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 annualized inflation, ranging between zero and 20 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 46% and for restaurants by 73%. Finally, the relationship between inflation and price dispersion does not flatten much at higher inflation, so that the marginal cost of additional inflation does not vanish as inflation rises—a pattern standard menu-cost models do not generate. 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, 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 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 hard 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 comovement 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.

[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.

As shown in Nakamura et al. (2018), when assuming time-dependent pricing à la Calvo, the welfare 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 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 over 60,000 restaurants and supermarkets across 18 countries and covers the recent global high-inflation episode. Notably, the dataset spans diverse levels of inflation across the 18 countries: (annualized) average month-on-month inflation rates range across countries from about 2.5 percent to 20 percent for restaurants, and from about 0.3 percent to 9.2 percent for supermarkets, averaging 6.4 and 3.9 percent respectively.[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 that paper they show that, while the level of the price gap cannot be precisely estimated, one can still test whether 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 together with 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 data also deliver, as a by-product, the moments of the price-change distribution that the menu-cost literature relies on, and these moments prove decisive later. Restaurants are markedly stickier than supermarkets—an implied price-spell duration of 15.2 months against 4.1—mirroring the U.S. evidence in Nakamura and Steinsson (2008, 2010) even though restaurants faced higher infla-

[3]The median interquartile range of country–sector inflation runs from roughly 3.3 to 6.8 percent for restaurants and from 0.6 to 6.25 percent for supermarkets, leaving in both sectors a large variation of inflation environments to exploit.

tion. Both sectors absorb inflation along two margins, the frequency and the size of adjustments, but in different proportions: restaurants respond relatively more through the size of adjustments and supermarkets relatively more through the frequency, the signatures of more time-dependent and more state-dependent price setting. Price changes are also strongly leptokurtic in both sectors (a kurtosis of standardized changes of 5.9 for restaurants and 4.4 for supermarkets), a feature that standard menu-cost models struggle to reproduce and that could be informative about the dispersion of price gaps governing misallocation.

I first document, descriptively, a robust positive comovement between inflation and cross-sectional price dispersion. Using four measures of dispersion—from raw relative prices within narrow categories to fully residualized prices that remove product-specific introduction prices and trends—I show that the comovement with absolute annualized inflation is positive and economically large throughout. For the baseline (residualized) measure, an increase in annualized month-on-month inflation from zero to 10% is associated with an increase in inefficient price dispersion of about 53% pooled across sectors, with pronounced cross-sectoral heterogeneity: dispersion rises by about 73% for the stickier, less studied restaurant sector and by about 46% for supermarkets. Crucially, this comovement of inflation and price dispersion seems to remain significant even at high levels of inflation, indicating a more sustained impact of inflation on price dispersion than previously estimated.

I then show that this comovement reflects a *causal* distortionary effect of inflation rather than a mere correlation. Using the identification strategy of Adam et al. (2023), I estimate the marginal effect of suboptimal inflation on product-level relative price distortions (gaps) separately for each category and city. The estimated marginal effects are positive in 98.5% of the more than 5,000 estimated category-city combinations, as predicted by the theory, and significantly positive (t-stat > 2) in 86% of them. These results hold internationally despite the significant heterogeneity in inflation. Across sectors, the effect is larger and far better identified in restaurants, exactly the product-level counterpart of the cross-sectional sectoral gap and consistent with the marginal effect being increasing in stickiness. This step also validates retrospectively the use of the residualized standard deviation as a measure of inefficient dispersion in the cross-sectional analysis.

Finally, I relate these findings to a calibrated standard menu-cost model and approximate the implied welfare cost of inefficient price dispersion. In the data, a rise in annualized inflation from zero to 10% is associated with a loss of between roughly 0.2% and 0.6% of flex-price consumption—depending on the frequency at which inflation is measured. Abstracting from the level of dispersion at zero inflation and leveraging the heterogeneity across countries, the variance of price gaps—and hence the misallocation cost—rises nearly sixfold (about 570%) as inflation increases from zero to 10%. By contrast, a standard New Keynesian menu-cost model calibrated to my data generates an almost negligible comovement between inflation and inefficient price dispersion, and fails to match both the kurtosis of price changes and the strong comovement of the size of adjustments with inflation. Applying my estimator to data simulated from the model confirms that the empirical relationship is not an artifact of the two-stage estimation. 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.

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 on countries with exceptional inflation, such as Argentina. Among the 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, find that for low inflation, below 10%, cross-sectional price dispersion varies very little with inflation but varies significantly for higher levels. Both Sheremirov (2020) and Sara-Zaror (2021) examine price dispersion across 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 that 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 degrees of stickiness, and across countries. Previous related empirical research has focused on periods of suboptimally low inflation (Adam et al., 2023) or on 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 between inflation and inefficient price dispersion, the results in this paper are essential for informing models used to assess the optimal level of inflation. Four 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, the 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

[4] This paper also contributes to the broader literature on the cost of inflation that focuses on a wide range of welfare losses due to inflation. While this paper focuses on price distortions, other papers 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).

with menu costs. Fourth, the paper contributes a broad set of price-setting moments by sector and country, alongside estimates of how inflation comoves with price dispersion, that future work can use to discipline and calibrate the models used to guide optimal monetary policy.

Two main reasons could explain why I obtain a more sustained relationship between 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 data averaged 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 retailers but also by producing 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 large differences in price dispersion may still exist 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 used in the analysis together with some summary statistics, including the main price-setting moments. Section 3 constructs several measures of cross-sectional price dispersion and documents how each comoves with inflation. Section 4 introduces the identification strategy and isolates the causal role of suboptimal inflation for product-specific price distortions. Section 5 approximates the implied costs of high inflation and relates the results to the predictions of a calibrated standard menu-cost model. Finally, Section 6 concludes.

2. Data and Summary Statistics

Introduction to the data. For the empirical analysis, I gathered online prices from one of the world's largest food delivery companies, which operates in 25 countries at the time of collecting the data. Weekly price data was collected from all available restaurants and supermarkets in 18 countries. 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, and a sale flag indicating whether a listed price is a temporary promotion. I conduct the analysis on regular (non-sale) prices: whenever a price is flagged as being on sale, I use the corresponding regular price rather than the promotional one, so that temporary sales do not enter the measurement of price changes or price dispersion. Daily

[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: two products could have different prices in every week of a month but still have the same average price.

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 were collected 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]

Table 1: Descriptive Statistics of the Main Dataset by Sector

	Restaurants						Supermarkets					
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Kurt.	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Kurt.
AM	951	116,298	2.63	25.42	14.15	5.24	132	114,141	0.30	10.05	12.98	4.57
CI	1,127	55,098	4.31	17.11	19.66	4.41	76	125,982	5.92	5.14	11.00	6.91
ES	12,810	1,126,222	3.13	15.72	13.37	5.14	969	649,527	3.95	3.20	8.63	6.94
GE	2,308	191,913	5.15	12.70	13.85	5.60	353	147,248	3.51	4.24	19.26	3.16
GH	439	20,049	20.40	6.29	15.36	6.33	16	28,656	3.45	3.59	18.93	3.41
HR	1,054	110,606	6.99	13.07	12.80	7.38	132	87,678	5.23	3.83	17.17	3.29
IT	12,288	1,066,667	2.83	29.49	15.07	4.83	656	436,957	2.10	4.00	14.19	4.08
KE	1,766	182,664	6.10	21.16	16.93	4.40	304	424,012	5.41	8.28	12.10	5.46
KG	886	94,839	7.47	9.57	10.88	7.71	81	62,722	4.26	4.41	9.58	6.72
KZ	1,805	225,162	7.19	10.67	12.92	6.32	124	247,387	5.28	2.37	16.54	3.37
MA	2,178	181,087	3.62	14.39	15.11	4.25	268	435,302	2.21	4.21	10.86	5.46
PL	4,552	435,219	6.45	9.40	11.79	6.06	242	343,807	2.76	2.41	14.88	3.55
PT	6,441	392,956	2.46	24.13	16.25	4.33	412	301,459	1.55	3.91	21.86	2.21
RO	2,669	331,655	8.17	9.40	14.72	5.55	297	270,736	6.44	1.48	12.28	4.51
SI	430	28,934	5.21	17.64	10.78	8.94	45	14,836	3.11	2.77	24.64	1.69
TN	1,547	93,292	5.31	13.16	12.61	6.61	65	54,420	4.32	3.32	11.70	4.27
UA	2,789	440,574	11.44	5.56	11.54	7.64	268	471,174	9.19	1.32	14.87	3.55
UG	1,278	88,782	6.61	18.25	18.11	5.08	224	293,912	1.55	5.94	10.71	6.80
All	57,318	5,182,017	6.42	15.17	14.22	5.88	4,664	4,509,956	3.92	4.14	14.57	4.44

Notes: Countries appear in the following order: Armenia, Côte d'Ivoire, Spain, Georgia, Ghana, Croatia, Italy, Kenya, Kyrgyzstan, Kazakhstan, Morocco, Poland, Portugal, Romania, Slovenia, Tunisia, Ukraine, and Uganda. Inflation is the sample average of the annualized four-week (month-on-month) inflation rate. Mean Abs. Adj. and Kurt. are computed on *standardized* price changes, conditional on adjustment, following Klenow and Kryvtsov (2008): within each city $\times$ narrow-category cell the log price change is demeaned and rescaled by the cell standard deviation and re-expressed in the country $\times$ sector reference distribution. Mean Abs. Adj. is the mean absolute standardized change (in percent), and Kurt. is the kurtosis of the standardized changes. Duration is computed from the weekly frequency of adjustment for products observed more than eight weeks, averaged (unweighted) across products and converted to a monthly duration as $-1/[4\ln(1-freq)]$. Appendix Tables B.4 and B.5 report additional moments by city and sector.

[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.

Across the 18 countries and two sectors, I observe around 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 7,000 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.

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 over 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 345 categories: 81 categories for restaurant products and 264 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. From the over 10 million products in Table 1, 87% were classified with a confidence probability of above 75% and were used in the analysis sections.

For the calculations 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

[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.

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.

The data used in this paper offers four 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 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. Finally, the automated categorization of products, tailored for this specific international dataset, facilitates cross-country comparisons while minimizing composition effects.

External validation. To demonstrate that the data tracks official inflation statistics, I first 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 345 categories were first matched to "Classification of Individual Consumption" (COICOP) codes and then to official consumer price statistics. For each week-COICOP-country 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 nine countries: Spain, Georgia, Croatia, Italy, Kazakhstan, Poland, Portugal, Romania and Slovenia. Inflation rates between April 2023 and October 2025 were considered.[9]

Appendix Figure A.1 plots the average month-on-month (m-on-m) country-COICOP inflation

[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

[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).

from the online data against inflation for the same country and category from official sources, for all countries and categories. Of 182 cells compared, 172 with monthly inflation below 1% appear in the figure; the 10 above are omitted from the figure but included in the averages. The linear fitted line in subfigure A.1(a) has a slope of 1.20, a R^2 of 0.63 and includes 172 country-COICOPs. The correlation weighted by number of products is 0.79. Sub-figure (b) contains a binscatter from the same observations included in Sub-figure (a). The average annualized inflation from the 182 compared country-COICOP combinations was 3.62% in the official data and 3.56% in the online data. 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]

To benchmark other moments in my data against official statistics, Appendix Table A.1 and Figure A.2 compare, at the COICOP4–month level, the frequency and average absolute size of price adjustments in my online data with the corresponding official moments for Spain. The official moments were shared with me at the COICOP5 level and correspond to the moments that underlie the Spanish moments in Gautier et al. (2026). Reassuringly, the central tendencies are broadly aligned over the common period (2023m4–2025m10): the average monthly frequency of price change is 18.0% online versus 15.4% in the official data, the average absolute size is of similar magnitude (9.6% versus 11.7%), and the sectoral ordering is preserved, with restaurants adjusting far less frequently than supermarkets (4.4% versus 18.8% online). The two sources are positively correlated across category–month cells after trimming the top 5% of the official measure—most clearly for the frequency in restaurants (0.59)—confirming that they capture the same underlying price-setting variation.

The most striking difference between the two sources is the dispersion of the moments in the official data and the number of products behind each statistic. The official data rests on a thin set of quotes per category–month: on average only about 740 observations for the entire restaurant sector (COICOP CP1111) and roughly 11,000 across the eighteen supermarket categories, against about 331,000 restaurant and 147,000 supermarket observations per month online. The online sample is thus between roughly thirteen times (supermarkets) and more than four hundred times (restaurants) larger. This difference in coverage is the most plausible source of the much larger dispersion of the official moments: across category- month cells the standard deviation of the official frequency and size is roughly 1.5 to 3 times that of the online moments (for restaurants, 2.13 versus 0.65 for the frequency and 1.85 versus 0.79 for the size). With only a few hundred products per category, the official category–month averages are estimated with substantial sampling error, which shows up both as inflated dispersion and as the extreme realizations along the horizontal axis of Figure A.2—adjustment

[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.

