to the paper. First, I show that my results are not driven by the methodology employed. Second, I show that standard New Keynesian menu cost models fail to match key empirical moments and may then be inadequate for measuring the costs associated with inflation-driven inefficient price dispersion.

5.1 Approximate Estimates of The Costs of Inefficient Price Dispersion

The welfare costs of high inflation in New Keynesian models are usually attributed to two sources, from the misallocation due to inefficient price dispersion and from the resources used to adjust prices. This section focuses on the first, which has perhaps received more attention, the welfare cost of inefficient price dispersion at a given level of inflation.

This cost, should rather be seen as a lower bound on the cost of inflation. Within the framework of the New Keynesian models, Coibion et al. (2012) perform a detailed welfare analysis of inflation and identify, in addition to the direct costs due to inefficient price dispersion and misallocation in the steady state, two additional costs associated with inflation and price dispersion. The first one, is that a positive inflation level increases the welfare cost of inflation volatility around the inflation level. This is because inflationary shocks around this level will be more costly as firms will have to compensate for the increasingly high marginal disutility of sector-specific labour. The second one captures that the fact that at higher inflation levels, price-setting turns more forward-looking, and this increments the inflation volatility, further reducing aggregate welfare.

Since measuring how the disutility of labor increases with price dispersion or how higher inflation induces price volatility that further increases price dispersion, is beyond the scope of this project, in this paper I will limit myself to analyzing the costs related from misallocation induced by inefficient price dispersion. However, it is important to keep in mind that this will may be a lower bound that ignores other paths related to price dispersion through which higher inflation reduces welfare. Further research should focus on estimating the approximate role of these channels and how they interact with my increase in inefficient price dispersion.[13]

This welfare cost is usually represented as the percentage loss of flex-price consumption per period and it can be shown that, in a broadly used second-order approximation (Galí, 2008; Alvarez et al., 2019; Blanco et al., 2024a), it is equal to:

$$\phi = \frac{\sigma}{2}\mathbb{V}[x], \tag{5.1}$$

where σ is the elasticity of substitution between goods and $\mathbb{V}[x]$ is the variance of price gaps which usually depends on the level of inflation π.

Given that my measures of the dispersion of price gaps may not capture the level well, one option

[13]Outside the framework of New Keynesian models, there are other costs associated with inflation. For example Shiller (1997) and Stantcheva (2024) focus on the perceived adverse effects of inflation by the population in an attempt to understand why people dislike inflation. These perceived consequences trigger stress and emotional effects that reduce the utility of inflation and are not included in the models considered here.

for getting an estimate of the costs of inflation is to measure how the dispersion of prices changes when we move from zero inflation to a specific inflation rate π. For example, Alvarez et al. (2019) measure price dispersion from the variance of residualized log-prices, using a regression similar to (4.5). They then estimate the cost of inflation at a certain inflation rate π by subtracting from the variance observed with π inflation ($\mathbb{V}[x](\pi)$) the variance observed around zero inflation, $\phi(\pi) = \frac{\sigma}{2}(\mathbb{V}[x](\pi) - \mathbb{V}[x](0))$. Using this method, they find a cost of inflation of only 0.6% for an annual inflation rate of 50%, and almost no cost of inflation for inflation rates below 10%.

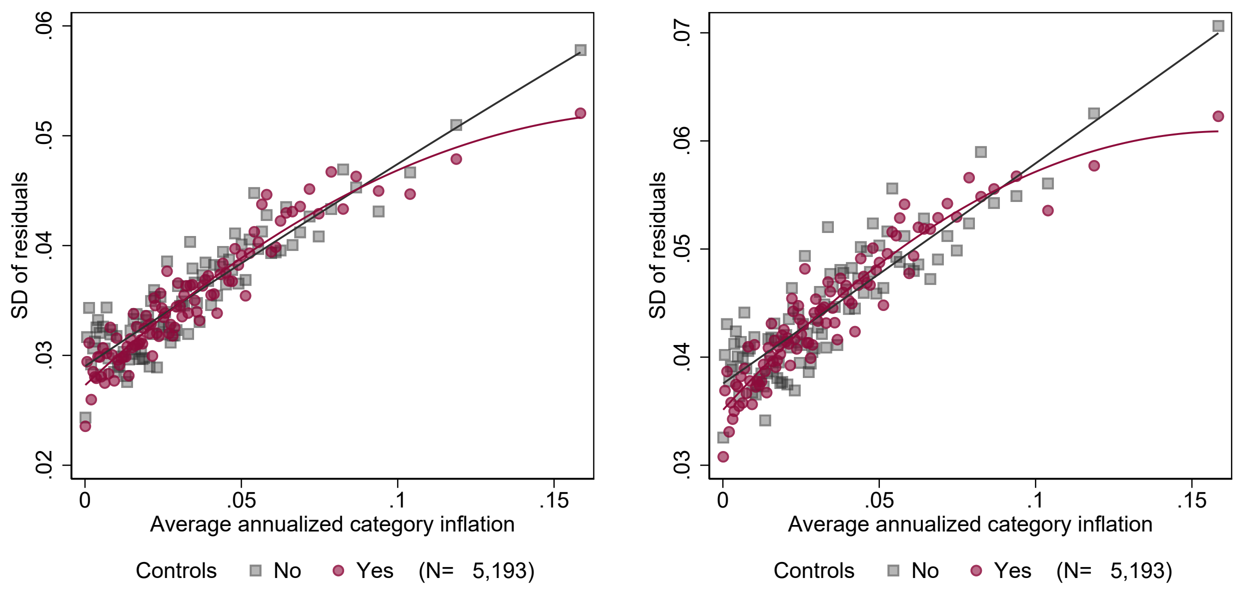
Given the high frequency of the data analyzed here and the persistence of inefficient price dispersion, I start by showing that such an analysis is strongly sensitive to the choice of zero inflation price dispersion and to the measure of inflation used. The results in Cavallo et al. (2023) indicate that inefficient price dispersion due to a large shock, such as the one recently observed, takes more than a year to fully dissipate. This can also be observed comparing Figure 7 panel (a) and B.3 panel (a), where moving from to month-on-month inflation to weekly week-on-week inflation would yield a very different estimate of the welfare cost of inflation. Making use of equation (5.1) with an elasticity of substitution of 6, an annualized inflation rate of 10%, would imply a cost of inflation of 0.40% when using m-on-m inflation rates and of 0.24% when using w-on-w inflation rates.[14] Changing the measure of price dispersion barely changes the results. Focusing instead on the residualized relative prices, panel (b) in Figures 7 and B.3, results in a cost of inflation of approximately 0.53% (0.33%) for an annualized month-on-month (week-on-week) inflation rate of 10 percent.

Since the use of a monthly frequency may not be adequate for a persistent price dispersion, which may take a year to dissipate after a large shock (Cavallo et al., 2023), I next exploit the cross-country heterogeneity. Taking advantage of the international dimension of the data and the narrow categorization of products using the same methodology, I estimate the costs of inflation from the relation of the category-city (absolute) average annualized monthly inflation and the average dispersion of price gaps over the analyzed sample. Annualized absolute inflation was constructed by first averaging the weekly month-on-month inflation rates and then annualizing this monthly inflation and taking the absolute value.

Figure 8 shows the relationship between the city-category average price dispersion and the average city-category inflation over all weeks annualized for product-city combinations in a binscatter. Only city-categories observed in at least 52 weeks and with at least 50 products included, this is 5,193 observations. Panel (a) shows the relation using $\text{SD}_{gct}(u_{irgct})$ as inefficient price dispersion measure

[14] These numbers are derived from the average price dispersion for the bins with an inflation of zero and from average price dispersion of the bin closer to the 10% annualized inflation. For example, in Figure 7 Panel (a), the bins with an average inflation of zero have a price dispersion of 0.0174. The bin closest to a m-on-m inflation of 10% (10 percent annualized), has a standard deviation of residuals of 0.0404. Computing the variance from the standard deviations and using $\phi(\Delta 10) = \frac{\sigma}{2}(\mathbb{V}[x](\pi = 10) - \mathbb{V}[x](0))$ yields 0.40% with $\sigma = 6$.

Figure 8: Price Dispersion and Mean Inflation



(a) Mean $\mathrm{SD}_{gct}(u_{irgct})$ and mean m-on-m inflation (b) Mean $\mathrm{SD}_{gct}(\varepsilon_{irgct})$ and mean m-on-m inflation

Notes: shows the relationship of the city-category average price dispersion and the average city-category inflation across all weeks annualized for product-city combinations in a binscatter. The coloured bins are based on the residualized variables after controlling for category fixed effects and number of products included in the category-city combination. Only city-categories observed in at least 52 weeks and with at least 50 products included, this is 5,193 observations.

while panel (b) uses $\mathrm{SD}_{gct}(\varepsilon_{irgct})$ as inefficient price dispersion measure. Since I want to exploit the inflation variation across countries, the main focus is based on the residualized variables after controlling for category fixed effects and the number of products included in the category-city combination. Both figures display the binscatter before and after controlling for these variables.

Both figures again show a positive relationship between inflation and price dispersion and average annualized inflation, even at elevated levels of inflation. Making use of Equation 5.1, and using the closest bin to zero inflation and to an inflation rate of 10%, for $\mathrm{SD}_t^{cg}(u_{irgct})$ an increase in inflation from zero to 10% is associated with an additional loss of about 0.43% of flex price consumption. An increase of inflation to 5%, where there are more observations, is 0.29%. When using the other dispersion measure $\mathrm{SD}_{gct}(\varepsilon_{irgct})$ these numbers jump to 0.58% and 0.43%. When being less restrictive on the number of products available in a category-city combination, and considering also the ones with 25 products, these numbers are slighly higher. Appendix D shows the relation using scatter plots instead of binscatters and when keeping category-city combinations with less than 50 products.

Abstracting from the change in price dispersion in levels between two inflation rates, another insightful number is the percent change in ϕ relative to zero inflation associated with a given inflation change, $\Delta\phi(\pi) = \frac{\mathbb{V}[x](\pi)-\mathbb{V}[x](0)}{\mathbb{V}[x](0)}$. According to Figure 8, $\mathrm{SD}_t^{g}(u_{irgct})$ jumps from 0.023 to 0.045 when going from zero to 10% inflation. This implies that the $\mathbb{V}(u_i)$ almost triplicates (2.6), so that the costs is about 2.6 times what they would be around zero inflation. These numbers are rough approximations and indicate that there are significant costs associated with a higher inflation rate, which is inconsistent with menu cost models.

5.2 Model and Estimated Relation of Inflation and Inefficient Price Dispersion

In New Keynesian models, the precise relationship between the variance of price gaps $\mathbb{V}[x]$ and inflation strongly depends on how nominal price rigidities are modeled. In a classical (single-product) one-sector menu cost model in which the price can be adjusted at a given cost in each period, inefficient price dispersion remains roughly constant even at high levels of inflation (Nakamura et al., 2018). Intuitively, when the relative price gap is large, firms find it optimal to pay the adjustment cost, setting a cap on how disperse prices can be. In a Calvo model with fixed probabilities of price adjustment in each period, price dispersion rises rapidly with inflation. On the one hand, the observed rapid increase in the frequency of price adjustments with inflation during the recent period with high inflation (Cavallo et al., 2023), makes models with fixed fractions of price adjustments implausible. On the other hand, results of the previous sections suggest that $\mathbb{V}[x]$ positively correlate with inflation, a pattern inconsistent with standard state-dependent models. This section compares my empirical estimates and methodology with a calibrated standard menu cost model. The results suggest that standard New Keynesian menu cost models fail to match key moments and are thus inadequate for measuring the costs associated with inflation-induced inefficient price dispersion.