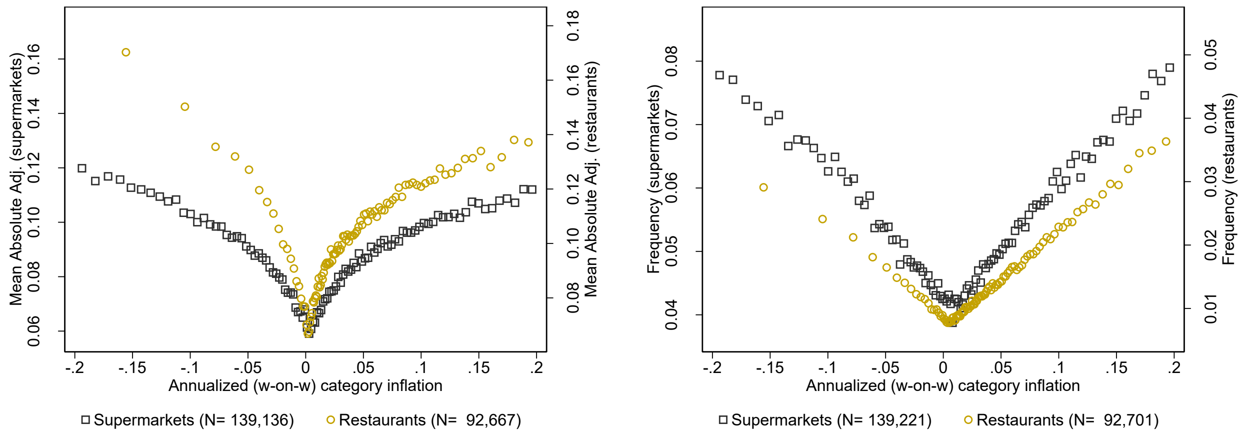
fractions approaching 0.7–0.8 and average sizes above 0.5 that have no counterpart in the far more tightly distributed online measures on the vertical axis. Because my analysis relies on how the moments and dispersion of the category-level price-change distribution co-move with inflation, measurement noise of this magnitude would be especially damaging if we relied on the official micro data alone; the very large online samples deliver category–month moments that are arguably better measured, motivating their use for the type of analysis conducted in this paper.

Price-setting facts. Three moments of the price-change distribution have become standard for summarizing nominal rigidity and its consequences for the cost of inflation: the frequency of adjustment (equivalently, the implied duration of a price spell), the average absolute size of price changes, and the kurtosis of price changes. The first two are the classic objects of the menu-cost literature (Nakamura and Steinsson, 2008, 2010; Nakamura et al., 2018), and jointly they discipline both the degree of monetary non-neutrality and the welfare cost of inflation-induced price dispersion. The kurtosis has more recently been placed at the center of this mapping because it is informative about the shape of the price-gap distribution that governs misallocation: under certain assumptions, in a low-inflation steady state the cross-sectional variance of price gaps—the object that enters the cost of dispersion—satisfies $\mathbb{V}[x] = \mathbb{V}[\Delta p]\,\mathrm{Kurt}[\Delta p]/6$ (Alvarez et al., 2016; Cavallo et al., 2023), so for a given dispersion of realized price changes a more leptokurtic distribution—a larger mass of firms that adjust only once their price gap has grown large—implies greater gap dispersion and hence larger misallocation.

Table 1 reports the three moments by sector. Average annualized inflation over the sample is considerably higher for restaurants (6.42%) than for supermarkets (3.92%), with substantial dispersion across countries: the 25th-to-75th percentile range of country-sector inflation runs from 3.3% to 6.8% for restaurants and from 0.6% to 6.25% for supermarkets. This variation across countries and sectors, recorded during a period of elevated and heterogeneous aggregate inflation, is the variation the rest of the paper exploits. Two features stand out. First, despite their higher inflation, restaurants adjust prices far less often than supermarkets: the implied price-spell duration is 15.2 months for restaurants against 4.14 months for supermarkets. This ordering—restaurant prices markedly stickier than supermarket prices—mirrors the U.S. evidence in Nakamura and Steinsson (2008, 2010), and it holds even though restaurants faced the higher inflation rate. Second, the average absolute price change is essentially the same in the two sectors (14.2% and 14.6%). This similarity may be misleading, however, as equal means can mask differences in the composition of adjustments—notably in the share that are price decreases—so this aggregate is best read alongside the more detailed moments reported in Appendix Tables B.4 and B.5. The kurtosis of price changes is sizeable in both sectors and larger for restaurants (5.9) than for supermarkets (4.4), in line with their greater stickiness.

Firms can absorb inflation along two margins—the frequency of adjustment and the size of each

Figure 1: Conditional Mean Absolute Price Adjustment, Frequency and Inflation



(a) Mean Absolute Price Adjustment and Inflation

(b) Frequency of Adjustments and Inflation

Notes: The figure plots, in a binscatter, the city-category mean absolute price adjustment (conditional on adjustment, panel a) and the frequency of adjustment (the share of products adjusting in a given week-city-category, panel b) against annualized week-on-week city-category inflation. Both variables are residualized on category-city fixed effects and the number of products in the category-city-week cell. The sample retains category-city-week cells with more than 50 products and with annualized inflation below 20% in absolute value, leaving more than 139,000 supermarket and 92,000 restaurant observations.

adjustment—and their relative use is informative about the nature of price rigidity. As Nakamura et al. (2018) emphasize, a price setter whose timing is largely time-dependent (adjusting at fixed intervals, regardless of the state) absorbs inflation primarily by making larger adjustments, leaving the frequency roughly unchanged, whereas a state-dependent setter (adjusting once the price gap is large enough) responds by adjusting more often. Figure 1 plots, separately by sector, the conditional mean absolute price change (panel a) and the adjustment frequency (panel b) against annualized category inflation, after residualizing out category-city fixed effects and the number of products in the category-city-week cell. Both margins trace out a pronounced and broadly symmetric V-shape in each sector: as inflation moves away from zero in either direction, firms adjust both more frequently and by larger amounts. The sectors differ, however, in which margin dominates. Restaurants respond more strongly through the size of adjustments and supermarkets more strongly through the frequency, indicating that some time-dependence is present in both sectors but is more pronounced among restaurants.

Appendix Table B.3 reports the corresponding regressions, for both week-on-week and month-on-month category-city inflation. All slopes are positive and significant at the 0.1% level. Pooling sectors, a one-percentage-point increase in annualized absolute inflation is associated with a 0.29-percentage-point increase in the mean absolute adjustment and a 0.18-percentage-point increase in the adjustment share (week-on-week). The split by sector confirms the pattern in Figure 1: the size response is larger for restaurants than for supermarkets (0.370 versus 0.260), while the frequency response is larger for supermarkets than for restaurants (0.194 versus 0.150). Restaurants thus accommodate inflation relatively more on the intensive (size) margin and supermarkets relatively more on the extensive (frequency) margin—the signatures, respectively, of more time-dependent and more state-dependent price setting.

Appendix Tables B.4 and B.5 report the full set of price-setting moments by country and sector, computed on price changes adjusted for product heterogeneity following Klenow and Kryvtsov (2008). They confirm the sectoral contrasts above and document substantial cross-country heterogeneity in every moment. The tables also report the heterogeneity-corrected kurtosis of Alvarez et al. (2022): these values are mechanically smaller than the raw kurtosis—on average around 2.4 for restaurants and 1.6 for supermarkets—but preserve the ordering, remaining larger for restaurants.[11]

3. Inflation and Cross-Sectional Price Dispersion

Introduction to price distortions. For intuition, consider a unique product i sold in a specific location by a particular supermarket or restaurant in period t. Under flexible pricing, the firm's desired optimal relative price $p^*_{it} = P^*_{it}/P_t$ 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. If the gross inflation rate exceeds this value, the relative price is eroded too rapidly, necessitating nominal adjustments; if it is below, the product appreciates too fast, again necessitating adjustments. There is thus a gross inflation rate that is optimal for product i, and any deviation from this value is suboptimal. For example, computers with different technologies may require different rates of depreciation over time, and cheap and expensive goods within a narrow category may 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. When some degree of price stickiness exists, however, these adjustments are costly or infeasible in a given period, leading to a product- and time-specific gap_{it} between the flexible

[11] The correction requires at least two observed adjustments per product and is therefore computed on a small and selected subset of products, reported in the final column; the selection is especially severe for restaurants, whose long price spells leave only a minority of products with two or more adjustments over their observed lifespan. I therefore treat the kurtosis of standardized adjustments as my preferred summary.

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 through misallocation. The standard deviation of these gaps is what is often referred to as inefficient price dispersion.

Several papers attempt to measure the relationship between inflation and price distortions by estimating gap_{it} directly from micro-data. One could argue, for instance, that the dispersion in relative prices of a category as narrow as "restaurant pizza margherita" stems from price distortions. Accurately determining the level of distortion is, however, highly complex. Once we move beyond the simple process for optimal relative prices in equation (3.1) and allow for product-specific idiosyncratic shocks ε^*_{it}, the situation becomes more challenging.

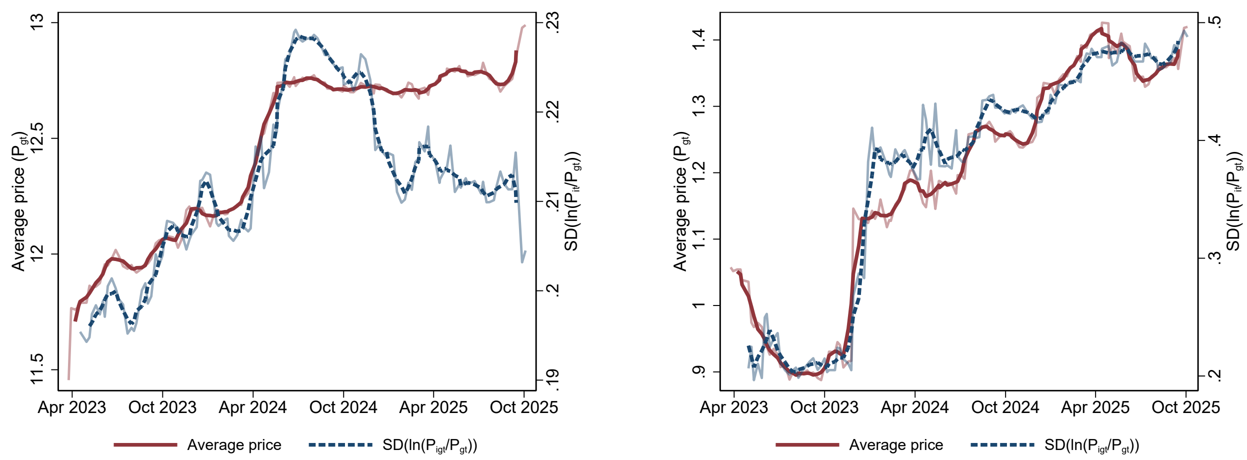
This section proceeds in two steps. In this first part I construct three measures of cross-sectional price dispersion—from raw relative prices, from fixed-effect residuals, and from residuals that also remove product-specific introduction prices and trends—and then document how each comoves with inflation. The measures are descriptive: they establish that price dispersion rises with inflation, but they cannot by themselves separate inflation-induced distortions from desired relative-price variation or idiosyncratic shocks. Section 4.1 addresses this with the identification strategy of Adam et al. (2023), which causally links suboptimal inflation to price distortions and can be used to show that a substantial share of the measured price dispersion stems from these distortions.

3.1 Measuring Cross-Sectional Price Dispersion

Dispersion of actual relative prices. A natural starting point would be to measure price dispersion directly for individual products or very narrow categories. However, using relative prices directly is challenging because few datasets contain a large number of products classified into categories with little product heterogeneity. Sheremirov (2020) provides a clean solution to this problem: examining price dispersion across stores for identical products identified by barcodes in U.S. scanner data, ensuring that the compared products are actually the same. Unfortunately, this strategy is infeasible in my setting, and in most sectors more generally, since most products lack barcodes. Moreover, recent research finds that retailers and firms adopt synchronized pricing strategies, leading to convergence of prices for specific products even across retailers (Bhattarai and Schoenle, 2014); when products are highly synchronized by the producing firm, only a small fraction of price variation is left for analysis, even though large differences in dispersion may still exist across, for example, brands of still water.

Despite these limitations, to capture this dispersion and to build intuition, I group one share of the products into very narrow categories that consumers would arguably treat as homogeneous, such as "pizza margherita in a restaurant in Madrid" or "Coke 330 ml in a supermarket," while allowing the

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. Raw weekly series shown alongside a five-week moving average (thicker line). Over time, on average 436 products are included in the category Pizza Margherita and 204 in the category Coke 330 ml.

restaurant or brand to vary within each category. These definitions are finer than the 345 categories into which the fine-tuned model classifies all products. [12]

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 Coke sold by supermarkets, over 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 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.

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 roughly 1.04 to 1.40 euros. More importantly, cross-sectional dispersion tracked the price level closely throughout, rising in episodes of rapid price increase and only beginning to fall once prices stabilized—the pattern predicted by sticky-price theory. For the Coke, dispersion more than doubled, from around 0.20 to over 0.45. A simple

[12] 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 five percentiles of prices were dropped for the calculations. The full list of product definitions is, for restaurants: beer 330 ml, beer 500 ml, Caesar chicken salad, California roll 4 pcs, California roll 8 pcs, cheeseburger, cheesecake portion, chicken burger, chicken nuggets 6 pcs, Coke 330 ml, Coke 500 ml, Coke 1500 ml, fries, other maki 8 pcs, other soda 330 ml, other soda 500 ml, Philadelphia roll 8 pcs, pizza margherita, pizza pepperoni, pizza prosciutto, salmon maki 8 pcs, and water 500 ml; and for supermarkets: beer 330 ml, beer 500 ml, breakfast cereals 400–500 g, chocolate bar 90–100 g, coffee 200–250 g, Coke 330 ml, Coke 500 ml, deodorant 50 ml, deodorant 150 ml, deodorant 200 ml, dried pasta 400–500 g, liquid soap 250 ml, liquid soap 500 ml, other soda 330 ml, other soda 500 ml, shampoo 350–450 ml, sweet biscuits 150–250 g, water 500 ml, water 1000 ml, yogurt 100–150 g, and yogurt 100–150 g (4-pack).

regression of log dispersion on log average price confirms a strong and significant relationship: a coefficient of 1.21 (robust standard error 0.09, $R^2 = 0.60$) for the pizza and 1.97 (robust standard error 0.04, $R^2 = 0.92$) for the Coke.

These patterns are suggestive evidence that inflation distorts prices and generates dispersion, but the analysis has three caveats. First, even within "Pizza Margherita" and "330 ml Coke" some residual product heterogeneity remains—in size, ingredients, or packaging—and the observed dispersion partly reflects efficient differences. Moving from "Restaurant Pizza" dropping the top and bottom one percent prices, to "Restaurant Pizza Margherita" already reduces measured dispersion substantially, from 0.32 to 0.21, but it is unclear that the remainder is entirely inefficient. This issue is amplified by products entering and exiting the sample. In addition, finding very specific categories with enough products in one city would strongly restrict the sample: I observe on average over 8,500 products per week in "restaurant pizza" in Madrid, but only around 400 in "restaurant pizza margherita." Second, the optimal inflation rate for each product need not be zero: a product whose relative price should depreciate over time is optimally associated with a positive inflation rate, and the relevant distortion is the deviation from this product-specific optimum. Third, the correlations in Figure 2 are not necessarily causal; even after cleaning relative prices with product fixed effects and trends, the residual could reflect distortive inflation or desired idiosyncratic shocks. These limitations motivate the two additional measures below and, ultimately, the identification strategy of Adam et al. (2023) in Section 4.1.

Dispersion correcting for unobserved heterogeneity. To absorb product specifics unrelated to inflation distortions, a common approach in the literature controls for retailer- and product-specific heterogeneity (Sheremirov, 2020; Alvarez et al., 2019). I estimate the first-step regression

$$\ln P_{irgct} = \alpha_{gc} + \delta_{ct} + \gamma_{rct} + \eta_{irgc} + \varepsilon_{irgct}, \tag{3.2}$$

where $\ln P_{irgct}$ is the log price of product i sold by retailer r in category g, city c, and week t, and α_{gc}, δ_{ct}, γ_{rct}, and η_{irgc} are category×city, city×time, retailer×city×time, and product fixed effects, respectively. I then compute, for each category-city-week, the standard deviation of the residual, $\mathrm{SD}_{gct}(\varepsilon_{irgct})$. This removes variation from retailer-products that are consistently more expensive within a category and from retailers charging higher prices for all products in a given week. As an alternative to fixed effects, I also control for product specifics using information contained in the product name, focusing on beverage categories (beer, cider, energy drinks, fruit juices, iced tea, sodas, and water bottles), whose product names usually report the container size. Using regular expressions, I extract the product volume and estimate inflation and dispersion at the volume-category-city-week level.

Dispersion controlling for product-specific price trends. The final and preferred measure estimates, for each product, the regression

$$\ln p_{igt} = \ln a_{ig} - (\ln b_{ig})\, t + u_{igt}, \tag{3.3}$$

where $\ln p_{igt}$ is the log relative price of product i in category g, $\ln a_{ig}$ is a product fixed effect capturing the optimal relative introduction price $\ln p_i^*$, and $(\ln b_{ig})$ is the trend coefficient capturing $\ln \Pi_i^*$. Even if $\ln a_{ig}$ and $(\ln b_{ig})$ converge to the true introduction price and trend, as in the previous measures, the residualized relative prices may still contain both a true distortion (gap_{it}) and variation from idiosyncratic shocks (ν_{it}). While accurately determining the level of distortions is challenging in the presence of idiosyncratic shocks, Adam et al. (2023) show that one can still identify the marginal effect of suboptimal inflation on distortions using the residuals from equation 3.3. I focus here on the comovement of this dispersion measure with inflation, and show in Section 4.1 the extent to which these gaps are caused by suboptimal inflation.

3.2 Cross-Sectional Price Dispersion and Inflation

Measuring the comovement. To measure the comovement of inflation with price dispersion, my general specification regresses a measure of price dispersion, computed at the category-city-week level, on a category fixed effect and the absolute annualized month-on-month city-category inflation:

$$D_{gct} = \gamma_g + \beta\, |\Delta p_{gct-4}^{Annual}| + v_{gct}, \tag{3.4}$$

where D_{gct} denotes one of the four dispersion measures defined above—$\text{SD}_{gct}(\ln p_{it})$, $\text{SD}_{vgct}(\ln p_{it})$, $\text{SD}_{gct}(\varepsilon_{it})$, and $\text{SD}_{gct}(u_{it})$—each computed at a different level of aggregation and after removing a different set of sources of desired relative-price variation. The term γ_g is a category intercept and $|\Delta p_{gct-4}^{Annual}|$ is the absolute annualized month-on-month inflation in category g, city c, and week t. For the narrow product categories, for instance, the regression estimates the standard deviation of relative prices at the narrow-category-city-week level on the absolute month-on-month inflation rate and a narrow-category intercept.

I use the *absolute* deviation of inflation because, as equation (3.1) indicates, the relationship between inflation and dispersion depends on the average optimal inflation rate of the category, $\ln\Pi_g$. Suppose this optimal rate is zero. Then an increase in inflation from -2% to -1% moves inflation *closer* to the optimum and *reduces* inefficient dispersion, whereas an increase from 1% to 2% moves it *further* from the optimum and *raises* dispersion. What matters for inefficient dispersion is therefore the absolute deviation of inflation from its optimal level, not its signed level. Taking the optimal rate to be zero is itself an approximation: the optimal rate may be slightly positive if firms prefer to let relative prices depreciate gradually. I adopt the zero benchmark to keep my results comparable to previous work on cross-sectional price dispersion, which is reasonable for the food, beverage, and household products in this sample, whose relative prices are not expected to trend strongly, and because the weekly and monthly inflation rates used are in any case close to zero.

Table 2: Price Dispersion and Inflation Comovement

Dep. var:	(1) $SD_{gct}(\ln p_{it})$	(2) $SD_{gct}(\ln p_{it})$	(3) $SD_{gct}(\ln p_{it})$	(4) $SD_{vgct}(\ln p_{it})$	(5) $SD_{gct}(\varepsilon_{it})$	(6) $SD_{gct}(u_{it})$	(7) $SD_{gct}(u_{it})$	(8) $SD_{gct}(u_{it})$	(9) $SD_{gct}(u_{it})$
$\lvert\Delta p^{Ann}_{gct}\rvert$	0.123***	0.374***	0.104	0.247***	0.129***	0.130***	0.134***	0.128***	0.225***
	(0.024)	(0.068)	(0.060)	(0.035)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)
$\lvert\Delta p^{Ann}_{gct}\rvert^2$									-0.624***
									(0.021)
SD at $\pi = 0$	0.261	0.201	0.299	0.243	0.032	0.024	0.018	0.028	0.023
SD at $\pi = 10\%$	0.273	0.238	0.310	0.268	0.045	0.037	0.032	0.041	0.039
Change %	4.7%	18.7%	3.5%	10.1%	40.8%	53.3%	72.5%	46.1%	72.0%
Specification	Narrow product	Same prod. rest.	Same prod. super.	Beverages volume	FEs adjusted	Baseline	Baseline rest.	Baseline super.	Baseline squared
N	67,722	14,272	10,548	29,586	344,496	344,496	128,436	216,060	344,496
R^2	0.36	0.22	0.20	0.47	0.39	0.36	0.34	0.29	0.37
Within R^2	0.01	0.04	0.00	0.02	0.11	0.14	0.26	0.12	0.15

Notes: This table shows the relationship between different weekly measures of cross-sectional price dispersion and the absolute annualized month-on-month inflation at the category-city-week level. Column (1) uses the standard deviation of log relative prices within narrow product categories, $SD_{gct}(\ln p_{it})$; columns (2) and (3) restrict this measure to the set of products observed in both sectors, separately for restaurants and supermarkets; column (4) uses the standard deviation of log prices within beverage categories controlling for container volume, $SD_{vgct}(\ln p_{it})$; column (5) uses the dispersion of product-level log prices after residualizing out product fixed effects, $SD_{gct}(\varepsilon_{it})$; and columns (6)–(9) use the dispersion of log prices after additionally removing product-specific introduction prices and trends, $SD_{gct}(u_{it})$. Columns (6)–(9) report the baseline specification for both sectors, restaurants only, supermarkets only, and a specification adding a quadratic inflation term. The explanatory variable is the category-city annualized weekly month-on-month inflation, $\lvert\Delta p^{Annual}_{gct-4}\rvert$, except in the beverage column, which uses the category-volume-city annualized inflation, $\lvert\Delta p^{Annual}_{vgct-4}\rvert$. The rows "SD at $\pi = 0$" and "SD at $\pi = 10\%$" report the average predicted dispersion evaluated at absolute annualized inflation of 0 and 0.10, and "Change %" is their percentage difference. Standard errors clustered at the category-city level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Main results. Table 2 reports the estimated comovement across the four dispersion measures. The estimated comovement is positive and economically large throughout. Alongside each coefficient, the table reports the predicted price dispersion at inflation rates of zero and 10% and the percentage change between the two. The predicted dispersion at a given rate is the average fitted value of the regression evaluated at $\lvert\Delta p^{Annual}_{gct-4}\rvert = 0$ and 0.10, averaging over the estimated category fixed effects; for the quadratic specification the prediction also includes the squared term.

The four measures differ markedly in their predicted dispersion at zero inflation, reflecting how much relative-price variation each retains. The raw standard deviation of log prices within narrow categories (column 1) is 0.261 at zero inflation, and the beverage-volume measure (column 4) is similar at 0.243: even within very narrow definitions, products differ substantially in their relative prices. Removing product fixed effects collapses this baseline by an order of magnitude, to 0.032 (column 5), and removing product-specific trends as well leaves 0.024 (column 6). The slope on inflation should be read against these different baselines: a given absolute increase in dispersion is a small share of the raw measure but a large share of the residualized one.

The raw measure in column 1 yields a coefficient of 0.123. Because both the dependent variable and the regressor are in the same units—standard deviations and rates of log prices—the coefficient is a marginal effect that can be read directly: a one percentage point increase in absolute annualized inflation is associated with an increase of 0.00123 in the within-category standard deviation of log prices, so a 10 percentage point increase raises it by about 0.012, or roughly 4.7% relative to its level at zero inflation. The coefficient is identified within categories, since the category fixed effect absorbs permanent differences in dispersion across products, so it reflects how a category's dispersion moves when its own inflation deviates from its average.

The same absolute increase represents a far larger proportional change for the residualized measures. The predicted increase as inflation moves from zero to 10% is 4.7% for the raw measure (column 1), 40.8% after removing product fixed effects (column 5), and 53.3% for the baseline measure that also removes product-specific trends (column 6). The contrast across columns 1, 5, and 6 shows that the choice of dispersion measure matters a great deal: measures that retain more desired variation deliver smaller proportional responses, since the inflation-driven component is diluted by a large and stable desired component, while measures that strip out desired variation isolate a component that moves more closely with inflation.

Sectoral heterogeneity. A robust pattern in the table is the difference between sectors: restaurants, the stickier sector, display a stronger comovement of dispersion with inflation than supermarkets. Columns 2 and 3 isolate a small set of very homogeneous products sold in both sectors—beer (330 and $500\,\mathrm{ml}$), Coke (330 and $500\,\mathrm{ml}$), other sodas (330 and $500\,\mathrm{ml}$), and water ($500\,\mathrm{ml}$)—and compare the slope across sectors. These products are arguably almost identical across the two sectors: both restaurants and supermarkets source them from the same manufacturers and deliver them to households with little difference in value added. Despite this, an increase in inflation from zero to 10% is associated with an 18.7% rise in dispersion for restaurants but only 3.5% for supermarkets. The same ordering holds for the baseline measure: dispersion rises by 72.5% for restaurants (column 7) against 46.1% for supermarkets (column 8). That the gap appears in two very different measures—raw dispersion of nearly identical products (columns 2–3) and fully residualized dispersion (columns 7–8)—makes it unlikely to reflect composition or the cleaning procedure, and points instead to the difference in price stickiness between the sectors.

This sectoral gap connects directly to the price-setting evidence in Section 2. Restaurants adjust prices far less frequently than supermarkets, so when aggregate inflation pushes their desired prices up, a larger share of restaurant prices remains stale at any point in time, and the cross-sectional gaps between recently adjusted and not-yet-adjusted prices grow wider. Supermarkets, which reprice more often, keep relative prices closer to their desired levels even at high inflation, so a given amount of inflation translates into less inefficient dispersion. A natural implication is that the cost of inflation is not uniform across the economy: it falls disproportionately on stickier sectors, and measures that focus on more flexible sectors might mask how distortionary inflation is.