I begin by showing that the comovement of inflation and inefficient price dispersion in a standard New Keynesian model does not align with the empirical evidence and that this discrepancy is not driven by the methodology used in the previous empirical sections. To do so, I calibrate a standard one-sector menu cost model similar to the one used in Nakamura et al. (2018). I find that while the methodology may overestimate the level of price dispersion, both the estimated and the true gap dispersion have a similar correlation with inflation.[15]

In my baseline calibration, I set the cost of price adjustments K and the standard deviation of the idiosyncratic shocks σ_ε to match the mean fraction of price adjustments and the mean absolute size of price adjustments observed in my data. To mitigate the concern that the dispersion of price changes is the result of ex-ante heterogeneity, I follow Klenow and Kryvtsov (2008) and Blanco et al. (2024a) and standardize the distribution of price changes by the city-category mean and standard deviation, see Appendix C for the details on the standardization.

Table 4 reports some of the moments when averaging across countries and Madrid, Spain, sep-

[15] For details on the model and solution procedure used, see Nakamura et al. (2018) and Nakamura and Steinsson (2010).

Table 4: Data and Model Moments

Moment	Description	Data (all)	Data (MAD)	Model	Targeted
Mean Frac. Δp	Frequency of price adjustment	0.110	0.109	0.109	Yes
Mean $\lvert\Delta p\rvert$	Mean absolute size of price adjustment	0.129	0.093	0.094	Yes
Share Adj $\Delta p > 0$	Fraction of positive adjustments	0.647	0.593	0.682	No
Std. dev. Δp	Standard deviation of price adjustment	0.165	0.118	0.091	No
Kurtosis Δp	Kurtosis of price adjustment	3.639	3.567	1.778	No

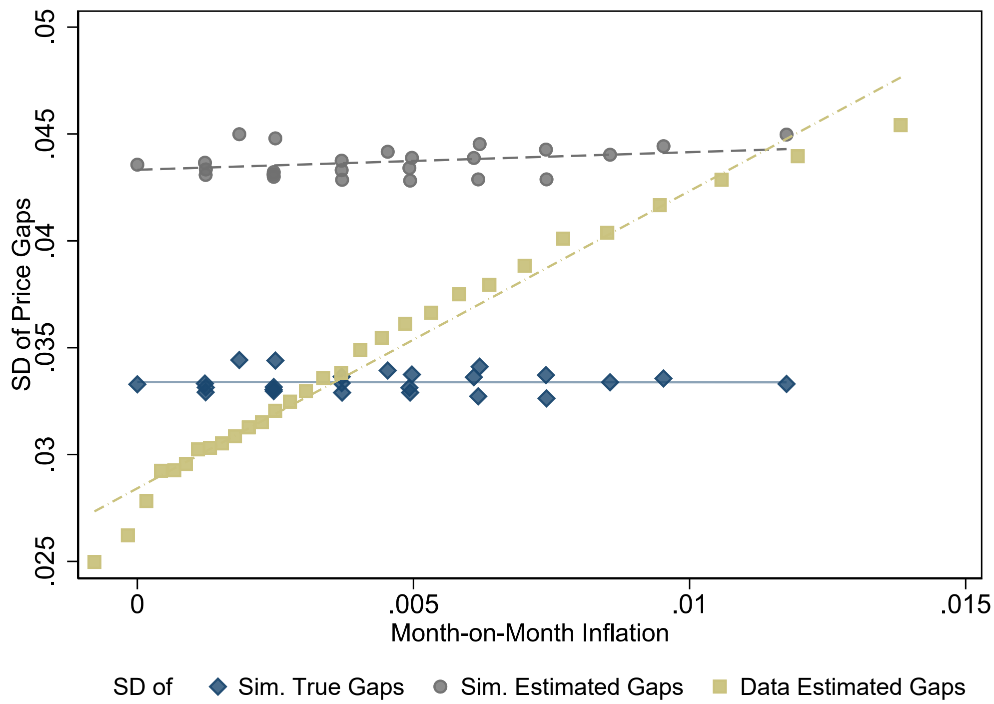
Notes: This table shows the two targeted and additional moments in the data and in the calibrated model. The empirical moments targeted are the ones from Madrid (MAD), Spain. The moments for the other countries can be found in Appendix Table C.6. All empirical moments are standardized, see Appendix C.

arately. Appendix Table C.6 report detailed summary statistics on the fraction and size of price adjustments by city and sector. Averaging the statistics across countries, the average fraction of price adjustments is 11% and the average (absolute) adjustment size is 12.9% while the median is lower at 9.8%. Since targeting moments from the cross-country average might be misleading, for example given the heterogeneity in the share of observations coming from restaurants or because heterogeneous price setting, I match the moments of the model to those of Madrid. Then I calibrate the menu cost (K) and the mean absolute size of price adjustment to target the fraction of price adjustments of 11%, and the mean absolute size of price adjustments of 12.9% when month-on-month inflation is at 0.335 %. This is achieved at a menu cost of $K = 0.042$ and at a standard deviation of product idiosyncratic shocks at $\sigma_\varepsilon = 0.045$. Both values are higher than those considered in Nakamura et al. (2018), however this is not surprising given the (slightly) lower frequency and higher adjustment size targeted here. I set the elasticity of substitution σ at 6, as used in related literature (see, for example, Alvarez et al. (2019)).[16]

For the simulations I calibrate the model for a range of values of average inflation by adjusting the average change in nominal aggregate demand and for each value of average inflation I simulate the dynamics of prices, desired prices and inflation for 300 firms and 100 periods. The range of average inflation targeted goes from zero to 0.75% month-on-month. The simulated data will still contain observations with inflation rates well above this value driven mainly by the volatility of aggregate shocks. Using the simulated data I then estimate the standard deviation of true price gap, the difference between relative price and desired relative price, and the standard deviation of price gaps

[16]As in Nakamura et al. (2018), I set the subjective discount factor to $\beta = 0.96^{\frac{1}{12}}$ and the first-order autoregressive parameter for the idiosyncratic productivity to $\rho = 0.7$. Given the recent high volatility of nominal GDP in recent years and the countries studied here, I deviate from their standard deviation of nominal aggregate demand shocks and set this parameter at a the value of $\sigma_\eta = 0.006$, higher than the value used in their paper (0.0039).

Figure 9: Price Dispersion in Theory and in the Data



Notes: This figure displays the relationship between inefficient price dispersion an inflation using the true gaps, the estimated gaps in the simulated data and the estimated gaps in the actual data. Each dot corresponds to the average price dispersion for 30 equally sized inflation bins. The unit of observation is a category × city × week for the true data and a sample × target average inflation × month in the simulated data. The standard deviation of price gaps from the data were residualized controlling for category fixed effects.

estimated using Equation 3.2.

Figure 9 depicts in a binscatter the relation of absolute month-on-month inflation with the three measures of price dispersion. The first measure is the standard deviation of the true price gaps resulting from the simulation. The second measure is the standard deviation of price gaps estimated from the simulated prices. The last price dispersion measure one is the standard deviation of the previously estimated price gaps on the true data. As in the regressions in the previous section, I control adjust the price dispersion measure based on actual data controlling for category heterogeneity and number of observations using the residualized date-city-category standard deviations. In all samples, I drop observations with absolute month-on-month inflation above 1.5%, which is about 20% when annualized.

The first conclusion that one can draw from the figure is that the "fixed effects" estimated price gaps may overestimate inefficient price dispersion, but they do not artificially generate a positive slope between inflation and inefficient price dispersion. On the simulated data, the estimated inefficient price dispersion is about 30% higher than inefficient price dispersion from the true data. However, the displayed slope is very low for the true and estimated inefficient price dispersion, 0.074 and 0.089 respectively, and not significant different from each other.[17]

The second conclusion is that the inefficient price dispersion comoves much more strongly with inflation in the data than what the menu cost model predicts. This indicates that New Keynesian models with menu costs models miss a key relation for estimating one of the main costs associated with high inflation.

The menu cost model also fails to match one trivial statistic related to the dispersion of price gaps, the kurtosis of price adjustments. A large kurtosis points to a large mass of firms adjusting late, implying greater misallocation, making it a key statistic to measure misallocation. In fact, it has been shown that the variance of price gaps, key statistic for measuring the costs of price dispersion, equals $\mathbb{V}[x] = \mathbb{V}[\Delta p]\text{Kurt}[\Delta p]/6$ in a low inflation steady state (Alvarez et al., 2016; Cavallo et al., 2023). As reported in Table 4, the model yields a kurtosis of 1.778, a value that is far from the estimated one for Madrid of 3.567 and also far from the average kurtosis across countries of 3.639, both using data from both sectors.[18]

A natural question to ask now is: how does the frequency of price adjustments and the size of the adjustments vary with inflation in the recent period? Under high inflation, such as the one that in particular restaurants experienced in the cities and period analyzed, as pointed out in Nakamura et al. (2018), we should expect an increase in the absolute size of price adjustments if price-setting is time-dependent. In contrast, if prices are state-dependent, we would instead expect an increase in the frequency of price adjustments. The remainder of the section focuses in the relation of inflation with these two dimensions, in order to shed some light on the extent to which time-dependent pricing occurs independently of the state and the cost of adjustment.

To better understand how the frequency and magnitude of adjustments change with inflation, I regress either the mean absolute price adjustment (conditional on adjustment) and the frequency of adjustments measured as the share of price adjustments in a given week-city-category.

This is, I run the following regressions

[17] One reason behind the large overestimation of the that menu cost models need large (product) idiosyncratic shocks for reproducing moments observed in the data, as pointed out in Blanco et al. (2024a). These large idiosyncratic shocks that move desired relative prices in all directions, are (incorrectly) captured by the "fixed effects" approach as price gaps. Blanco et al. (2024a) argue that these large idiosyncratic shocks are not consistent with the fluctuations in the fraction of price adjustments with inflation, so that they may be artificially exaggerated in standard menu costs and might be less of a concern in other models.

[18] (Alvarez et al., 2022) propose an adjustment of the kurtosis to control for unobserved heterogeneity. In Table C.6, I also report these numbers. There, the kurtosis values are smaller, though still larger for restaurants. However, this estimation requires two observed price adjustments per product for the correction, which probably results in strong selection bias among products for restaurants given that only a minority of products had two or more adjustments during the observed life span.

$$MeanAbsoluteAdj._{gct} = \gamma_{gc} + \beta_1 |\Delta p^{Annual}_{gct}| + \varepsilon_{gct} \tag{5.2}$$

and

$$Adj.Share_{gct} = \gamma_{gc} + \beta_2 |\Delta p^{Annual}_{gct}| + \varepsilon_{gct} \tag{5.3}$$

where $MeanAbsoluteAdj._{gct} = \frac{1}{N_{i \in I_{gct}}} \sum_{i \in I_{gct}} (|\Delta p_{igct}|)$ is the mean absolute price adjustment conditional on a price change ($i \in I_{gct}$) and $Adj.Share_{gct}$ is the fraction of prices that adjusted within a city, category and week ($N_{i \in I_{gct}} / N_{i \in gct}$). As before, $|\Delta p^{Annual}_{gct}|$ is the annualized category-city-week week-on-week inflation and γ_{gc} is a city-category fixed effect. I abstract from weeks in which this inflation is zero.