The relationship at different levels of inflation. A central question for the optimal-inflation debate is not only *whether* dispersion comoves with inflation, but *at which levels* the relationship is present and whether it flattens out at higher rates. The evidence so far is mixed: Sara-Zaror (2021) finds a strong comovement that flattens for annualized inflation above roughly 2%, whereas Alvarez et al. (2019) find that dispersion barely changes below 10% and rises strongly above it. My data are well suited to this question because they span a wide range of inflation environments across categories and countries.

To examine this, I plot the relationship in a binned scatterplot, following Sara-Zaror (2021). I divide the category-city-week observations into 100 equally sized bins of annualized inflation and compute the average dispersion within each bin, for both the $\mathrm{SD}_{gct}(u_{irgct})$ and $\mathrm{SD}_{gct}(\varepsilon_{irgct})$ measures. Because some categories have persistently higher dispersion—owing to a stronger idiosyncratic component or to a larger number of products—I also construct a residualized version, plotting dispersion after partialling out a category fixed effect and the number of products. Concretely, I estimate

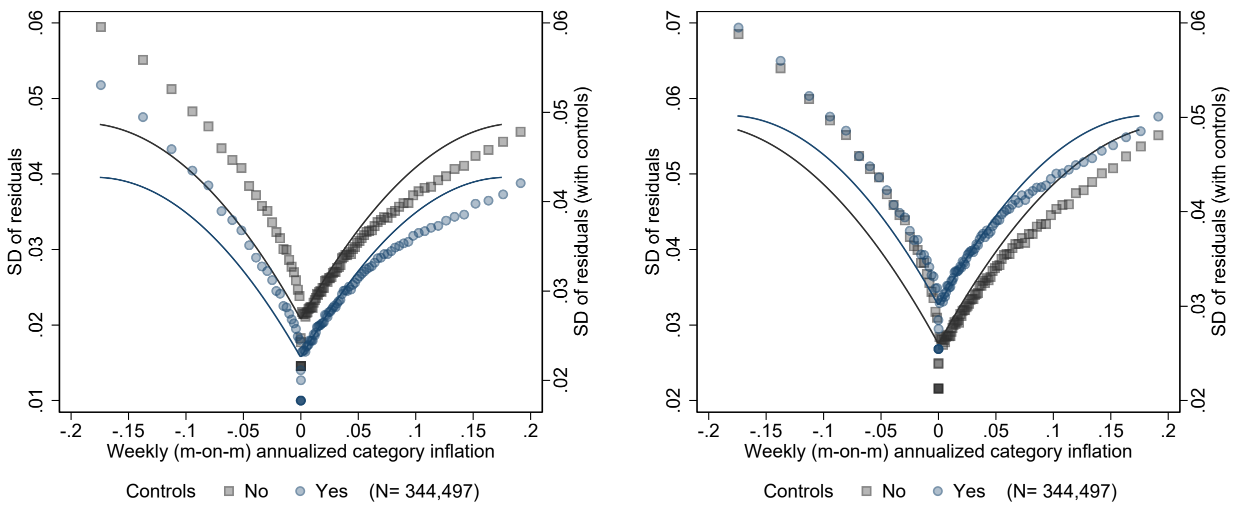
$$\widetilde{\mathrm{SD}}_{gct}(u_{irgct}) = \delta_g + \delta_1 |\Delta p^{Annual}_{gct-4}| + \delta_2 N^i_{gct} + \varepsilon_{gct}, \tag{3.5}$$

and plot $\widehat{\mathrm{SD}}_{gct}(u_{irgct}) = \mathrm{SD}_{gct}(u_{irgct}) - \hat{\delta}_2 N^i_{gct}$ against inflation. Observations with absolute annualized inflation above 20% are excluded. I also construct the measure for the dispersion measure correcting for unobserved heterogeneity.

Figure 3 shows the result. Each panel includes 344,497 category-city-week combinations, so that each of the 100 bins contains around 3,500 observations. For both measures, and whether or not category controls are included, dispersion is lowest near zero inflation and rises as inflation deviates from zero in either direction. Crucially, the relationship does not flatten out: even at annualized inflation rates of 20% the link persists, tracing a clear "V" shape rather than the near-complete flattening above 2% reported in Sara-Zaror (2021). Because each bin rests on around 3,500 observations, the pattern in the tails is not an artifact of a thin sample.

The relationship across countries. Finally, the comovement is not driven by a few countries and appears in all cities in my sample. Appendix Table C.7 estimates the baseline regression separately for each city. The coefficient is positive and significant at the 0.1% level in every one of the 24 cities,

Figure 3: 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 two measures of price dispersion, $\text{SD}_{gct}(u_{irgct})$ and $\text{SD}_{gct}(\varepsilon_{irgct})$. Each dot is the average dispersion within one of 100 equally sized inflation bins; the unit of observation is a category×city×week. The number of category×city×week combinations is 344,497 in panel (a) and (b), so each bin contains around 3,500 observations. Grey markers show raw bin means; coloured markers show bin means after partialling out category fixed effects and the number of products. Both panels use weekly annualized month-on-month average category-city inflation rates ($\Delta p^{Annual}_{gct-4}$) below 20%.

ranging from about 0.03 to 0.10, with a pooled estimate of 0.053 when category×city fixed effects are included across all cities. The consistency of the relationship across countries at very different inflation levels, exchange-rate regimes, and stages of development indicates that the link between inflation and inefficient price dispersion is a general feature of price-setting rather than a property of any particular environment. [13]

The lower slope obtained when estimating the regression city by city, or when including city-category fixed effects, nonetheless points to the importance of the cross-country dimension. Even though products are classified by the same algorithm across countries, average category-city price dispersion is correlated with average category-city inflation: categories and cities that experience higher average inflation also display higher average dispersion. An analysis that relies only on the within-city-category variation—absorbing this cross-sectional component through fixed effects—would miss this part of the relationship. Exploiting the variation across countries, rather than only within them, is therefore essential to capturing the full comovement of inflation and price dispersion.

Robustness. Appendix Table C.6 reports additional robustness checks, all of which leave the main conclusions intact. Setting the minimum number of products per category-city-week to 20 or 100

[13] A substantial share of the cross-city heterogeneity in the coefficients can be explained by the inflation environment of the city. Regressing the 24 city-specific estimates on the median category inflation in that city yields a coefficient of -0.588 with a standard error of 0.194, with a R^2 of 0.30.

rather than the baseline 50 does not change the results. Restricting to absolute inflation below 10% slightly steepens the relationship, with dispersion rising by 76.2% from zero to 10% inflation. Adding a quadratic term separately by sector raises the implied increase at 10% inflation but preserves the sectoral ordering, with restaurants still more responsive than supermarkets. Trimming the top five percent of $\mathrm{SD}_{gct}(u_{it})$ lowers the slopes only marginally, and dropping negative-inflation observations barely affects them. Adding week×city fixed effects, which absorb common shocks within a city-week, reduces the coefficients moderately but leaves the relationship positive and significant.

4. Suboptimal Inflation and Product-Level Price Distortions

Section 3 documented a robust positive comovement between inflation and the dispersion of the residual u_{igt} from equation (3.3). As noted there, however, this residual conflates two components: a genuine inflation-induced distortion (gap_{it}) and variation from product-specific idiosyncratic shocks (ν_{it}). The comovement is therefore suggestive that inflation distorts relative prices, but it does not by itself establish causality. This section uses the identification strategy of Adam et al. (2023) to isolate the causal effect of suboptimal inflation on product-level distortions, and shows that the residuals used in Section 3 reflect, to a large extent, inflation-induced price distortions.

4.1 Identifying the Distortionary Effects of Inflation

Identification strategy. The key insight of Adam et al. (2023) is that, although the product-level variance of the *desired* relative price is independent of inflation, the variance of the *actual* relative price contains information about price distortions and should correlate with inflation if and only if inflation is distortionary. In their framework, the variance over time of the residual u_{igt} from the product-level regression (3.3) can be written as

$$\mathrm{Var}_i(u_{igt}) = v_g + c_g\,(\ln\Pi_g - \ln\Pi^*_{ig})^2, \tag{4.1}$$

where the intercept,

$$v_g \equiv \mathrm{Var}_g\left((1-\alpha_g)\,E_t\sum_{j=0}^{\infty}\alpha_g^j \ln\nu_{igt+j}\right), \tag{4.2}$$

depends on the idiosyncratic shock process and the Calvo stickiness parameter α_g, and the slope,

$$c_g \equiv \frac{\alpha_g}{(1-\alpha_g)^2}, \tag{4.3}$$

depends only on the stickiness parameter under time-dependent pricing.[14] The intercept v_g mixes efficient idiosyncratic variation with distortions, so the *level* of dispersion is uninformative about misallocation on its own. The second term, however, captures how suboptimal inflation raises distortions: the slope c_g is the marginal effect of suboptimal inflation on price distortions, and equation (4.3) shows it is increasing in stickiness, so stickier categories should display a more pronounced effect. Estimating c_g is the goal of this section.

The estimation has two auxiliary (first-stage) regressions feeding a second stage, all run within a city-category combination. The first first stage is regression (3.3), already introduced in Section 3: from it I take the variance over time of the residuals u_{igt} for each product, which is the left-hand side of (4.1). The second first stage recovers the suboptimal inflation rate of each product from the trend in its nominal price,

$$\ln P_{igt} = \ln \tilde{a}_{ig} + (\ln \Pi_g / \Pi^*_{ig})\, \mathrm{t} + \tilde{u}_{igt}, \tag{4.4}$$

where P_{igt} is the nominal price: intuitively, products whose nominal prices trend most steeply are those for which actual inflation most exceeds the product's optimal rate. The second stage then estimates the marginal effect for each category by OLS,

$$\widehat{\mathrm{Var}}_i(u_{igt}) = v_g + c_g\, (\ln \widehat{\Pi_g / \Pi^*_{ig}})^2 + \varepsilon_{ig}, \tag{4.5}$$

where the regressors are the product-level moments recovered from the two first stages. The identifying logic is that if the products whose relative prices fluctuate most around their trend are precisely those facing the largest wedge between actual and optimal inflation, then inflation is distorting relative prices.

This methodology is well suited to *rejecting* the hypothesis that inflation does not distort relative prices, but it delivers a conservative estimate of the level of c_g: Adam et al. (2023) show that the first-stage estimation error biases c_g toward zero, and this bias is especially pronounced in category-cities with few products, which complicates level comparisons across sectors and countries. Importantly, the bias works against finding an effect.

I estimate the first stages on all products satisfying the sample criteria in Section 2, which leaves 5,765,701 classified products and over 256 million product-weeks. Following Adam et al. (2023), I drop the top 5% of $\widehat{\mathrm{Var}}(u_{igt})$ and of $\widehat{\Pi_g / \Pi^*_{ig}}$, and require at least 50 products per category-city for the second stage, leaving on average 672 products per category-city combination.

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

4.2 Main Results on Product-Level Price Distortions

First-stage moments. Appendix Figure C.3 summarizes the product-level moments entering the second stage, across the $5,775$ city-categories with at least 50 products. Two features stand out. First, suboptimal inflation is overwhelmingly positive in this sample: 87% of city-categories have a positive average annualized suboptimal inflation rate, with a median of 1.9% (0.037% week-on-week), rising to 98% and 2% for restaurants. This is a markedly different environment from Adam et al. (2023), where a large share of categories lay in negative territory, and reflects the high-inflation period studied here—precisely the regime in which the distortionary effects of inflation are most relevant. Second, the standard deviations of both moments display substantial variation across products within a city-category, which is what identifies the second stage. Reassuringly, the distributions of the dispersion moments are very similar to those in Adam et al. (2023); the level of suboptimal inflation is the only input that differs substantially.

Second-stage estimates. Figure 4 presents the distribution of the estimated c_g across the 5,637 city-categories retained for display.[15] Table 3 reports additional statistics of the estimates. The results strongly support the prediction that inflation distorts relative prices: 98.5% of the estimated coefficients are positive. Among the t-statistics, 86% exceed 2 and 50% exceed 5, while fewer than 0.5% fall below -2. Restricting to city-categories with more than 100 products—where the downward bias is less severe—92% exceed 2 and 57.5% exceed 5, consistent with the bias being most acute in small categories. The average second-stage R^2 is 22%, indicating that squared suboptimal inflation explains a sizeable portion of the cross-product variance of the first-stage residuals; it is higher (25%) among categories with a positive significant coefficient and lower (3%) among the few with a negative significant one.