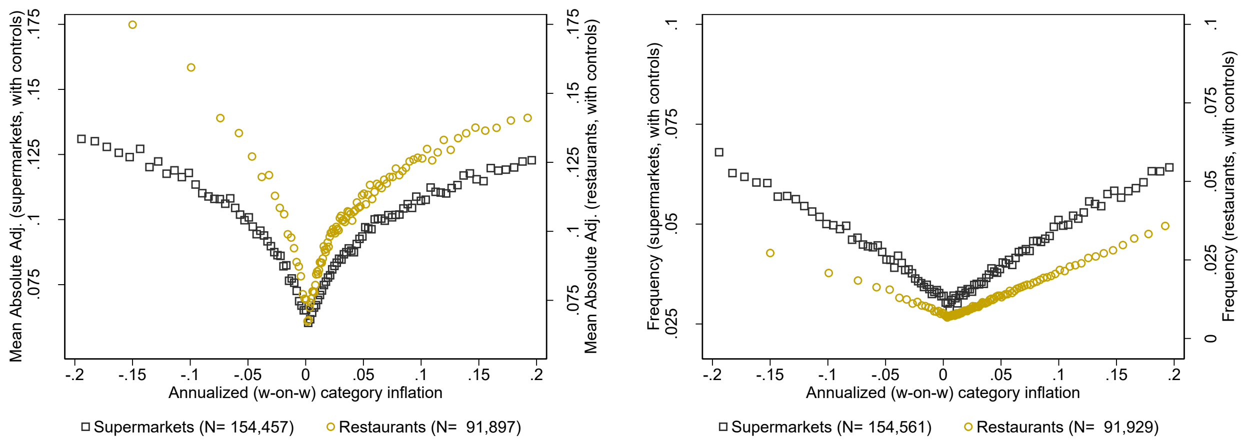
Table 5: Conditional Mean Absolute Price Adjustment, Frequency and Inflation

	Mean Absolute Adjustment					Frequency				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\lvert\Delta p^{Annual}_{gct}\rvert$	0.336***	0.313***	0.400***	0.328***	0.336***	0.172***	0.181***	0.147***	0.174***	0.225***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
City×Category FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FEs	N	N	N	N	Y	N	N	N	N	Y
$\Delta p < 0$ excl.	N	N	N	Y	N	N	N	N	Y	N
Sector	Both	Supermarkets	Restaurants	Both	Both	Both	Supermarkets	Restaurants	Both	Both
N	247,065	155,087	91,978	166,090	247,082	247,203	155,193	92,010	166,160	323,358
R^2	0.30	0.31	0.28	0.30	0.31	0.44	0.32	0.48	0.47	0.49
Within R^2	0.09	0.08	0.10	0.09	0.09	0.07	0.06	0.28	0.09	0.14

Notes: This table shows the relation of the mean absolute adjustment conditional on adjustment, $MeanAbsoluteAdj._{gct}$) and of the frequency of price adjustments measured as the adjustment share ($Adj.Share_{gct}$) and week-on-week annualized inflation at the category-city-week level. Only category-city-week combinations with non-zero inflation included. Standard errors clustered at the category-city level in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The results are reported in table 5. The results indicate that an increase in inflation is driven by both, an increase in the size of price adjustments and an increase in the frequency of adjustments. A one percentage point increase in annualized absolute inflation is associated with an increase of 0.336 percentage points in the mean absolute size of price adjustments conditional on adjustment. The same increase in inflation, increases the share of price adjusters by 0.17 percentage points. When comparing across sectors, supermarkets have a significantly lower coefficient for the mean absolute adjustment and a higher coefficient for the frequency of price adjustments than restaurants. This indicates that restaurants tend to adjust the intensive margin more than restaurants and the extensive margin less

Figure 10: Conditional Mean Absolute Price Adjustment, Frequency and Inflation



(a) Mean Absolute Price Adjustment and Inflation

(b) Frequency of Adjustments and Inflation

Notes: This figure shows the relationship of the city-category mean absolute price adjustment (conditional on adjustment) and frequency of adjustments (measured as the share of price adjustments in a given week-city-category) with the annualized weekly city-category inflation in a binscatter. Variables residualized after controlling for category-city fixed effects and number of products included in the category-city-week combination. Only category-city-week combinations with more than 50 products and with annualized inflation below 20% included, this is over 154,000 observations for supermarkets and over 91,000 observations for restaurants.

than supermarkets with inflation.

Figure 10 shows the two measures over the distribution of inflation with a binscatter. In order to control for city-category specific price-setting, the two variables are residualized separately controlling for category-city fixed effects and number of products. The figure indicates that as inflation increases from zero, both the absolute size of price adjustments and the frequency of price adjustments increase, but with a strong heterogeneity across sectors. While restaurants seem to react more strongly with the size of price adjustments, supermarkets react more strongly with the share of prices adjusting. Suggesting that time-dependent pricing is present in both sectors but more present for restaurants.

The idea of some degree of time dependency in pricing observed in the data is reinforced by looking at the distribution of price adjustments Figure D.6. The figure displays the distribution of the (non-zero) price adjustments in the two sectors. The results in previous sections could be the result of some degree of time-dependent pricing. Meaning that a share of price adjustments are independent of the state. If this is the case we would also observe a large share of small adjustments. Despite the period of high inflation analyzed, especially for restaurants, one can still observe a large density of price adjustments around the $\Delta p_{irgct} = 0$ area. The share of price adjustments that are smaller than one (five) percent are 2% (24%) and 4.5% (35%) for restaurants and supermarkets respectively, also indicating to some extend the existence of some time-dependent price setting.[19]

[19] In a related exercise Alvarez et al. (2022) study the "Calvo-ness" in price setting using generalized hazard functions and

6. Conclusion

By analyzing novel product-level web-scraped data from over 60,000 restaurants and supermarkets across 18 countries facing high and low inflation periods, I provide in this paper new international evidence of a significant positive relationship between inflation and inefficient price dispersion.

First, the findings reveal that inflation has distortionary effects on product-level relative prices also in environments with substantial inflation. The marginal effect of suboptimal inflation on price distortions are significant for all countries and sectors, with a more pronounced effect for restaurants. Second, I find that inflation is significantly associated with an increase in inefficient price dispersion. This relationship does not flatten out even at elevated levels of inflation, maintaining a distinct "V" shape around zero inflation. Analyzing the heterogeneity across sectors, I find that an increase of annualized inflation from zero to 10 percent is associated with an increase in inefficient price dispersion of 61% for restaurants and of 41% for supermarkets. This points to the importance of analyzing different sectors when analyzing the welfare costs of high inflation. Across countries, in contrast, the results do not vary significantly. Using a rough approximation, the cost of an increase in annualized inflation from zero to 10% is associated with a loss of around 0.50% in flexible price consumption. However, my results indicate that this estimate is highly sensitive to the time frequency used and the assumption of zero inflation price dispersion.

Finally, I show that a standard New Keynesian menu cost model fails to match key empirical moments associated with inflation-driven inefficient price dispersion. This indicates that these models may be inadequate for measuring the costs associated with inflation-driven inefficient price dispersion and that other models should be considered to derive the optimal level of inflation.

This paper suggests a sustained impact of inflation on inefficient price dispersion, implying that central banks should be cautious about accommodating higher inflation levels since these incur greater welfare costs than initially estimated. In future research, I aim to provide a deeper understanding of the role of sectoral heterogeneity in welfare analysis and the overall welfare costs of inflation. This will be crucial for informing monetary policy decisions aimed at minimizing the adverse effects of inflation on the economy.

find that about 6% of the price changes show some time dependence.

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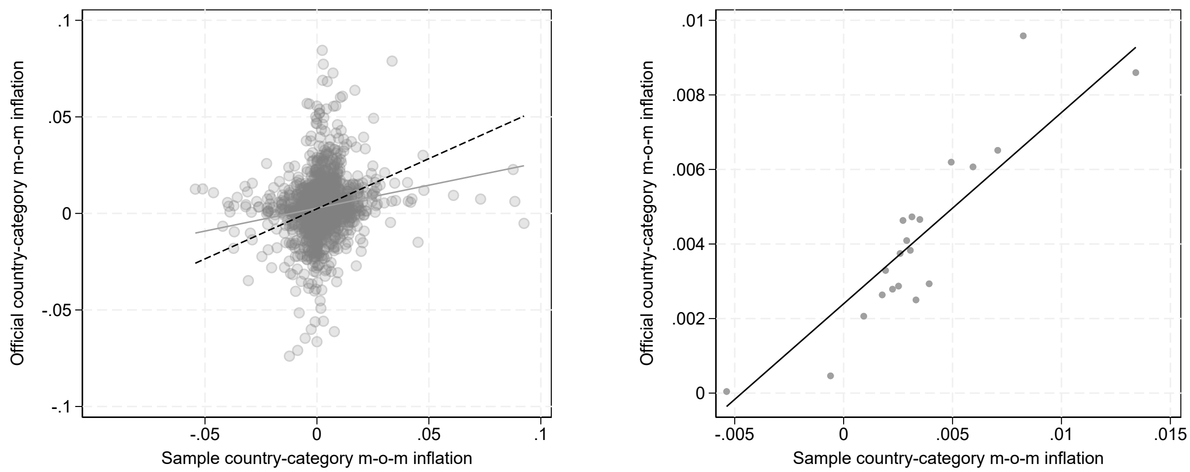
Appendix

A. Online Data Categories and Official Inflation

Figure A.1: Official vs. Online Data (monthly)



(a) Scatter (b) Bincatter

Notes: These figures display the monthly month-on-month inflation between April 2023 and May 2024 calculated from online data against the official value. Figure (a) includes 2,035 COICOP-country-month combinations and figure (b) 20 equally sized bins out of these observations. Two fitted lines are included in subfigure (a), one weigthing each observation with the number of products included (black dashed line) and one without weights (gray continuos line). Not including weights yields a slope of 0.17 and a R^2 of 0.018. Including weights yields a slope of 0.51 and a R^2 of 0.085.

Table A.1: Online Categories and COICOP Categories

	Sector	Online Category	COICOP Code	COICOP Category	COICOP Level
1	Restaurants	Beef Dish	11.1.1	Restaurants, cafés and the like	3
2	Restaurants	Beer	11.1.1	Restaurants, cafés and the like	3
3	Restaurants	Bento Box	11.1.1	Restaurants, cafés and the like	3
4	Restaurants	Bread, Focaccia, Naan	11.1.1	Restaurants, cafés and the like	3
5	Restaurants	Breakfast Plate	11.1.1	Restaurants, cafés and the like	3
6	Restaurants	Breakfast Scrambled Eggs	11.1.1	Restaurants, cafés and the like	3
7	Restaurants	Burger	11.1.1	Restaurants, cafés and the like	3
8	Restaurants	Burger Menu	11.1.1	Restaurants, cafés and the like	3
9	Restaurants	Burrito	11.1.1	Restaurants, cafés and the like	3
10	Restaurants	Cake	11.1.1	Restaurants, cafés and the like	3
11	Restaurants	Cheesecake	11.1.1	Restaurants, cafés and the like	3
12	Restaurants	Chicken Dish	11.1.1	Restaurants, cafés and the like	3
13	Restaurants	Cider	11.1.1	Restaurants, cafés and the like	3
14	Restaurants	Coffee	11.1.1	Restaurants, cafés and the like	3
15	Restaurants	Coke	11.1.1	Restaurants, cafés and the like	3
16	Restaurants	Croissants	11.1.1	Restaurants, cafés and the like	3
17	Restaurants	Dessert	11.1.1	Restaurants, cafés and the like	3
18	Restaurants	Dumplings	11.1.1	Restaurants, cafés and the like	3
19	Restaurants	Empanadas	11.1.1	Restaurants, cafés and the like	3
20	Restaurants	Energy Drinks	11.1.1	Restaurants, cafés and the like	3
21	Restaurants	Falafel	11.1.1	Restaurants, cafés and the like	3
22	Restaurants	Fish Dish	11.1.1	Restaurants, cafés and the like	3
23	Restaurants	Fried Chicken	11.1.1	Restaurants, cafés and the like	3
24	Restaurants	Fries	11.1.1	Restaurants, cafés and the like	3
25	Restaurants	Fruit Juice	11.1.1	Restaurants, cafés and the like	3
26	Restaurants	Hot Dog	11.1.1	Restaurants, cafés and the like	3
27	Restaurants	Ice Cream	11.1.1	Restaurants, cafés and the like	3
28	Restaurants	Ice Tea	11.1.1	Restaurants, cafés and the like	3
29	Restaurants	Kebab	11.1.1	Restaurants, cafés and the like	3
30	Restaurants	Lasagna	11.1.1	Restaurants, cafés and the like	3
31	Restaurants	Meatballs	11.1.1	Restaurants, cafés and the like	3
32	Restaurants	Milk Drink	11.1.1	Restaurants, cafés and the like	3
33	Restaurants	Mozzarella Sticks	11.1.1	Restaurants, cafés and the like	3
34	Restaurants	Noodles	11.1.1	Restaurants, cafés and the like	3
35	Restaurants	Other Meat Dish	11.1.1	Restaurants, cafés and the like	3
36	Restaurants	Pancakes	11.1.1	Restaurants, cafés and the like	3
37	Restaurants	Pasta Dish	11.1.1	Restaurants, cafés and the like	3
38	Restaurants	Piadina	11.1.1	Restaurants, cafés and the like	3
39	Restaurants	Pizza	11.1.1	Restaurants, cafés and the like	3
40	Restaurants	Poke Bowl	11.1.1	Restaurants, cafés and the like	3

41	Restaurants	Pork Dish	11.1.1	Restaurants, cafés and the like	3
42	Restaurants	Potatoes	11.1.1	Restaurants, cafés and the like	3
43	Restaurants	Quesadilla	11.1.1	Restaurants, cafés and the like	3
44	Restaurants	Rice Dish	11.1.1	Restaurants, cafés and the like	3
45	Restaurants	Salad	11.1.1	Restaurants, cafés and the like	3
46	Restaurants	Salty Pancakes	11.1.1	Restaurants, cafés and the like	3
47	Restaurants	Salty Pie Or Quiche	11.1.1	Restaurants, cafés and the like	3
48	Restaurants	Samosas	11.1.1	Restaurants, cafés and the like	3
49	Restaurants	Sandwich	11.1.1	Restaurants, cafés and the like	3
50	Restaurants	Sauce	11.1.1	Restaurants, cafés and the like	3
51	Restaurants	Schnitzel, Milanese, Cordon Bleu	11.1.1	Restaurants, cafés and the like	3
52	Restaurants	Sodas	11.1.1	Restaurants, cafés and the like	3
53	Restaurants	Soup	11.1.1	Restaurants, cafés and the like	3
54	Restaurants	Sparkling Wine	11.1.1	Restaurants, cafés and the like	3
55	Restaurants	Spring Rolls	11.1.1	Restaurants, cafés and the like	3
56	Restaurants	Strong Alcohols	11.1.1	Restaurants, cafés and the like	3
57	Restaurants	Sushi	11.1.1	Restaurants, cafés and the like	3
58	Restaurants	Tea	11.1.1	Restaurants, cafés and the like	3
59	Restaurants	Toast	11.1.1	Restaurants, cafés and the like	3
60	Restaurants	Vegetables	11.1.1	Restaurants, cafés and the like	3
61	Restaurants	Water Bottle	11.1.1	Restaurants, cafés and the like	3
62	Restaurants	Wine	11.1.1	Restaurants, cafés and the like	3
63	Restaurants	Wrap	11.1.1	Restaurants, cafés and the like	3
64	Restaurants	Yoghurt	11.1.1	Restaurants, cafés and the like	3
65	Supermarkets	Iron	-	-	-
66	Supermarkets	Kettle	-	-	-
67	Supermarkets	Mixed Drinks	-	-	-
68	Supermarkets	Puzzles	-	-	-
69	Supermarkets	Toys	-	-	-
70	Supermarkets	Bread (Not Toast Bread)	01.1.1	Bread and cereals	3
71	Supermarkets	Breakfast Cereals	01.1.1	Bread and cereals	3
72	Supermarkets	Cereal Bars	01.1.1	Bread and cereals	3
73	Supermarkets	Chips And Snacks	01.1.1	Bread and cereals	3
74	Supermarkets	Doughs	01.1.1	Bread and cereals	3
75	Supermarkets	Ebly, Barley And Quinoa	01.1.1	Bread and cereals	3
76	Supermarkets	Noodles, Rigatoni, Farfelle, Fusilli	01.1.1	Bread and cereals	3
77	Supermarkets	Other Flours And Starches	01.1.1	Bread and cereals	3
78	Supermarkets	Packed Toast Sliced Bread	01.1.1	Bread and cereals	3
79	Supermarkets	Pastries, Cakes And Confectionery	01.1.1	Bread and cereals	3
80	Supermarkets	Penne	01.1.1	Bread and cereals	3
81	Supermarkets	Popcorn	01.1.1	Bread and cereals	3
82	Supermarkets	Rice	01.1.1	Bread and cereals	3
83	Supermarkets	Rice Wafers	01.1.1	Bread and cereals	3
84	Supermarkets	Rusks, Crispbread, Crackers	01.1.1	Bread and cereals	3

85	Supermarkets	Semolina, Couscous, Boulgour And Polenta	01.1.1	Bread and cereals	3
86	Supermarkets	Spaghetti	01.1.1	Bread and cereals	3
87	Supermarkets	Sweet Biscuits	01.1.1	Bread and cereals	3
88	Supermarkets	Waffle Biscuit	01.1.1	Bread and cereals	3
89	Supermarkets	White Flour	01.1.1	Bread and cereals	3
90	Supermarkets	Beef (Offal And Liver Excluded)	01.1.2	Meat	3
91	Supermarkets	Burger (Meat)	01.1.2	Meat	3
92	Supermarkets	Cold Cuts, Ham, Beacon, Dried Meat, Mortadella	01.1.2	Meat	3
93	Supermarkets	Cordon Bleu, Schnitzel, Marinated Meat	01.1.2	Meat	3
94	Supermarkets	Horse, Wild, Rabbits Or Offal Or Liver, Fresh	01.1.2	Meat	3
95	Supermarkets	Minced Meat	01.1.2	Meat	3
96	Supermarkets	Pate	01.1.2	Meat	3
97	Supermarkets	Pork Meat (Offal And Liver Excluded)	01.1.2	Meat	3
98	Supermarkets	Poultry (Offal And Liver Excluded)	01.1.2	Meat	3
99	Supermarkets	Sausages	01.1.2	Meat	3
100	Supermarkets	Canned Tuna	01.1.3	Fish and seafood	3
101	Supermarkets	Fish, Fresh	01.1.3	Fish and seafood	3
102	Supermarkets	Fish, Frozen	01.1.3	Fish and seafood	3
103	Supermarkets	Other Preserved Fish	01.1.3	Fish and seafood	3
104	Supermarkets	Smoked Fish	01.1.3	Fish and seafood	3
105	Supermarkets	Almondmilk	01.1.4	Milk, cheese and eggs	3
106	Supermarkets	Blue Cheese	01.1.4	Milk, cheese and eggs	3
107	Supermarkets	Camembert, Brie, Moldcheese	01.1.4	Milk, cheese and eggs	3
108	Supermarkets	Cheese Sliced	01.1.4	Milk, cheese and eggs	3
109	Supermarkets	Choco Or Flavour Milk	01.1.4	Milk, cheese and eggs	3
110	Supermarkets	Cream	01.1.4	Milk, cheese and eggs	3
111	Supermarkets	Cream Or Fresh Cheese	01.1.4	Milk, cheese and eggs	3
112	Supermarkets	Dairy Dessert	01.1.4	Milk, cheese and eggs	3
113	Supermarkets	Eggs	01.1.4	Milk, cheese and eggs	3
114	Supermarkets	Feta	01.1.4	Milk, cheese and eggs	3
115	Supermarkets	Grated Cheese	01.1.4	Milk, cheese and eggs	3
116	Supermarkets	Hard Cheese	01.1.4	Milk, cheese and eggs	3
117	Supermarkets	Liquid Coffee	01.1.4	Milk, cheese and eggs	3
118	Supermarkets	Mascarpone	01.1.4	Milk, cheese and eggs	3
119	Supermarkets	Milk	01.1.4	Milk, cheese and eggs	3
120	Supermarkets	Mozzarella	01.1.4	Milk, cheese and eggs	3
121	Supermarkets	Oatmilk	01.1.4	Milk, cheese and eggs	3
122	Supermarkets	Powder Milk	01.1.4	Milk, cheese and eggs	3
123	Supermarkets	Ricemilk	01.1.4	Milk, cheese and eggs	3
124	Supermarkets	Ricotta	01.1.4	Milk, cheese and eggs	3
125	Supermarkets	Soymilk	01.1.4	Milk, cheese and eggs	3
126	Supermarkets	Spread Cheese	01.1.4	Milk, cheese and eggs	3
127	Supermarkets	Yoghurt Drink	01.1.4	Milk, cheese and eggs	3
128	Supermarkets	Yogurt	01.1.4	Milk, cheese and eggs	3

129	Supermarkets	Butter	01.1.5	Oils and fats	3
130	Supermarkets	Lard	01.1.5	Oils and fats	3
131	Supermarkets	Margarine	01.1.5	Oils and fats	3
132	Supermarkets	Olive Oil	01.1.5	Oils and fats	3
133	Supermarkets	Other Oil	01.1.5	Oils and fats	3
134	Supermarkets	Sunflower Oil	01.1.5	Oils and fats	3
135	Supermarkets	Apples	01.1.6	Fruit	3
136	Supermarkets	Avocados	01.1.6	Fruit	3
137	Supermarkets	Bananas	01.1.6	Fruit	3
138	Supermarkets	Berries	01.1.6	Fruit	3
139	Supermarkets	Dried Fruits, Nuts And Oilseeds	01.1.6	Fruit	3
140	Supermarkets	Frozen Fruits	01.1.6	Fruit	3
141	Supermarkets	Fruit Puree/Compote	01.1.6	Fruit	3
142	Supermarkets	Grapes	01.1.6	Fruit	3
143	Supermarkets	Kiwi	01.1.6	Fruit	3
144	Supermarkets	Lemons	01.1.6	Fruit	3
145	Supermarkets	Melon	01.1.6	Fruit	3
146	Supermarkets	Nectarines, Peaches And Apricots	01.1.6	Fruit	3
147	Supermarkets	Oranges	01.1.6	Fruit	3
148	Supermarkets	Other Fruit Preserves (Cherries, Apricots)	01.1.6	Fruit	3
149	Supermarkets	Other Fruits (Not In Other Categories)	01.1.6	Fruit	3
150	Supermarkets	Pears	01.1.6	Fruit	3
151	Supermarkets	Pineapple Fresh	01.1.6	Fruit	3
152	Supermarkets	Preserved Pineapples	01.1.6	Fruit	3
153	Supermarkets	Tangerin, Clementin, Mandarin	01.1.6	Fruit	3
154	Supermarkets	Broccoli	01.1.7	Vegetables	3
155	Supermarkets	Cabbage	01.1.7	Vegetables	3
156	Supermarkets	Canned Corn	01.1.7	Vegetables	3
157	Supermarkets	Carrots	01.1.7	Vegetables	3
158	Supermarkets	Cauliflower	01.1.7	Vegetables	3
159	Supermarkets	Cucumbers (Fresh)	01.1.7	Vegetables	3
160	Supermarkets	Frozen Vegetables	01.1.7	Vegetables	3
161	Supermarkets	Garlic	01.1.7	Vegetables	3
162	Supermarkets	Gherkins, Preserved Cucumbers	01.1.7	Vegetables	3
163	Supermarkets	Leek	01.1.7	Vegetables	3
164	Supermarkets	Lentils	01.1.7	Vegetables	3
165	Supermarkets	Mushrooms	01.1.7	Vegetables	3
166	Supermarkets	Olives	01.1.7	Vegetables	3
167	Supermarkets	Onions	01.1.7	Vegetables	3
168	Supermarkets	Other Fresh Vegetables (Not In Other Categories)	01.1.7	Vegetables	3
169	Supermarkets	Other Potato Products	01.1.7	Vegetables	3
170	Supermarkets	Other Preserved Vegetables	01.1.7	Vegetables	3
171	Supermarkets	Pepperoni, Bell Pepper	01.1.7	Vegetables	3
172	Supermarkets	Potatoes	01.1.7	Vegetables	3