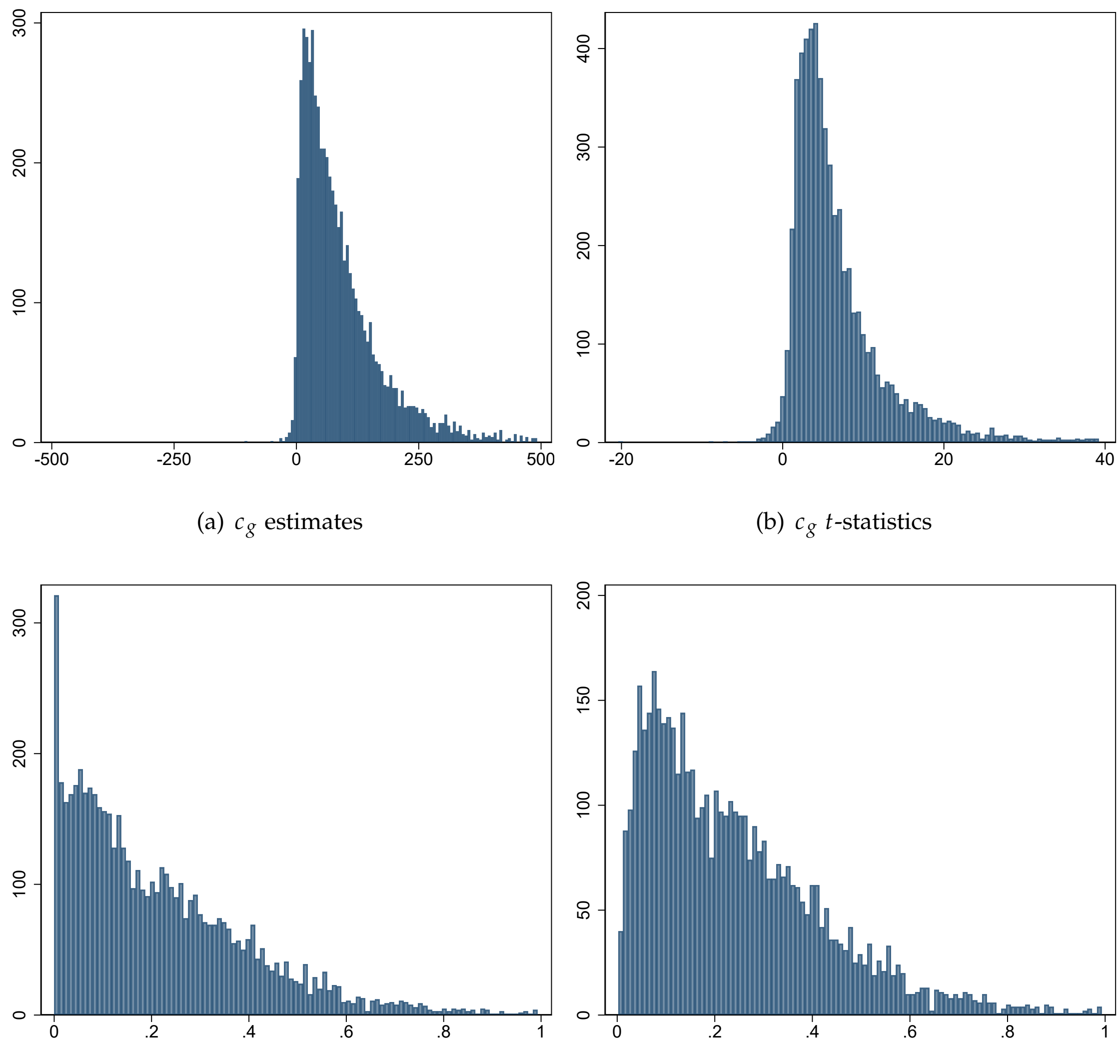
Taken together, these results establish that the first-stage residuals u_{igt} capture, to a large extent, distortions caused by suboptimal inflation rather than desired idiosyncratic variation. This validates retrospectively the use of $\mathrm{SD}_{gct}(u_{igt})$ as a measure of inefficient price dispersion in the cross-sectional analysis of Section 3: the comovement documented there is not merely a correlation, but reflects a causal effect of inflation on relative-price misallocation.

4.3 Cross-Sectoral and Cross-Country Heterogeneity

I now turn to how the estimated marginal effect c_g varies across sectors and countries. Table 3 reports summary statistics on the c_g estimates by country, together with the median separately for restaurants and supermarkets, and Figure C.4 shows the by-sector distributions of the estimates, their t-statistics, and the second-stage R^2.

[15] Category-cities with $|c_g| > 500$ or $|t\text{-stat}| > 40$ are excluded from the figures for readability, around 2.5% of the sample.

Figure 4: Marginal Effects of Suboptimal 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-stat of $c_g > 2$

Notes: This figure shows descriptive statistics of the second-stage regression. Observations with $|c_g| > 500$ or $|t\text{-stat of } c_g| > 40$ are excluded for readability, around 2.5% of the sample, leaving 5, 637 city-category combinations in panels (a)–(c). Panel (d) additionally drops observations with a t-statistic of $c_g < 2$.

Sectoral heterogeneity. The distortionary effect of inflation is more pronounced in restaurants, the stickier sector. The median c_g is higher for restaurants (85.16 pooled, versus 58.95 for supermarkets), the distribution of t-statistics is shifted right (Figure C.4, panel b), and the second-stage R^2 is substantially larger—a median of 35% for restaurants against 17% for supermarkets—so suboptimal inflation explains a larger share of product-level price variation where prices are stickiest. This is exactly the product-level counterpart of the cross-sectional result in Section 3: restaurants' dispersion responds more strongly to inflation because the underlying marginal effect of suboptimal inflation on distortions is itself larger in that sector. The pattern is also consistent with equation (4.3), in which

Table 3: Suboptimal Inflation and Product-Level Inefficient Price Distortions by Country and Sector

	$c_g > 0$	t-stat < -2	t-stat > 2	t-stat > 5	Median c_g	Restaurants Median c_g	Supermarkets Median c_g
AM	98.45%	0.52%	92%	64%	39.79	108.80	21.26
CI	99.13%	0.00%	80%	39%	69.07	107.63	64.24
ES (Barcelona)	99.37%	0.32%	90%	58%	109.75	188.36	92.11
ES (Madrid)	99.35%	0.00%	87%	54%	95.03	133.18	85.41
ES (Valencia)	100.00%	0.00%	94%	61%	21.03	42.81	15.26
GE	99.19%	0.41%	84%	41%	64.79	86.93	55.41
GH	97.39%	0.00%	83%	31%	30.19	31.61	26.91
HR	97.74%	0.45%	76%	40%	94.50	94.50	92.66
IT (Milan)	98.31%	0.34%	84%	51%	161.66	198.86	145.42
IT (Naples)	100.00%	0.00%	100%	76%	23.57	23.57	.
IT (Rome)	99.32%	0.00%	85%	50%	131.51	255.38	106.95
KE	100.00%	0.00%	94%	65%	94.56	161.02	85.20
KG	97.14%	1.14%	87%	51%	86.84	75.61	93.18
KZ	98.45%	0.39%	87%	48%	74.34	65.58	80.30
MA	96.28%	1.69%	89%	54%	39.92	107.34	27.29
PL (Krakow)	100.00%	0.00%	92%	45%	26.73	33.98	20.18
PL (Warsaw)	97.35%	0.33%	85%	50%	40.09	60.20	34.29
PT (Lisbon)	100.00%	0.00%	87%	50%	93.14	100.93	92.11
PT (Porto)	100.00%	0.00%	93%	50%	43.96	40.67	45.50
RO	94.44%	0.98%	72%	38%	47.58	100.94	33.55
SI	98.96%	0.00%	86%	46%	109.06	96.24	135.76
TN	98.91%	0.55%	87%	44%	34.52	56.59	29.08
UA	96.35%	0.00%	84%	51%	50.39	45.77	54.37
UG	100.00%	0.00%	88%	44%	65.71	85.31	57.61
Pooled	98.49%	0.32%	86%	50%	65.82	85.16	58.95

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-statistic 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. The following countries (cities) are included (same order): Armenia, Côte d'Ivoire, Spain (Madrid, Barcelona, and Valencia), Georgia, Ghana, Croatia, Italy (Rome, Milan, and Naples), Kenya, Kyrgyzstan, Kazakhstan, Morocco, Poland (Warsaw and Krakow), Portugal (Lisbon and Porto), Romania, Slovenia, Tunisia, Ukraine, and Uganda. No supermarket data is available for Naples (IT).

c_g is increasing in stickiness. The level comparison should nonetheless be read with caution, because the downward bias is more severe for categories with few products, and restaurant categories are larger on average (1,930 products versus 515 for supermarkets); part of the lower supermarket c_g could therefore reflect a stronger attenuation toward zero rather than a genuinely smaller effect. Either way, the qualitative ranking—a stronger and better-identified effect in the stickier sector—is robust, and reinforces that confining attention to the retail sector, as most of the literature does, misses where inflation is most distortionary.

Cross-country evidence. The effect is present across countries despite very heterogeneous inflation environments. In every country the share of positive c_g exceeds 94%, and in most countries the share of positive and significant estimates (t-statistic > 2) is above 80%. The differing sample sizes again make level comparisons difficult, but even cities with many observations and very different average inflation—such as Kyiv and Rome—display a similar share of significant coefficients. This is direct evidence that inflation continues to distort relative prices even in high-inflation environments, and complements the reduced-form by-city evidence in Section 3: there, the cross-sectional comovement of dispersion and inflation held in every city; here, the underlying causal marginal effect holds in every country as well.

5. The Costs of Inflation and a Standard Menu-Cost Model

In this section I provide several approximations of the costs of (high) inflation, which should be read as 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. First, it shows that my results are not driven by the methodology employed. Second, it shows that standard New Keynesian menu-cost models fail to match key empirical moments and may therefore 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: the misallocation due to inefficient price dispersion, and 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 be seen as a lower bound on the cost of inflation. Within the New Keynesian framework, Coibion et al. (2012) perform a detailed welfare analysis and identify, in addition to the direct cost from inefficient price dispersion and misallocation in the steady state, two further costs. The first is that a positive inflation level raises the welfare cost of inflation volatility around that level, because inflationary shocks become more costly as firms compensate for the increasingly high marginal disutility of sector-specific labor. The second is that at higher inflation price-setting becomes more forward-looking, which raises inflation volatility and further reduces welfare. Since measuring how the disutility of labor rises with price dispersion, or how higher inflation induces volatility that further raises dispersion, is beyond the scope of this paper, I limit myself to the cost from misallocation induced by inefficient price dispersion. It is worth keeping in mind that this may be a lower bound that ignores other dispersion-related channels through which higher inflation reduces welfare.[16]

This welfare cost is usually expressed as the percentage loss of flex-price consumption per period. In a widely used second-order approximation (Galí, 2008; Alvarez et al., 2019; Blanco et al., 2024a), it

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

equals

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

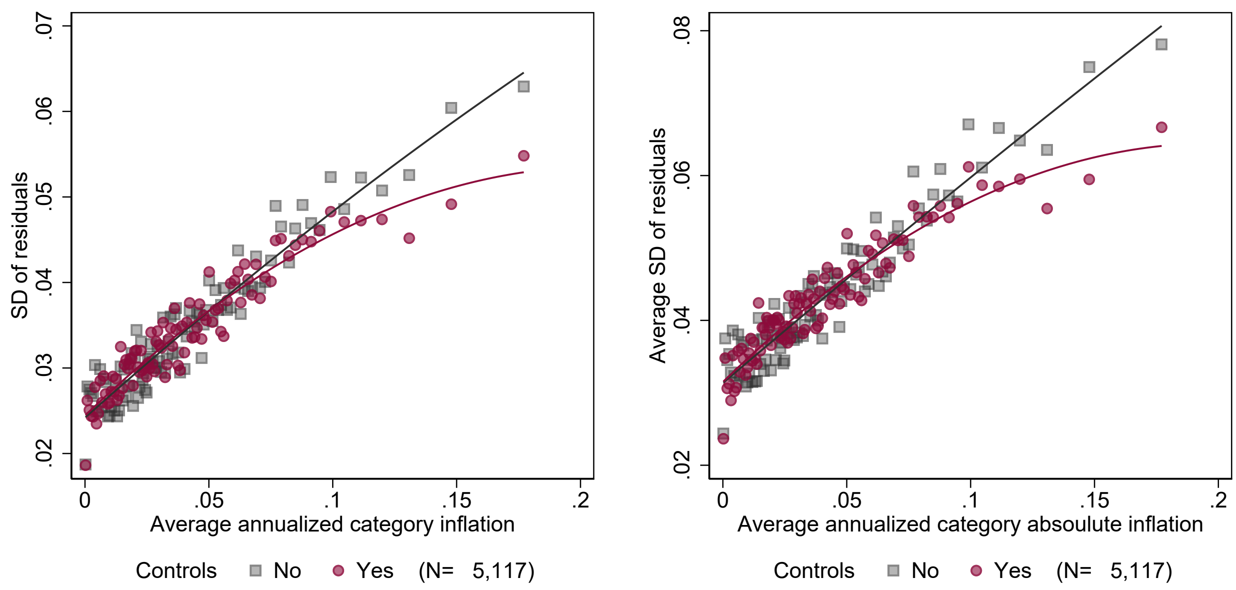
where σ is the elasticity of substitution between goods and $\mathbb{V}[x]$ is the variance of price gaps, which depends on the level of inflation π. Because ϕ is linear in σ, every cost estimate below scales proportionally with this parameter. I set $\sigma = 6$ in the baseline, consistent with the elasticity used in the menu-cost model below and slightly more conservative than the value of 7 used by Coibion et al. (2012); Appendix Table D.8 reports all estimates for elasticities ranging from 3 to 10.

Because my measures of the dispersion of price gaps may not capture the level well, one way to obtain an estimate of the cost of inflation is to measure how dispersion changes when moving from zero inflation to a rate π. Alvarez et al. (2019), for instance, measure dispersion from the variance of residualized log prices, using a regression similar to (3.2), and estimate the cost at rate π by subtracting the variance around zero inflation, $\phi(\pi) = \frac{\sigma}{2}\left(\mathbb{V}[x](\pi) - \mathbb{V}[x](0)\right)$. Using this method they find a cost of only 0.6% for an annual inflation rate of 50%, and almost no cost below 10%.