173	Supermarkets	Preserved Mushrooms	01.1.7	Vegetables	3
174	Supermarkets	Preserved Peas, Chickpeas And Beans	01.1.7	Vegetables	3
175	Supermarkets	Salads, Lettuces, Chicory	01.1.7	Vegetables	3
176	Supermarkets	Tomato Puree, Mashed, Peeled	01.1.7	Vegetables	3
177	Supermarkets	Tomatoes (Fresh)	01.1.7	Vegetables	3
178	Supermarkets	Zucchini	01.1.7	Vegetables	3
179	Supermarkets	Candy	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
180	Supermarkets	Chewing Gum	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
181	Supermarkets	Chocolate Bar	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
182	Supermarkets	Chocolate Candy (Mars, KitKat...)	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
183	Supermarkets	Chocolate Spread (Nutella,…)	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
184	Supermarkets	Cocoa Powder	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
185	Supermarkets	Honey	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
186	Supermarkets	Ice Cream	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
187	Supermarkets	Jam	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
188	Supermarkets	Peanut Butter	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
189	Supermarkets	Pralines And Bonbons	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
190	Supermarkets	Sugar	01.1.8	Sugar, jam, honey, chocolate and confectionery	3
191	Supermarkets	Baby Food	01.1.9	Food products n.e.c.	3
192	Supermarkets	Baking Ingredients (Baking Powder, Vanilla Sugar,…)	01.1.9	Food products n.e.c.	3
193	Supermarkets	Broth, Bouillon Cubes	01.1.9	Food products n.e.c.	3
194	Supermarkets	Cake And Pudding Mixes	01.1.9	Food products n.e.c.	3
195	Supermarkets	Fresh Pasta	01.1.9	Food products n.e.c.	3
196	Supermarkets	Ketchup	01.1.9	Food products n.e.c.	3
197	Supermarkets	Liquid Sauce	01.1.9	Food products n.e.c.	3
198	Supermarkets	Liquid Soup	01.1.9	Food products n.e.c.	3
199	Supermarkets	Mayonnaise	01.1.9	Food products n.e.c.	3
200	Supermarkets	Mustard	01.1.9	Food products n.e.c.	3
201	Supermarkets	Pepper Corns Or Powder	01.1.9	Food products n.e.c.	3
202	Supermarkets	Pizza And Quiche	01.1.9	Food products n.e.c.	3
203	Supermarkets	Ready-To-Cook Foods (Pizza Not Included)	01.1.9	Food products n.e.c.	3
204	Supermarkets	Salt	01.1.9	Food products n.e.c.	3
205	Supermarkets	Seasoning Mix	01.1.9	Food products n.e.c.	3
206	Supermarkets	Soups	01.1.9	Food products n.e.c.	3
207	Supermarkets	Soy Sauce	01.1.9	Food products n.e.c.	3
208	Supermarkets	Spices And Herbs Other Than Pepper	01.1.9	Food products n.e.c.	3
209	Supermarkets	Spread Salted	01.1.9	Food products n.e.c.	3
210	Supermarkets	Tofu	01.1.9	Food products n.e.c.	3
211	Supermarkets	Vinegar	01.1.9	Food products n.e.c.	3
212	Supermarkets	Coffee	01.2.1	Coffee, tea and cocoa	3
213	Supermarkets	Coffee Capsules	01.2.1	Coffee, tea and cocoa	3
214	Supermarkets	Instant Coffee	01.2.1	Coffee, tea and cocoa	3
215	Supermarkets	Juices	01.2.1	Coffee, tea and cocoa	3
216	Supermarkets	Tea (Not Liquid)	01.2.1	Coffee, tea and cocoa	3

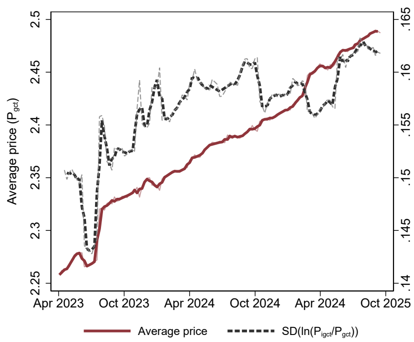
217	Supermarkets	Energy Drinks	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
218	Supermarkets	Icetea	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
219	Supermarkets	Isotonic	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
220	Supermarkets	Sodas	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
221	Supermarkets	Syrup	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
222	Supermarkets	Water	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
223	Supermarkets	Brandies And Liqueurs (Cointreu, Cognac...)	02.1.1	Spirits	3
224	Supermarkets	Gin	02.1.1	Spirits	3
225	Supermarkets	Martini, Porto, Sherry, Vermout, Bitters, Aperitif	02.1.1	Spirits	3
226	Supermarkets	Rum	02.1.1	Spirits	3
227	Supermarkets	Tequila	02.1.1	Spirits	3
228	Supermarkets	Vodka	02.1.1	Spirits	3
229	Supermarkets	Whiskey	02.1.1	Spirits	3
230	Supermarkets	Red Wine	02.1.2	Wine	3
231	Supermarkets	Rosé Wine	02.1.2	Wine	3
232	Supermarkets	Sparkling Wine	02.1.2	Wine	3
233	Supermarkets	White Wine	02.1.2	Wine	3
234	Supermarkets	Beer	02.1.3	Beer	3
235	Supermarkets	Cider	02.1.3	Beer	3
236	Supermarkets	Cigarettes	02.3	Narcotics	2
237	Supermarkets	Bowl	05.4	Glassware, tableware and household utensils	2
238	Supermarkets	Cup, Mug	05.4	Glassware, tableware and household utensils	2
239	Supermarkets	Cutlery	05.4	Glassware, tableware and household utensils	2
240	Supermarkets	Dinner Plate	05.4	Glassware, tableware and household utensils	2
241	Supermarkets	Other Kitchen Utensils	05.4	Glassware, tableware and household utensils	2
242	Supermarkets	Pots, Pans	05.4	Glassware, tableware and household utensils	2
243	Supermarkets	Tablecloths	05.4	Glassware, tableware and household utensils	2
244	Supermarkets	Water, Wine Or Beer Glass	05.4	Glassware, tableware and household utensils	2
245	Supermarkets	Batteries	05.5.2.2	Miscellaneous small tool accessories	4
246	Supermarkets	Candles	05.5.2.2	Miscellaneous small tool accessories	4
247	Supermarkets	Light Bulb, Fluorescent Tubes	05.5.2.2	Miscellaneous small tool accessories	4
248	Supermarkets	Air Freshener	05.6.1	Non-durable household goods	3
249	Supermarkets	Aluminum Foil	05.6.1	Non-durable household goods	3
250	Supermarkets	Baking Paper	05.6.1	Non-durable household goods	3
251	Supermarkets	Broom	05.6.1	Non-durable household goods	3
252	Supermarkets	Cleaning Agents	05.6.1	Non-durable household goods	3
253	Supermarkets	Cleaning Rags And Clothes	05.6.1	Non-durable household goods	3
254	Supermarkets	Cling Film	05.6.1	Non-durable household goods	3
255	Supermarkets	Dishwashing Liquid	05.6.1	Non-durable household goods	3
256	Supermarkets	Disposable Cleaning Wipes	05.6.1	Non-durable household goods	3
257	Supermarkets	Disposable Tableware	05.6.1	Non-durable household goods	3
258	Supermarkets	Floor Mop Or Cleaning System	05.6.1	Non-durable household goods	3
259	Supermarkets	Garbage Bags	05.6.1	Non-durable household goods	3
260	Supermarkets	Glass Cleaner	05.6.1	Non-durable household goods	3

261	Supermarkets	Gloves	05.6.1	Non-durable household goods	3
262	Supermarkets	Glue	05.6.1	Non-durable household goods	3
263	Supermarkets	Insecticide/Repellent	05.6.1	Non-durable household goods	3
264	Supermarkets	Kitchen Paper Rolls	05.6.1	Non-durable household goods	3
265	Supermarkets	Laundry Detergent	05.6.1	Non-durable household goods	3
266	Supermarkets	Laundry Softener	05.6.1	Non-durable household goods	3
267	Supermarkets	Powder Or Tabs For Dishwashers	05.6.1	Non-durable household goods	3
268	Supermarkets	Rinse Aid For Dishwashers	05.6.1	Non-durable household goods	3
269	Supermarkets	Shoe Care	05.6.1	Non-durable household goods	3
270	Supermarkets	Sponges	05.6.1	Non-durable household goods	3
271	Supermarkets	Storage Bags	05.6.1	Non-durable household goods	3
272	Supermarkets	Toilet Hanger	05.6.1	Non-durable household goods	3
273	Supermarkets	Cat Food	09.3.4	Pets and related products	3
274	Supermarkets	Cat-Dog Treats	09.3.4	Pets and related products	3
275	Supermarkets	Dog Food	09.3.4	Pets and related products	3
276	Supermarkets	Other Animal Feed	09.3.4	Pets and related products	3
277	Supermarkets	Pet Items Other Than Food	09.3.4	Pets and related products	3
278	Supermarkets	Books	09.5.1	Books	3
279	Supermarkets	Colors And Crayons For Drawing	09.5.4	Stationery and drawing materials	3
280	Supermarkets	Pens And Pencils	09.5.4	Stationery and drawing materials	3
281	Supermarkets	Scissors	09.5.4	Stationery and drawing materials	3
282	Supermarkets	Writing Pad, Notebooks	09.5.4	Stationery and drawing materials	3
283	Supermarkets	Blade Razor	12.1.3	Other appliances, articles and products for personal care	3
284	Supermarkets	Body Milk/Cream	12.1.3	Other appliances, articles and products for personal care	3
285	Supermarkets	Condoms	12.1.3	Other appliances, articles and products for personal care	3
286	Supermarkets	Cotton Rondelles	12.1.3	Other appliances, articles and products for personal care	3
287	Supermarkets	Cotton Sticks	12.1.3	Other appliances, articles and products for personal care	3
288	Supermarkets	Dental Floss	12.1.3	Other appliances, articles and products for personal care	3
289	Supermarkets	Deodorant	12.1.3	Other appliances, articles and products for personal care	3
290	Supermarkets	Depilation Sheets And Cream	12.1.3	Other appliances, articles and products for personal care	3
291	Supermarkets	Diapers	12.1.3	Other appliances, articles and products for personal care	3
292	Supermarkets	Face Cream	12.1.3	Other appliances, articles and products for personal care	3
293	Supermarkets	Facial Cleansing	12.1.3	Other appliances, articles and products for personal care	3
294	Supermarkets	Hair Conditioner	12.1.3	Other appliances, articles and products for personal care	3
295	Supermarkets	Hair Dye	12.1.3	Other appliances, articles and products for personal care	3
296	Supermarkets	Hair Styling Gel	12.1.3	Other appliances, articles and products for personal care	3
297	Supermarkets	Hairspray	12.1.3	Other appliances, articles and products for personal care	3
298	Supermarkets	Hand Or Foot Cream	12.1.3	Other appliances, articles and products for personal care	3
299	Supermarkets	Handkerchiefs Packets	12.1.3	Other appliances, articles and products for personal care	3
300	Supermarkets	Lipstick	12.1.3	Other appliances, articles and products for personal care	3
301	Supermarkets	Liquid Soap	12.1.3	Other appliances, articles and products for personal care	3
302	Supermarkets	Makeup	12.1.3	Other appliances, articles and products for personal care	3
303	Supermarkets	Manicure And Pedicure	12.1.3	Other appliances, articles and products for personal care	3
304	Supermarkets	Mouthwash	12.1.3	Other appliances, articles and products for personal care	3

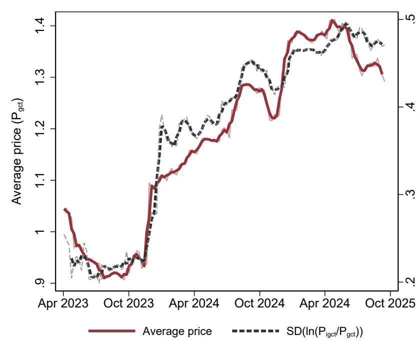
305	Supermarkets	Nail Lacquer	12.1.3	Other appliances, articles and products for personal care	3
306	Supermarkets	Nail Polish Remover, Acetone	12.1.3	Other appliances, articles and products for personal care	3
307	Supermarkets	Paper Napkins	12.1.3	Other appliances, articles and products for personal care	3
308	Supermarkets	Perfume, Eau De Toilette	12.1.3	Other appliances, articles and products for personal care	3
309	Supermarkets	Quick Bandages, Band-Aids	12.1.3	Other appliances, articles and products for personal care	3
310	Supermarkets	Sanitary Napkins	12.1.3	Other appliances, articles and products for personal care	3
311	Supermarkets	Shampoo	12.1.3	Other appliances, articles and products for personal care	3
312	Supermarkets	Shaving Care	12.1.3	Other appliances, articles and products for personal care	3
313	Supermarkets	Soap Bar	12.1.3	Other appliances, articles and products for personal care	3
314	Supermarkets	Sunscreen	12.1.3	Other appliances, articles and products for personal care	3
315	Supermarkets	Tampons	12.1.3	Other appliances, articles and products for personal care	3
316	Supermarkets	Tissues In A Box	12.1.3	Other appliances, articles and products for personal care	3
317	Supermarkets	Toilet Paper Roll	12.1.3	Other appliances, articles and products for personal care	3
318	Supermarkets	Toothbrush Replacements	12.1.3	Other appliances, articles and products for personal care	3
319	Supermarkets	Toothbrush, Manual	12.1.3	Other appliances, articles and products for personal care	3
320	Supermarkets	Toothpaste	12.1.3	Other appliances, articles and products for personal care	3
321	Supermarkets	Wet Wipes	12.1.3	Other appliances, articles and products for personal care	3

Notes: this table includes a list of the categories used for the categorization of the online products (online category) and the associated COICOP category with the respective code and level.

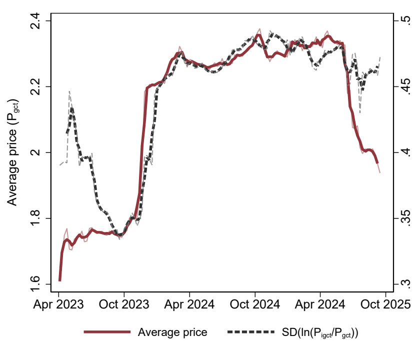
Figure B.2: Prices and Price Dispersion for Additional Specific Products



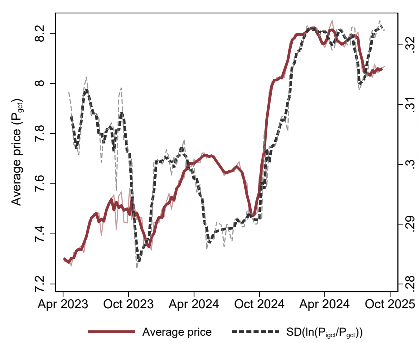
(a) Coke Can 330 ML, Restaurants (Madrid, ES)



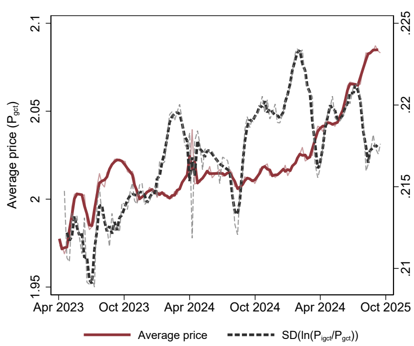
(b) Coke Can 330 ML, Supermarkets (Madrid, ES)



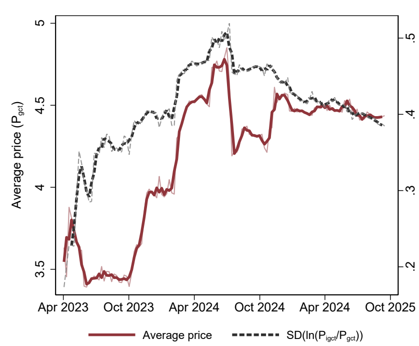
(c) 400-500 gr Pasta Package, Supermarkets (Madrid, ES)



(d) Salmon maki 8 units, Restaurants (Madrid, ES)



(e) Water bottle 500 ml, Restaurants (Madrid, ES)



(f) 350-450 ml Shampoo, Supermarkets (Madrid, ES)

Notes: These figures display the dynamics of average prices and dispersion of relative prices for additional very narrowly defined products in Madrid.

B. Robustness Inflation and Cross-Sectional Price Dispersion

Table B.2: Price Dispersion and Inflation Comovement Additional Robustness Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$
$\lvert\Delta p^{Annual}_{gct-4}\rvert$	0.124***	0.124***	0.124***	0.221***	0.084***	0.214***	0.099***	0.090***	0.139***	0.211***	0.226***
	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.001)	(0.003)	(0.005)	(0.006)
$\lvert\Delta p^{Annual}_{gct-4}\rvert^2$						-0.596***				-0.569***	-0.718***
						(0.020)				(0.024)	(0.031)
SD at $\pi = 0$	0.028	0.027	0.028	0.025	0.034	0.026	0.027	0.032	0.019	0.030	0.018
SD at $\pi = 10\%$	0.040	0.040	0.040	0.047	0.042	0.041	0.037	0.041	0.033	0.045	0.033
Change in %	37.23%	37.68%	36.96%	63.98%	22.18%	46.82%	31.19%	25.17%	55.83%	41.44%	62.14%
Restriction	$N_{gct} \geq 50$	$N_{gct} \geq 20$	$N_{gct} \geq 100$	$\lvert\Delta_4 p\rvert \leq 5\%$	$\lvert\Delta_4 p\rvert \geq 5\%$	Quadratic	Trimmed p95	Trimmed p95	Trimmed p95	Quadratic	Quadratic
Sector	Both	Both	Both	Both	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants
N	374,233	469,445	286,006	243,690	130,543	374,233	365,661	245,134	120,369	244,996	129,237
R^2	0.35	0.32	0.38	0.30	0.23	0.36	0.35	0.23	0.29	0.24	0.32
Within R^2	0.13	0.12	0.14	0.06	0.04	0.14	0.14	0.13	0.22	0.12	0.26

Notes: This table shows for each city separately the relation of the category-city-week standard deviation of product level residuals u_{irgct} from equation (3.2) the category-city weekly month-on-month inflation, $\lvert\Delta p_{gct-4}\rvert$. All specifications include category fixed-effects. Standard errors clustered at the category-city level in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.3: Price Dispersion and Inflation Comovement with Date×City FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\text{SD}^{gc}_t(u_{irgct})$	$\text{SD}^{gc}_t(u_{irgct})$	$\text{SD}^{gc}_t(u_{irgct})$	$\text{SD}^{gc}_t(u_{irgct})$	$\text{SD}^{gc}_t(u_{irgct})$	$\log(\text{SD}^{gc}_t(u_{irgct}))$	$\log(\text{SD}^{gc}_t(u_{irgct}))$	$\text{SD}^{gc}_t(\varepsilon_{irgct})$	$\text{SD}^{vgc}_t(\ln p_{irgct})$	$\Delta\text{SD}^{gc}_t(p_{irgct})$
$\lvert\Delta p^{Annual}_{gct-4}\rvert$	0.083***	0.050***		0.078***	0.062***	2.401***	2.846***	0.075***		0.030***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.06)	(0.13)	(0.00)		(0.00)
$\lvert\Delta p^{Annual}_{gct}\rvert$			0.047***							
			(0.00)							
$\lvert\Delta p^{Annual}_{vgct-4}\rvert$									0.153***	
									(0.03)	
Sector	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants	Both	Both	Both
Cat. FEs	Y	N	Y	Y	Y	Y	Y	Y	Y	N
Cat.× City FEs	N	Y	N	N	N	N	N	N	N	N
Cat.× Vol FEs	N	N	N	N	N	N	N	N	Y	N
N	374,233	374,216	323,362	244,992	129,237	244,988	129,237	374,233	39,120	381,788
R^2	0.55	0.76	0.53	0.51	0.74	0.30	0.39	0.58	0.55	0.03
Within R^2	0.08	0.05	0.04	0.06	0.11	0.01	0.02	0.05	0.00	0.01