Estimated costs and sensitivity to the inflation frequency. Given the high frequency of the data and the persistence of inefficient price dispersion, I first show that this analysis is strongly sensitive to the choice of zero-inflation dispersion and to the measure of inflation used. Cavallo et al. (2023) indicate that inefficient dispersion from a large shock, such as the one recently observed, takes more than a year to fully dissipate. At the baseline $\sigma = 6$, raising annualized inflation to 10% implies a welfare cost of about 0.30% of consumption when inflation is measured month-on-month, but only 0.19% when measured week-on-week. This gap likely reflects the persistence of price dispersion: dispersion generated by past price changes dissipates only gradually, so at higher frequency many periods see no adjustment at all—and measured inflation is zero—even though the dispersion inherited from earlier periods persists. High frequencies for calculating inflation might therefore understate how strongly dispersion comoves with inflation, and with it the implied cost. [17] Changing the dispersion measure barely changes the picture: using the relative prices residualized with fixed effects $\mathrm{SD}_{gct}(\varepsilon_{irgct})$ instead of the baseline measure gives costs of about 0.37% (month-on-month) and 0.23% (week-on-week). The first three columns of Appendix Table D.8 report the underlying variances at zero and at 10% inflation for each case, and the remaining columns trace out the full dependence on the elasticity. These month-on-month estimates are consistent with the regression evidence of Section 3: evaluating the cost at the predicted dispersion from the specification that adds a quadratic inflation term, or from the one that restricts the sample to positive inflation rates, yields essentially the same figure of about 0.30% for a rise from zero to 10% inflation (Table 2 and Appendix Table C.6).

[17] Appendix Figure C.5 shows the same binscatters as Figure 3 but using week-on-week annualized inflation rates.

Figure 5: 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: Relationship between city-category average price dispersion and 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 the number of products in the category-city combination. Only city-categories observed in at least 52 weeks and with at least 50 products are included, for 5,117 observations.

Since a monthly frequency may not be adequate for a persistent dispersion that can take a year to dissipate (Cavallo et al., 2023), I next exploit the cross-country dimension. Using the international variation and the narrow product categorization performed with the same methodology, I estimate the cost of inflation from the relation between the category-city absolute average annualized monthly inflation and the average dispersion of price gaps over the sample. Annualized absolute inflation is constructed by first averaging the weekly month-on-month rates, then annualizing and taking the absolute value.

Figure 5 shows this relationship. Panel (a) uses $\mathrm{SD}_{gct}(u_{irgct})$ as the dispersion measure and panel (b) uses $\mathrm{SD}_{gct}(\varepsilon_{irgct})$; because I want to exploit inflation variation across countries, the focus is on the residualized variables, after controlling for category fixed effects and the number of products, and both figures display the binscatter before and after these controls. Both again show a positive relationship between dispersion and average annualized inflation, even at elevated inflation. At the baseline $\sigma = 6$, an increase from zero to 10% is associated with an additional loss of about 0.60% of flex-price consumption for $\mathrm{SD}_{gct}(u_{irgct})$, and about 0.96% for $\mathrm{SD}_{gct}(\varepsilon_{irgct})$ (Appendix Table D.8). These cross-country estimates, which capture the persistent dispersion that the higher-frequency measures miss, are the largest of the three frequencies. Being less restrictive on the number of products, and including category-cities with at least 25 products, yields slightly higher numbers; Appendix D shows the relation using scatter plots and when keeping category-cities with fewer than 50 products.

Abstracting from the change in dispersion in levels between two inflation rates, another informative number is the percent change in ϕ relative to zero inflation, $\Delta\phi(\pi) = \frac{\mathbb{V}[x](\pi)-\mathbb{V}[x](0)}{\mathbb{V}[x](0)}$, reported in the $\Delta\mathbb{V}\,\%$ column of Appendix Table D.8; because the cost is linear in the variance, this is also the percentage increase in the welfare cost as inflation rises from zero to 10%, for any elasticity. For the cross-country baseline measure, the variance of price gaps rises by about 570%—from 0.00035 to 0.0023—so the misallocation cost at 10% inflation is roughly 6.6 times what it would be near zero inflation. These rough approximations indicate sizable costs associated with higher inflation, a pattern inconsistent with standard menu-cost models.

Sensitivity to the elasticity of substitution. Appendix Table D.8 makes the dependence on the elasticity explicit. Since ϕ is linear in σ, moving from the low end of plausible values ($\sigma = 3$) to the high end ($\sigma = 10$) scales each estimate by a factor of about 3.3. At the baseline cross-country measure, the cost of a rise to 10% inflation ranges from 0.30% of consumption at $\sigma = 3$ to 0.99% at $\sigma = 10$, with the headline 0.60% at $\sigma = 6$; the higher-frequency month-on-month and week-on-week measures are uniformly smaller, and the fixed-effects measure ε uniformly somewhat larger. Across all combinations of frequency, dispersion measure, and elasticity, the cost of moving from zero to 10% annualized inflation lies between roughly 0.1% and 1.6% of consumption. None of the qualitative conclusions—a positive and economically meaningful cost, an ordering in which the persistent cross-country relation implies the largest cost, and a relationship that does not vanish at high inflation—depends on the choice of σ, which merely rescales all estimates by a common factor.

5.2 Model and Estimated Relation of Inflation and Inefficient Price Dispersion

In New Keynesian models, the precise relationship between $\mathbb{V}[x]$ and inflation depends strongly on how nominal rigidities are modeled. In a classical single-product one-sector menu-cost model, in which the price can be adjusted at a cost each period, inefficient dispersion remains roughly constant even at high inflation (Nakamura et al., 2018): when the relative-price gap is large, firms find it optimal to pay the adjustment cost, capping how dispersed prices can be. In a Calvo model with fixed adjustment probabilities, dispersion instead rises rapidly with inflation. On one hand, the rapid increase in the frequency of adjustment with inflation during the recent high-inflation period (Cavallo et al., 2023) makes fixed-fraction models implausible. On the other, the results of the previous sections show that $\mathbb{V}[x]$ comoves positively with inflation, a pattern inconsistent with the flatness of standard state-dependent models. This section compares my estimates and methodology with a calibrated standard menu-cost model and finds that such a model fails to match key moments, making it inadequate for measuring the costs of inflation-induced dispersion.

I show that the comovement of inflation and inefficient dispersion in a standard menu-cost model does not align with the empirical evidence, and that this discrepancy is not driven by my methodology. I calibrate a one-sector menu-cost model similar to Nakamura et al. (2018) and find that, while the methodology may overestimate the level of dispersion, the estimated and the true gap dispersion comove similarly with inflation—so the methodology does not manufacture the empirical relationship.[18]

Calibration. In the baseline calibration I set the menu cost K and the standard deviation of idiosyncratic shocks σ_ε to match the mean fraction and the mean absolute size of price adjustments in the data. To mitigate the concern that the dispersion of price changes reflects 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 (Appendix B). Appendix Table D.9 reports the targeted and untargeted moments at the city level, together with the calibrated parameters. Since targeting cross-country averages may be misleading—owing to heterogeneity in the restaurant share of observations, inflation environment and possible price-setting heterogeneity —I calibrate for each city and sector one model, setting K and σ_ε to match the frequency and the absolute size of price adjustments with the city average month-on-month inflation rate. The cross-country median menu cost K is higher for restaurants (0.1204) than for supermarkets (0.0355), while the cross-country median standard deviation of idiosyncratic shocks σ_ε is higher for supermarkets (0.0804) than for restaurants (0.065). Both numbers are higher than in Nakamura et al. (2018), largely explained by the higher absolute size of price adjustments observed here. The calibration for restaurants and supermarkets is similar to the fifth services sector and to the unprocessed food sector in the fourteen-sector model in Nakamura and Steinsson (2010). I set the elasticity of substitution to $\sigma = 6$, as in related work (Alvarez et al., 2019). [19]

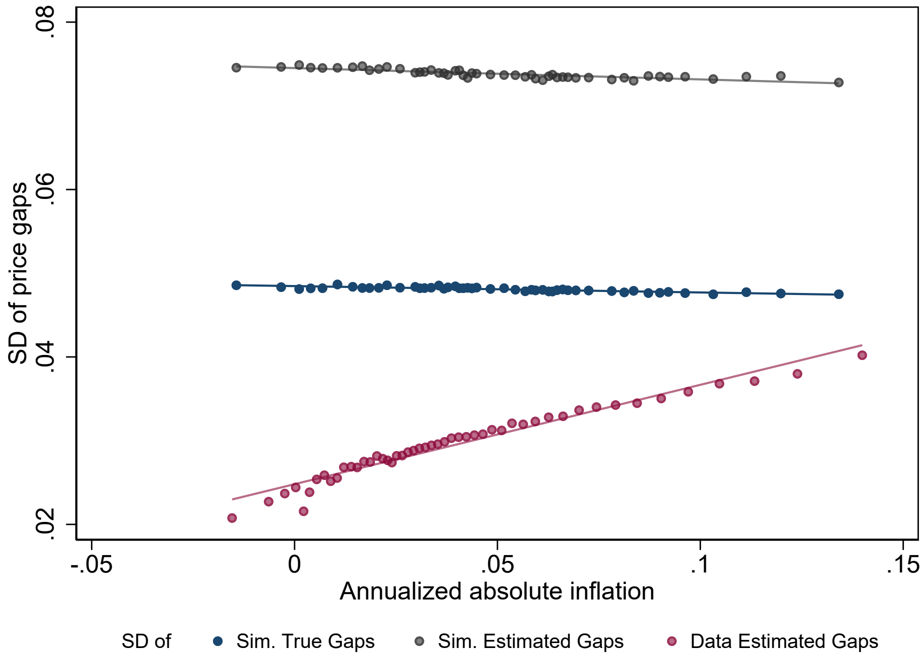
For each calibrated city-sector I run five simulations of inflation, prices and desired prices for 300 firms over 100 periods each. From the simulated data I compute the standard deviation of the true price gap (the difference between the relative price and the desired relative price) and the standard deviation of the gaps estimated with equation (3.3).

Simulation results. Figure 6 plots absolute month-on-month inflation against three dispersion measures: the standard deviation of the true simulated gaps, the standard deviation of the gaps estimated from the simulated prices, and the standard deviation of the estimated gaps in the real data. All city-category-sector-month dispersion measures are residualized for category-city heterogeneity

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

[19] As in Nakamura et al. (2018), I set $\beta = 0.96^{1/12}$ and the AR(1) parameter for idiosyncratic productivity to $\rho = 0.7$. Given the high volatility of nominal GDP in recent years and across the countries studied, I set the standard deviation of nominal aggregate demand shocks to $\sigma_\eta = 0.006$, higher than their 0.0039.

Figure 6: Estimating Price Gaps in Simulated Data



Notes: Relationship between inefficient price dispersion and inflation using the true gaps, the estimated gaps in the simulated data, and the estimated gaps in the actual data. Each dot is the average dispersion within one of 50 equally sized inflation bins. The unit of observation is a category × city × week for the data and a city × sector × sample × month in the simulation. Dispersion is residualized controlling for sector×city fixed effects.

in order to capture solely the role of inflation. In all samples I drop observations with absolute month-on-month annualized inflation above 15%.

The first conclusion is that the fixed-effects estimated gaps may overestimate the level of inefficient dispersion, but they do not artificially generate a positive slope between inflation and dispersion. In the simulated data the estimated dispersion is about 50% higher than the true dispersion, yet both slopes are negative and significantly different from zero —-0.008 for the true gaps and -0.013 for the estimated gaps, Appendix Table D.10.[20] This confirms that the strong empirical comovement documented in Sections 3 and 4 is not an artifact of the two-stage estimation.

The second conclusion is that inefficient dispersion comoves far more strongly with inflation in the data than in the menu-cost model: the model presents a negative slope of about -0.013 compared to the slope in the data over the same inflation range and same fixed effects of 0.119. Standard menu-cost models therefore miss a relationship that is central to one of the main costs of high inflation.

[20] The overestimation arises because menu-cost models need large idiosyncratic shocks to reproduce the observed price-change moments (Blanco et al., 2024a). These shocks move desired relative prices in all directions and are partly mislabeled as price gaps by the fixed-effects approach. Blanco et al. (2024a) argue that such large idiosyncratic shocks are inconsistent with the observed comovement of adjustment frequency and inflation, so they may be exaggerated in standard menu-cost models and less of a concern in other frameworks.

The model also fails to match a key statistic of the price-gap distribution, the kurtosis of price changes. A large kurtosis points to a mass of firms adjusting late, implying greater misallocation. Indeed, in a low-inflation steady state the variance of price gaps—the object relevant for the cost of dispersion—under certain assumptions satisfies $\mathbb{V}[x] = \mathbb{V}[\Delta p]\,\mathrm{Kurt}[\Delta p]/6$ (Alvarez et al., 2016; Cavallo et al., 2023). As Appendix Table D.9 shows, the model yields a median kurtosis of 2.61 for restaurants and 1.47 for supermarkets, far from the estimated cross-city median kurtosis of 5.26 and 4.27, respectively.

Which model can rationalize these facts is an open question. The patterns documented here—a V-shaped comovement of dispersion with inflation that flattens only mildly at very high rates, a size margin that responds strongly to inflation (especially in the stickier restaurant sector), and leptokurtic price changes—point away from pure state-dependence and toward frameworks with weaker selection, a larger time-dependent component, or strategic complementarities in price-setting. These results call for a model matched not to the unconditional level of the frequency and size of adjustments, but to how they—and the dispersion of price gaps—respond to inflation. Because the distortion is concentrated in the stickier sectors, such a model would also be essential for quantifying how sectoral heterogeneity shapes the welfare costs of inflation.