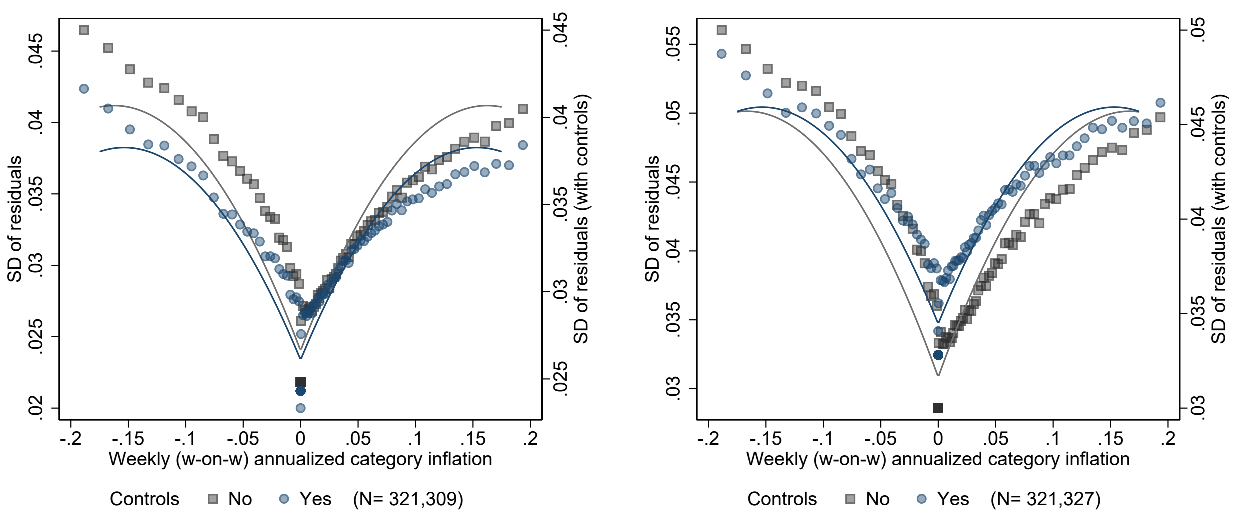
Notes: This table shows the relation of different weekly measures of cross-sectional price dispersion and inflation at the category-(product volume)-city level. All specifications include Date×Week fixed effects. The measures of price price dispersion considered are the category-city-week standard deviation of product level residuals u_{irgct} from equation (3.2), $\text{SD}_{gct}(u_{irgct})$, the category-city-week standard deviation of product level residualized log-prices, $\text{SD}_{gct}(\varepsilon_{irgct})$, the category-product volume-city-week standard deviation of log prices ($\text{SD}_{vgct}(\ln p_{irgct})$) calculated for homogeneous beverages categories and the change in the category-city-week standard deviation of log prices based on a balanced sample of products available in t and $t-1$ ($\Delta\text{SD}_{gct}(p_{irgct})$). The explanatory variables are either the category-city weekly month-on-month or week on week inflation, $\lvert\Delta p_{gct-4}\rvert$ and $\lvert\Delta p_{gct}\rvert$ respectively, and the category-volume-city weekly month-on-month inflation ($\lvert\Delta p_{vgct-4}\rvert$). Standard errors clustered at the category-city level in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.4: Price Dispersion and Inflation Comovement with Additional Category×City FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$SD_t^{gc}(u_{irgct})$	$SD_t^{gc}(u_{irgct})$	$SD_t^{gc}(u_{irgct})$	$SD_t^{gc}(u_{irgct})$	$SD_t^{gc}(u_{irgct})$	$\log(SD_t^{gc}(u_{irgct}))$	$\log(SD_t^{gc}(u_{irgct}))$	$SD_t^{gc}(\varepsilon_{irgct})$	$SD_t^{vgc}(\ln p_{irgct})$	$\Delta SD_t^{gc}(p_{irgct})$
$\lvert\Delta p_{gct-4}^{Annual}\rvert$	0.124***	0.061***		0.062***	0.058***	1.858***	2.425***	0.050***		0.033***
	(0.00)	(0.00)		(0.00)	(0.00)	(0.04)	(0.06)	(0.00)		(0.00)
$\lvert\Delta p_{gct}^{Annual}\rvert$			0.015***							
			(0.00)							
$\lvert\Delta p_{vgct-4}^{Annual}\rvert$									0.009	
									(0.01)	
Sector	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants	Both	Both	Both
Cat. FEs	Y	N	Y	Y	Y	Y	Y	Y	Y	N
Cat.× City FEs	N	Y	N	N	N	N	N	N	N	N
Cat.× Vol FEs	N	N	N	N	N	N	N	N	Y	N
N	374,233	374,216	371,486	244,980	129,236	244,976	129,236	374,216	39,166	381,788
R^2	0.35	0.69	0.69	0.63	0.71	0.75	0.86	0.75	0.97	0.01
Within R^2	0.13	0.06	0.06	0.06	0.10	0.02	0.06	0.04	0.00	0.01

Notes: This table shows the relation of different weekly measures of cross-sectional price dispersion and inflation at the category-(product volume)-city level. The measures of price price dispersion considered are the category-city-week standard deviation of product level residuals u_{irgct} from equation (3.2), $SD_{gct}(u_{irgct})$, the category-city-week standard deviation of product level residualized log-prices, $SD_{gct}(\varepsilon_{irgct})$, the category-product volume-city-week standard deviation of log prices ($SD_{vgct}(\ln p_{irgct})$) calculated for homogeneous beverages categories and the change in the category-city-week standard deviation of log prices based on a balanced sample of products available in t and $t-1$ ($\Delta SD_{gct}(p_{irgct})$). The explanatory variables are either the category-city weekly month-on-month or week on week inflation, $\lvert\Delta p_{gct-4}\rvert$ and $\lvert\Delta p_{gct}\rvert$ respectively, and the category-volume-city weekly month-on-month inflation ($\lvert\Delta p_{vgct-4}\rvert$). Standard errors clustered at the category-city level in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure B.3: Price Dispersion and Inflation



(a) $SD_t^g(u_{irgct})$ and w-on-w inflation

(b) $SD_t^g(\varepsilon_{irgct})$ and w-on-w inflation

Notes: These binscatters display the relation of inflation and different measures of price dispersion. Each dot corresponds to the average price dispersion for 100 equally sized inflation bins. The unit of observation is a category × city × week. The number of category × city × week included in panels (a) and (b) are 321,309 and 321,327, respectively. One bin represents around over 3,000 category × city × week combinations.

Table B.5: Price Dispersion and Inflation Comovement by City

	β	Observations	R^2	Within R^2
AM	0.089***	12,572	0.50	0.15
	(0.01)			
CI	0.055***	18,244	0.47	0.07
	(0.00)			
ES (Madrid)	0.053***	30,231	0.67	0.08
	(0.00)			
ES (Barcelona)	0.046***	32,109	0.62	0.06
	(0.00)			
ES (Valencia)	0.042***	4,019	0.65	0.06
	(0.00)			
GE	0.098***	17,204	0.50	0.12
	(0.01)			
GH	0.045***	3,244	0.54	0.04
	(0.01)			
HR	0.040***	15,602	0.56	0.02
	(0.00)			
IT (Rome)	0.064***	29,503	0.69	0.06
	(0.00)			
IT (Milan)	0.041***	28,122	0.71	0.04
	(0.00)			
IT (Naples)	0.098***	1,333	0.55	0.24
	(0.02)			
KE	0.089***	29,800	0.54	0.13
	(0.00)			
KG	0.062***	14,226	0.45	0.11
	(0.00)			
KZ	0.039***	17,409	0.57	0.02
	(0.00)			
MA	0.097***	25,516	0.68	0.07
	(0.00)			
PL (Warsaw)	0.051***	20,559	0.53	0.05
	(0.00)			
PL (Krakow)	0.050***	2,944	0.76	0.07
	(0.01)			
PT (Lisbon)	0.064***	9,418	0.75	0.08
	(0.01)			
PT (Porto)	0.034***	3,859	0.84	0.03
	(0.01)			
RO	0.054***	20,517	0.59	0.04
	(0.00)			
SI	0.076***	3,698	0.69	0.09
	(0.01)			
TN	0.073***	4,884	0.40	0.13
	(0.01)			
UA	0.053***	10,658	0.68	0.05
	(0.00)			
UG	0.071***	18,545	0.46	0.09
	(0.00)			

Notes: This table shows for each city separately the relation of the category-city-week standard deviation of product level residuals u_{irgct} from equation (3.2) the category-city weekly month-on-month inflation, $|\Delta p_{gct-4}|$. All specifications include category fixed-effects. Regressing the 24 city-specific estimates on the median category inflation in that city yields a coefficient of -0.654 with a standard error of 0.236, with a R^2 of 0.26. Standard errors clustered at the category level in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C. Additional Price Setting Moments and Parameterization

I follow Klenow and Kryvtsov (2008) and calculate for each price change Δp_{igt} of product i belonging to category g the standardized price change,

$$\hat{\Delta} p_{igct} = \frac{\Delta p_{igct} - \Delta p_{gct}}{\sigma_{\Delta p_{igt},gc}} \sigma_{\Delta p_{igct},c} + \Delta p_{ct} \tag{C.1}$$

where Δp_{gct} and Δp_{ct} are the category-city and city averages of non-zero price changes and $\sigma_{\Delta p_{igt},gc}$ and $\sigma_{\Delta p_{igt},c}$ the standard deviations, respectively.

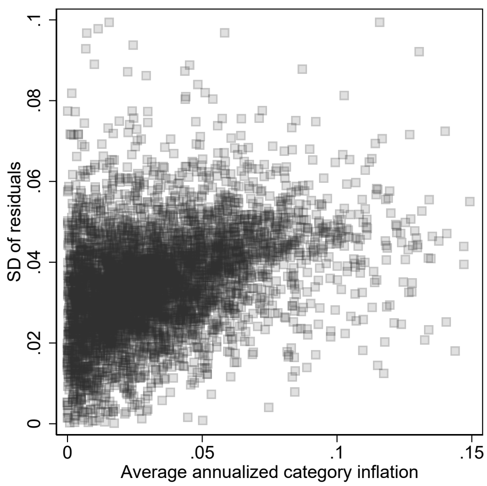
Table C.6: Additional Moments on Adjusted Price Changes

Supermarkets	Mean Frac. Δp_{it}	Share Adj $\Delta p_{it} > 0$	Mean $\lvert\Delta p_{it}\rvert$	Median $\lvert\Delta p_{it}\rvert$	std. dev. $\lvert\Delta p_{it}\rvert$	Kurtosis $\lvert\Delta p_{it}\rvert$	Kurtosis $^{adj}\lvert\Delta p_{it}\rvert$	Pctl 25 Δp_t	Pctl 75 Δp_t
AM	0.018	0.566	0.105	0.080	0.086	3.532	1.455	-0.372	1.734
CI	0.028	0.709	0.098	0.070	0.081	4.387	2.012	2.027	5.466
ES (Madrid)	0.073	0.560	0.078	0.056	0.066	4.033	1.690	0.579	5.027
ES (Barcelona)	0.060	0.563	0.080	0.056	0.072	4.200	1.703	0.728	4.655
ES (Valencia)	0.062	0.522	0.065	0.044	0.061	5.728	1.742	0.151	1.687
GE	0.033	0.569	0.173	0.158	0.117	2.248	1.457	0.337	3.528
GH	0.030	0.552	0.154	0.132	0.107	2.954	2.116	0.277	3.474
HR	0.055	0.571	0.150	0.105	0.124	2.177	1.438	0.562	5.633
IT (Rome)	0.048	0.538	0.136	0.100	0.110	2.643	1.242	-0.598	2.584
IT (Milan)	0.058	0.532	0.116	0.082	0.099	3.431	1.273	-0.207	4.903
IT (Naples)	-	-	-	-	-	-	-	-	-
KE	0.024	0.648	0.106	0.085	0.083	3.609	1.731	1.517	5.968
KG	0.041	0.601	0.084	0.064	0.069	3.888	1.815	1.081	4.963
KZ	0.075	0.557	0.142	0.113	0.111	2.442	1.455	-0.788	6.424
MA	0.052	0.526	0.106	0.079	0.095	3.552	1.730	0.015	3.299
PL (Warsaw)	0.079	0.565	0.143	0.125	0.100	2.604	1.331	-1.114	4.656
PL (Krakow)	0.078	0.534	0.133	0.114	0.093	2.696	1.435	-0.218	3.818
PT (Lisbon)	0.049	0.522	0.181	0.187	0.117	1.846	1.152	-0.281	2.096
PT (Porto)	0.069	0.563	0.178	0.186	0.119	1.776	1.221	-0.832	3.758
RO	0.102	0.564	0.115	0.082	0.101	2.983	1.602	0.756	7.986
SI	0.064	0.531	0.225	0.242	0.097	2.565	1.174	0.313	4.066
TN	0.056	0.535	0.099	0.070	0.087	3.482	1.466	0.777	3.718
UA	0.144	0.585	0.145	0.116	0.113	2.262	1.432	1.956	9.506
UG	0.023	0.570	0.091	0.065	0.080	4.472	1.445	-0.026	1.879
All (mean)	0.057	0.565	0.126	0.105	0.095	3.196	1.527	0.277	4.564
Restaurants	Mean Frac. Δp_{it}	Share Adj $\Delta p_{it} > 0$	Mean $\lvert\Delta p_{it}\rvert$	Median $\lvert\Delta p_{it}\rvert$	std. dev. $\lvert\Delta p_{it}\rvert$	Kurtosis $\lvert\Delta p_{it}\rvert$	Kurtosis $^{adj}\lvert\Delta p_{it}\rvert$	Pctl 25 Δp_t	Pctl 75 Δp_t
AM	0.007	0.778	0.126	0.107	0.086	3.375	1.733	1.379	3.210
CI	0.008	0.795	0.172	0.156	0.088	3.039	1.624	1.469	4.751
ES (Madrid)	0.012	0.726	0.111	0.091	0.082	3.688	1.568	2.231	3.457
ES (Barcelona)	0.011	0.734	0.121	0.096	0.091	3.478	1.727	2.425	3.574
ES (Valencia)	0.010	0.776	0.109	0.093	0.077	3.485	1.526	1.968	3.037
GE	0.017	0.762	0.122	0.099	0.086	3.550	1.742	3.224	4.928
GH	0.021	0.910	0.137	0.114	0.097	3.314	2.916	5.908	14.546
HR	0.017	0.865	0.116	0.098	0.082	3.979	1.960	4.830	7.877
IT (Rome)	0.007	0.758	0.137	0.119	0.084	3.379	1.490	1.753	2.847
IT (Milan)	0.007	0.774	0.135	0.115	0.087	3.384	1.590	1.664	3.338
IT (Naples)	0.007	0.751	0.143	0.129	0.084	3.263	1.389	1.834	2.703
KE	0.011	0.773	0.141	0.118	0.099	2.897	1.511	1.436	4.762
KG	0.023	0.821	0.097	0.077	0.073	4.455	2.538	4.346	7.293
KZ	0.019	0.820	0.115	0.094	0.083	3.811	2.171	5.209	7.621
MA	0.013	0.701	0.136	0.118	0.086	3.224	1.920	1.583	4.378
PL (Warsaw)	0.023	0.804	0.106	0.081	0.081	3.965	1.842	4.323	7.146
PL (Krakow)	0.017	0.790	0.091	0.075	0.068	4.242	1.824	2.930	3.835
PT (Lisbon)	0.009	0.726	0.138	0.113	0.100	3.051	1.654	1.781	2.985
PT (Porto)	0.010	0.793	0.124	0.101	0.092	3.437	1.503	1.534	3.900
RO	0.022	0.819	0.129	0.101	0.097	3.281	1.816	5.636	8.603
SI	0.012	0.921	0.099	0.082	0.070	4.283	2.214	3.291	6.569
TN	0.016	0.828	0.116	0.099	0.075	4.022	1.951	3.710	5.954
UA	0.034	0.818	0.104	0.080	0.086	4.332	1.867	6.613	10.667
UG	0.011	0.861	0.157	0.143	0.099	2.722	1.773	2.082	4.855
All (mean)	0.014	0.796	0.124	0.104	0.085	3.569	1.827	2.368	5.778

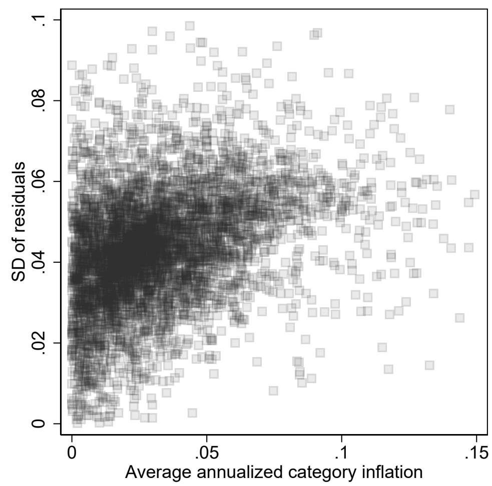
Notes: Moments calculated separately by sector and using standardized price adjustments. Standardization performed separately for each sector.

D. Price Dispersion and Annualized Inflation

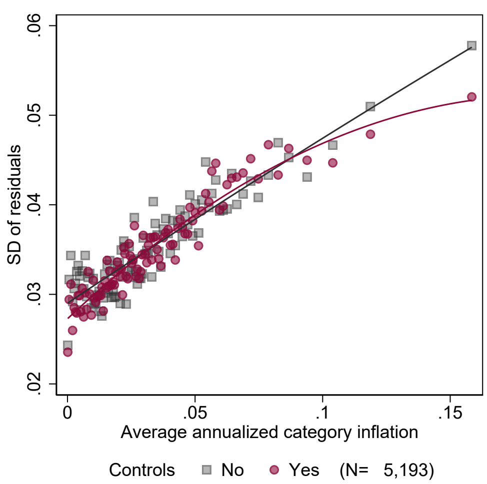
Figure D.4: Average Price Dispersion and Annualized Inflation When $N_{gc}^{i} > 50$



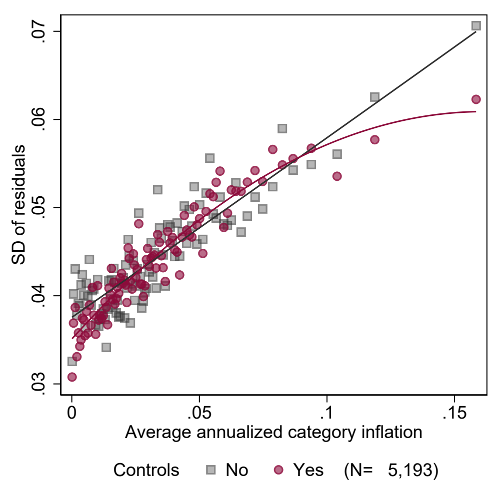
(a) $\mathrm{SD}_t^g(u_{irgct})$ and $N_{gc}^{i} > 50$



(b) $\mathrm{SD}_t^g(\varepsilon_{irgct})$ and $N_{gc}^{i} > 50$



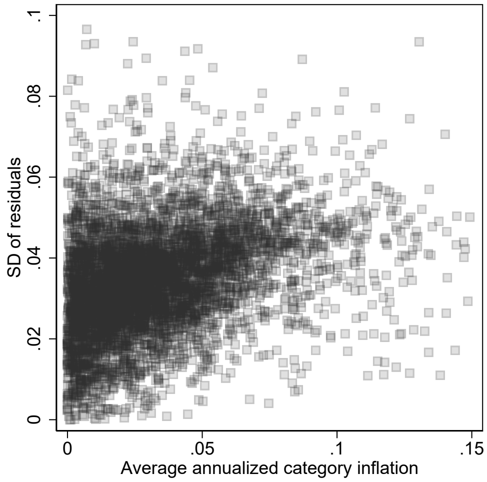
(c) $\mathrm{SD}_t^g(u_{irgct})$ and $N_{gc}^{i} > 50$



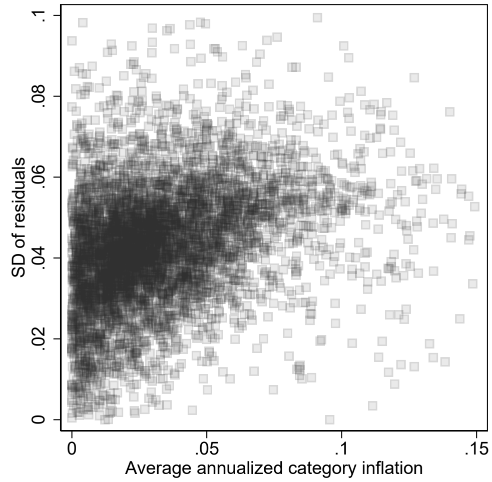
(d) $\mathrm{SD}_t^g(\varepsilon_{irgct})$ and $N_{gc}^{i} > 50$

Notes: This figure shows the relationship of the city-category average price dispersion and the average city-category inflation across all weeks annualized for product-city combinations in scatters and binscatters. The coloured bins are based on the residualized variables after controlling for category fixed effects and number of products included in the category-city combination. Only city-categories observed in at least 52 weeks and with at least 50 products included, this is 5,193 observations.

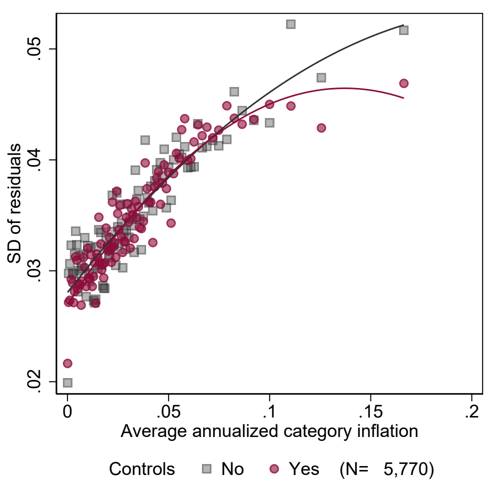
Figure D.5: Average Price Dispersion and Annualized Inflation When $N^i_{gc} > 25$



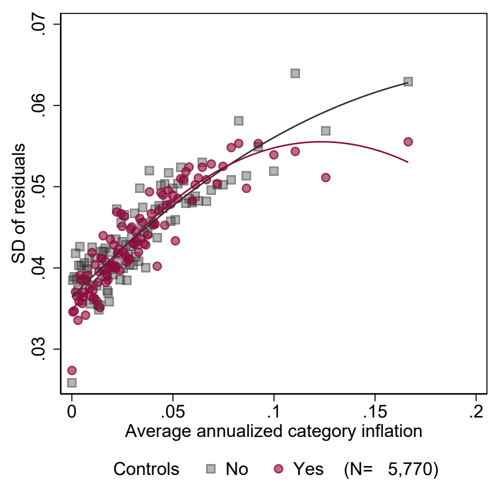
(a) $\text{SD}^g_t(u_{irgct})$ and $N^i_{gc} > 25$



(b) $\text{SD}^g_t(\varepsilon_{irgct})$ and $N^i_{gc} > 25$



(c) $\text{SD}^g_t(u_{irgct})$ and $N^i_{gc} > 25$



(d) $\text{SD}^g_t(\varepsilon_{irgct})$ and $N^i_{gc} > 25$

Notes: This figure shows the relationship of the city-category average price dispersion and the average city-category inflation across all weeks annualized for product-city combinations in scatters and binscatters. The coloured bins are based on the residualized variables after controlling for category fixed effects and number of products included in the category-city combination. Only city-categories observed in at least 52 weeks and with at least 25 products included, this is 5,770 observations.

Figure D.6: Distribution of Price Adjustments by Sector