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 is positive in 98.5% of category-city combinations and statistically significant in most of them, with a more pronounced and better-identified effect in the stickier restaurant sector. 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, an increase in annualized inflation from zero to 10 percent is associated with an increase in inefficient price dispersion of about 73% for restaurants and about 46% for supermarkets. This points to the importance of analyzing different sectors when assessing the welfare costs of high inflation, since confining attention to more flexible sectors masks how distortionary inflation can be.

The qualitative effect is present in every country and sector in the sample. At the same time, exploiting the variation in average inflation *across* countries—rather than only the within-country, high-frequency variation—turns out to be essential: it captures the persistent component of inefficient dispersion that higher-frequency measures miss, and it delivers the largest welfare-cost estimates. Using a rough approximation, the cost of an increase in annualized inflation from zero to 10% ranges from about 0.30% of flex-price consumption at monthly frequency to about 0.60% when exploiting the cross-country variation. Abstracting from the level of price dispersion at zero inflation, the variance of estimated price gaps—and hence the misallocation cost—rises nearly sixfold. These estimates, however, should be read as lower bounds on the total cost of inflation and are highly sensitive to the time frequency used and to the assumed level of dispersion at zero inflation.

Finally, I show that a standard New Keynesian menu-cost model, calibrated to my data, fails to match key empirical moments associated with inflation-driven inefficient price dispersion. The calibrated model generates an almost negligible—indeed slightly negative—comovement between inflation and inefficient dispersion, and generates far too little kurtosis of price changes. Applying my estimation strategy to data simulated from the model confirms that the empirical relationship is not manufactured by the two-stage procedure. This indicates that such models may be inadequate for measuring the costs associated with inflation-driven inefficient price dispersion, and that alternative frameworks should be considered when deriving the optimal level of inflation. To this end, I provide a broad set of standard price-setting moments by sector and country, together with estimates of the relationship between inflation and price dispersion, which future work can use to discipline and calibrate the models used to guide optimal monetary policy.

Taken together, the results already suggest 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 previously estimated. Future research should provide a deeper understanding of the role of sectoral heterogeneity in welfare analysis and of 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.

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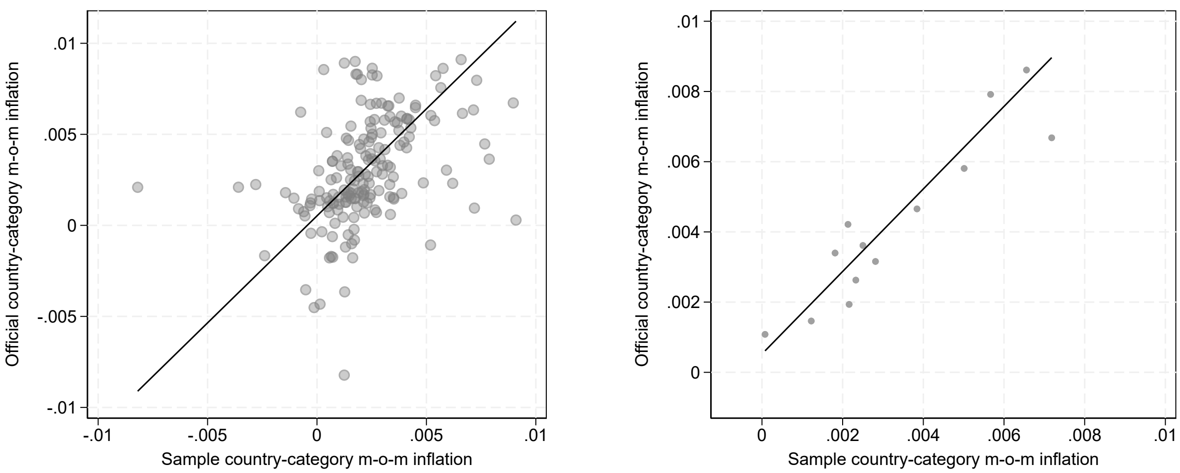
Appendix

A. Online Data Categories and Official Inflation

Figure A.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. Ten observations with an average absolute inflation larger than one percent monthly deleted. Binscatter weighted by number of observations included in each country-COICOP. Linear weighted fitted line in sub-figure (a) has a significant slope of 1.20, with robust standard error of 0.15, a R^2 of 0.63 and includes 172 country-COICOPs combinations – 10 country-COICOPs with an inflation rate above 1% m-on-m not included in the figure. The weighted correlation of these observations is 0.79.

Table A.1: Comparison of Price Setting Moments with Official CPI Data (Spain)

	Months	# coicops	Avg. official N^t_{igct}	Avg. online N^t_{igct}	Share adj. official % (Std. Dev.)	Share adj. online % (Std. Dev.)	Avg. size official % (Std. Dev.)	Avg. Size online % (Std. Dev.)	Corr. freq.	Corr. size
All	2023m4-2025m10	19	11,865	477,820	15.35 (11.56)	18.01 (7.54)	11.68 (5.65)	9.58 (2.75)	0.373	0.174
Restaurants	2023m4-2025m10	1	739	330,611	5.26 (2.13)	4.36 (0.65)	8.56 (1.85)	13.30 (0.79)	0.589	0.295
Supermarkets	2023m4-2025m10	18	11,126	147,209	15.91 (11.61)	18.77 (7.00)	11.85 (5.74)	9.38 (2.67)	0.311	0.252

Notes: The table compares official (Spanish CPI, INE) and online price-setting moments aggregated to the COICOP-4 × month level over the common sample. Columns report, by panel, the range of months compared; the number of COICOP categories present in both sources; the average monthly number of observations in each source (summed across categories within a month, then averaged across months); and the mean (standard deviation in parentheses, across category–month cells) of the frequency of price change and of the average absolute size of price changes, in percent. The online frequency is the share of products with a non-zero 4-week price change and the online size is the corresponding mean absolute log change, both aggregated to the category level as unweighted means across my product categories. The standard deviations (Std. Dev.) in parenthesis were computed across all matched COICOP-months. The last two columns report the correlation between the online and official measures across category–month cells, computed after dropping cells in the top 5% of the official measure. "Restaurants" corresponds to COICOP CP1111 and "Supermarkets" to all other matched COICOP-4 categories.

Table A.2: 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

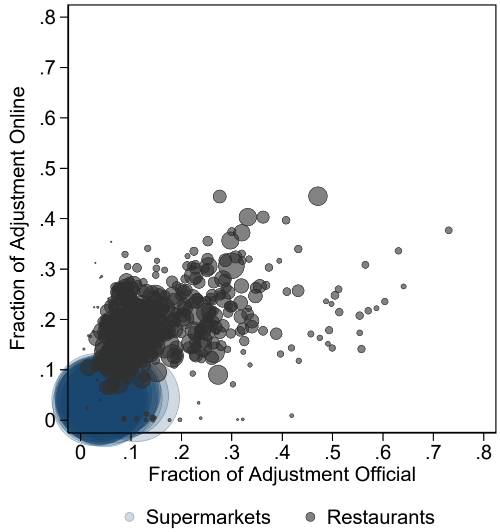
217	Supermarkets	Energy Drinks	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
218	Supermarkets	Icetea	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
219	Supermarkets	Isotonic	01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	3
220	Supermarkets	Sodas	01.2.2	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

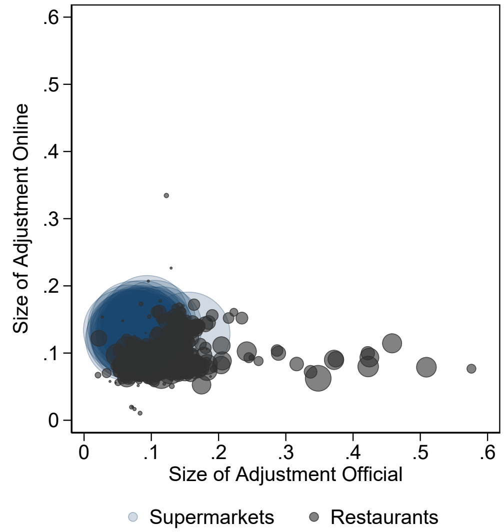
305	Supermarkets	Nail Lacquer	12.1.3	Other appliances, articles and products for personal care	3
306	Supermarkets	Nail Polish Remover, Acetone	12.1.3	Other appliances, articles and products for personal care	3
307	Supermarkets	Paper Napkins	12.1.3	Other appliances, articles and products for personal 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.

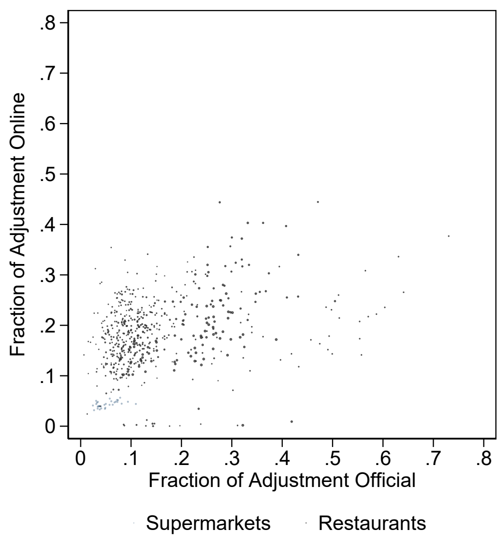
Figure A.2: Fraction and Absolute Size of Adjustments Online vs Official (Spain)



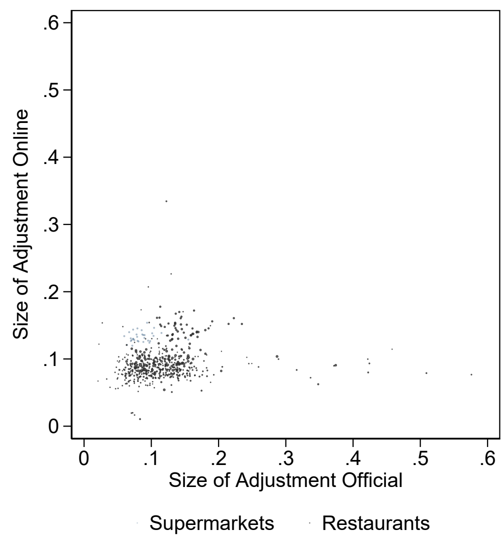
(a) Fraction of Adjustment Online N^g_{igt} Weighted



(b) Abs Size of Adjustment Online N^g_{igt} Weighted



(c) Fraction of Adjustment Official N^g_{igt} Weighted



(d) Abs Size of Adjustment Official N^g_{igt} Weighted

Notes: This figure compares the the fraction of adjusted prices (m-on-m) and the average absolute size of adjusted prices (m-on-m) between online and official CPI data for Spain at the COICOP4-month level. Panels (a) and (b) weight each COICOP4-month by the relative number of products in the online data, panels (c) and (d) are scaled within the figures with the relative number of products in the official data and scaled with the average number of of products observed in the official vs online data (627.68/25277.17=0.025).

B. Additional Price Setting Moments

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,

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

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 B.3: The Size and Frequency of Price Adjustments and Inflation

	Mean $\lvert\Delta p_{igct}\rvert$						Adj. Share Δp_{igct}					
	Weekly w-on-w $(t-1)$			Weekly m-on-m $(t-4)$			Weekly w-on-w $(t-1)$			Weekly m-on-m $(t-4)$		
	All	Super	Rest	All	Super	Rest	All	Super	Rest	All	Super	Rest
$\lvert\Delta p^{Ann}_{gct}\rvert$	0.293***	0.260***	0.370***	0.220***	0.195***	0.309***	0.181***	0.194***	0.150***	0.668***	0.671***	0.659***
	(0.004)	(0.005)	(0.008)	(0.004)	(0.004)	(0.009)	(0.002)	(0.003)	(0.002)	(0.007)	(0.008)	(0.009)
N	231,796	139,041	92,755	322,954	204,340	118,614	231,917	139,127	92,790	323,020	204,396	118,624

Notes: This table shows the relation of the mean absolute adjustment conditional on adjustment, Mean $\lvert\Delta p_{igct}\rvert$ and of the frequency of price adjustments measured as the adjustment share (Adj. Share Δp_{igct}) 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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.4: Additional moments on adjusted price changes: Supermarkets

	Inflation ($\overline{\Delta p_{ct}}$)	p25 Δp_{ct}	p50 Δp_{ct}	p75 Δp_{ct}	$N_{\Delta p}$	Mean Frac. Δp_{it}	Dur.	Share Adj $\Delta p_{it} > 0$	Mean $\lvert\Delta p_{it}\rvert$	Med. $\lvert\Delta p_{it}\rvert$	SD $\lvert\Delta p_{it}\rvert$	SD Δp_{it}	Kurt Δp_{it}	Kurt $\lvert\Delta p_{it}\rvert$	Adj. Kurt	N_i in Adj. Kurt
AM	0.30	-0.46	0.69	2.04	31,207	0.025	10.0	0.574	0.130	0.096	0.117	0.174	4.571	6.261	1.463	5,907
CI	5.92	2.90	5.47	7.82	121,549	0.047	5.1	0.712	0.110	0.070	0.111	0.152	6.909	9.059	2.218	27,392
ES	3.95	1.65	3.02	5.00	1,495,178	0.075	3.2	0.564	0.086	0.056	0.088	0.122	6.937	10.487	1.828	167,616
ES (Madrid)	4.57	1.21	3.26	5.42	721,188	0.079	3.0	0.566	0.086	0.057	0.088	0.122	7.033	10.662	1.909	78,960
ES (Barcelona)	3.49	1.23	3.08	5.34	723,118	0.073	3.3	0.563	0.087	0.057	0.088	0.123	6.772	10.239	1.803	77,573
ES (Valencia)	1.15	0.47	1.27	1.79	50,872	0.068	3.6	0.534	0.083	0.051	0.090	0.122	7.943	11.445	1.538	11,083
GE	3.51	0.49	3.63	6.54	124,766	0.057	4.2	0.570	0.193	0.162	0.150	0.243	3.163	3.805	1.522	21,300
GH	3.45	1.19	5.21	10.25	13,799	0.067	3.6	0.537	0.189	0.146	0.153	0.243	3.415	4.160	2.106	3,459
HR	5.23	1.75	3.97	8.49	159,003	0.063	3.8	0.579	0.172	0.113	0.151	0.228	3.291	3.151	1.444	17,666
IT	2.10	0.55	2.59	3.85	1,009,946	0.061	4.0	0.544	0.142	0.097	0.128	0.191	4.080	4.916	1.313	123,603
IT (Rome)	1.81	-0.16	1.64	3.67	466,692	0.053	4.6	0.542	0.143	0.098	0.128	0.192	3.822	4.406	1.315	55,302
IT (Milan)	2.60	0.97	2.75	5.18	543,254	0.069	3.5	0.546	0.141	0.096	0.128	0.190	4.308	5.359	1.313	68,301
KE	5.41	1.61	3.77	8.06	263,462	0.030	8.3	0.658	0.121	0.091	0.110	0.159	5.458	7.670	1.815	47,361
KG	4.26	1.69	3.86	6.91	100,256	0.055	4.4	0.586	0.096	0.068	0.093	0.132	6.722	10.447	2.089	17,711
KZ	5.28	-0.73	3.65	9.67	304,171	0.100	2.4	0.552	0.165	0.129	0.140	0.216	3.374	3.806	1.472	47,309
MA	2.21	0.23	1.78	3.68	357,461	0.058	4.2	0.544	0.109	0.077	0.107	0.152	5.464	7.449	1.372	57,097
PL	2.76	-0.92	2.44	5.95	404,034	0.098	2.4	0.566	0.149	0.120	0.120	0.191	3.548	4.796	1.390	72,452
PL (Warsaw)	2.73	-1.16	2.25	5.62	369,091	0.100	2.4	0.568	0.149	0.120	0.121	0.191	3.572	4.831	1.382	64,219
PL (Krakow)	2.52	0.45	2.59	3.79	34,943	0.091	2.6	0.546	0.152	0.124	0.118	0.192	3.297	4.404	1.455	8,233
PT	1.55	-0.86	0.74	2.31	161,791	0.062	3.9	0.535	0.219	0.224	0.145	0.262	2.212	2.616	1.198	31,311
PT (Lisbon)	1.83	-0.69	0.89	2.12	93,204	0.053	4.6	0.524	0.221	0.227	0.141	0.261	2.173	2.750	1.162	16,652
PT (Porto)	2.03	-1.44	0.33	4.36	68,587	0.075	3.2	0.549	0.216	0.221	0.150	0.262	2.265	2.456	1.241	14,659
RO	6.44	0.70	6.26	11.45	601,389	0.156	1.5	0.562	0.123	0.082	0.119	0.170	4.506	5.330	1.742	87,885
SI	3.11	-0.44	3.16	5.72	26,782	0.086	2.8	0.535	0.246	0.257	0.114	0.271	1.688	3.484	1.242	4,248
TN	4.32	1.40	2.80	5.38	30,702	0.072	3.3	0.579	0.117	0.080	0.108	0.158	4.268	5.143	1.502	7,151
UA	9.19	3.16	8.97	13.50	971,085	0.173	1.3	0.598	0.149	0.103	0.131	0.197	3.554	3.857	1.483	143,477
UG	1.55	-0.03	0.99	2.49	116,528	0.041	5.9	0.583	0.107	0.067	0.116	0.157	6.797	8.848	1.479	25,748
All (mean)	3.92	0.77	3.50	6.62	349,617	0.074	4.1	0.577	0.146	0.113	0.122	0.190	4.442	5.849	1.593	50,483
All (median)	3.73	0.63	3.39	6.25	160,397	0.063	3.9	0.568	0.136	0.097	0.118	0.183	4.174	5.029	1.481	29,352

Notes: Moments are computed on adjusted (standardized) price changes, following Klenow and Kryvtsov (2008): within each city $\times$ narrow-category cell the log price change is demeaned and rescaled by the cell standard deviation and re-expressed in the country $\times$ sector reference distribution. Multi-city countries show a pooled country total followed by their component cities (indented); single-city countries show one row. "All (mean)" averages over the country-level rows (component cities are not counted twice). Inflation ($\overline{\Delta p_{ct}}$) and p25/p50/p75 Δp_{ct} are the mean and quartiles of the sector-wide annualized inflation across weeks. $N_{\Delta p}$ is the number of standardized adjustments underlying the moments; Mean Frac. Δp_{it} and Dur. are the mean weekly adjustment frequency and the implied duration in months, $-1/[4\ln(1-freq)]$, based on the raw frequency of changes; Share Adj $\Delta p_{it} > 0$ is the share of adjustments that are increases. Mean, Med. and SD $\lvert\Delta p_{it}\rvert$, SD Δp_{it}, Kurt Δp_{it} and Kurt $\lvert\Delta p_{it}\rvert$ are the corresponding moments of the standardized adjustments. Adj. Kurt is the kurtosis further corrected for unobserved within-product heterogeneity following Alvarez et al. (2022) on products with at least two consecutive adjustments; N_i in Adj. Kurt is the number of such products.

Table B.5: Additional moments on adjusted price changes: Restaurants

	Inflation ($\overline{\Delta p_{ct}}$)	p25 Δp_{ct}	p50 Δp_{ct}	p75 Δp_{ct}	$N_{\Delta p}$	Mean Frac. Δp_{it}	Dur.	Share Adj $\Delta p_{it} > 0$	Mean $\lvert\Delta p_{it}\rvert$	Med. $\lvert\Delta p_{it}\rvert$	SD $\lvert\Delta p_{it}\rvert$	SD Δp_{it}	Kurt Δp_{it}	Kurt $\lvert\Delta p_{it}\rvert$	Adj. Kurt	N_i in Adj. Kurt
AM	2.63	1.64	2.41	3.52	35,488	0.010	25.4	0.770	0.141	0.112	0.112	0.168	5.239	6.429	2.371	6,968
CI	4.31	2.16	4.18	5.99	11,607	0.015	17.1	0.783	0.197	0.166	0.124	0.208	4.411	5.694	2.347	2,171
ES	3.13	2.68	3.19	3.63	569,013	0.016	15.7	0.715	0.134	0.101	0.114	0.168	5.136	6.698	1.833	100,880
ES (Madrid)	3.06	2.46	3.13	3.73	291,578	0.018	13.7	0.700	0.135	0.105	0.111	0.167	5.019	6.833	1.809	50,867
ES (Barcelona)	3.16	2.47	3.17	3.98	260,828	0.014	17.7	0.730	0.132	0.096	0.117	0.169	5.290	6.585	1.843	47,578
ES (Valencia)	2.78	2.22	2.98	3.25	16,607	0.013	18.6	0.752	0.134	0.105	0.111	0.166	4.615	6.099	2.042	2,435
GE	5.15	3.26	4.61	5.65	91,445	0.019	12.7	0.753	0.138	0.104	0.114	0.170	5.601	7.162	2.084	19,408
GH	20.40	10.49	16.49	28.11	8,417	0.039	6.3	0.890	0.154	0.118	0.125	0.154	6.332	5.899	3.919	1,911
HR	6.99	5.39	6.72	8.71	41,580	0.019	13.1	0.874	0.128	0.101	0.104	0.141	7.383	7.495	2.886	9,834
IT	2.83	2.17	2.62	3.42	326,066	0.008	29.5	0.761	0.151	0.123	0.110	0.171	4.827	6.495	1.942	54,366
IT (Rome)	2.59	1.99	2.62	3.15	155,259	0.008	30.3	0.754	0.152	0.124	0.108	0.171	4.746	6.578	1.894	25,900
IT (Milan)	3.61	1.80	2.74	3.82	159,745	0.009	28.8	0.770	0.149	0.119	0.113	0.172	4.934	6.406	1.978	26,950
IT (Naples)	2.54	2.07	2.48	2.95	11,062	0.009	29.1	0.746	0.155	0.131	0.106	0.172	4.395	6.738	2.149	1,516
KE	6.10	1.35	2.85	8.81	45,540	0.012	21.2	0.732	0.169	0.130	0.138	0.208	4.402	4.952	1.882	9,107
KG	7.47	4.77	6.41	7.92	78,186	0.026	9.6	0.811	0.109	0.080	0.097	0.131	7.708	9.360	2.796	16,840
KZ	7.19	5.74	7.22	8.35	144,151	0.023	10.7	0.809	0.129	0.098	0.108	0.151	6.318	7.562	2.990	33,831
MA	3.62	1.59	3.70	5.04	80,348	0.017	14.4	0.696	0.151	0.124	0.112	0.180	4.249	6.258	2.058	14,670
PL	6.45	4.38	5.96	7.82	252,163	0.026	9.4	0.796	0.118	0.085	0.103	0.146	6.064	7.200	2.311	54,205
PL (Warsaw)	6.50	4.63	5.97	7.82	241,515	0.027	9.1	0.797	0.118	0.084	0.103	0.146	6.062	7.187	2.306	52,100
PL (Krakow)	3.69	3.03	3.48	4.53	10,648	0.021	12.1	0.785	0.119	0.093	0.099	0.144	6.112	7.517	2.423	2,105
PT	2.46	1.92	2.42	3.17	84,681	0.010	24.1	0.717	0.162	0.122	0.136	0.204	4.327	4.896	1.851	14,494
PT (Lisbon)	2.38	1.79	2.41	3.17	77,110	0.010	24.9	0.713	0.163	0.122	0.136	0.205	4.304	4.883	1.848	13,100
PT (Porto)	2.90	1.67	2.46	4.19	7,571	0.013	19.5	0.758	0.160	0.120	0.135	0.201	4.566	5.034	1.880	1,394
RO	8.17	6.07	7.80	9.68	265,491	0.026	9.4	0.808	0.147	0.107	0.126	0.179	5.548	5.781	2.063	61,745
SI	5.21	3.45	4.75	7.11	8,304	0.014	17.6	0.915	0.108	0.083	0.090	0.113	8.939	8.870	1.765	1,603
TN	5.31	3.65	5.21	6.52	31,249	0.019	13.2	0.823	0.126	0.100	0.097	0.140	6.611	8.683	2.900	6,129
UA	11.44	8.08	10.55	13.40	340,556	0.044	5.6	0.825	0.115	0.079	0.111	0.147	7.644	8.461	2.074	76,152
UG	6.61	2.43	3.73	5.81	24,120	0.014	18.2	0.850	0.181	0.159	0.130	0.187	5.084	4.646	3.161	5,306
All (mean)	6.42	3.96	5.60	7.93	135,467	0.020	15.2	0.796	0.142	0.111	0.114	0.165	5.879	6.808	2.402	27,201
All (median)	5.70	3.35	4.68	6.81	79,267	0.018	13.8	0.802	0.140	0.106	0.112	0.168	5.574	6.597	2.198	14,582

Notes: Moments are computed on adjusted (standardized) price changes, following Klenow and Kryvtsov (2008): within each city × narrow-category cell the log price change is demeaned and rescaled by the cell standard deviation and re-expressed in the country × sector reference distribution. Multi-city countries show a pooled country total followed by their component cities (indented); single-city countries show one row. "All (mean)" averages over the country-level rows (component cities are not counted twice). Inflation ($\overline{\Delta p}_{ct}$) and p25/p50/p75 Δp_{ct} are the mean and quartiles of the sector-wide annualized inflation across weeks. $N_{\Delta p}$ is the number of standardized adjustments underlying the moments; Mean Frac. Δp_{it} and Dur. are the mean weekly adjustment frequency and the implied duration in months, $-1/[4\ln(1-freq)]$, based on the raw frequency of changes; Share Adj $\Delta p_{it} > 0$ is the share of adjustments that are increases. Mean, Med. and SD $|\Delta p_{it}|$, SD Δp_{it}, Kurt Δp_{it} and Kurt $|\Delta p_{it}|$ are the corresponding moments of the standardized adjustments. Adj. Kurt is the kurtosis further corrected for unobserved within-product heterogeneity following Alvarez et al. (2022) on products with at least two consecutive adjustments; N_i in Adj. Kurt is the number of such products.

C. Robustness Inflation and Cross-Sectional Price Dispersion

Table C.6: Price Dispersion and Inflation Comovement: Additional Robustness Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. var:	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$
$\lvert\Delta p^{Ann}_{gct-4}\rvert$	0.130***	0.130***	0.131***	0.173***	0.225***	0.236***	0.223***	0.106***	0.114***	0.104***	0.085***	0.122***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)	(0.005)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
$\lvert\Delta p^{Ann}_{gct-4}\rvert^2$					-0.624***	-0.751***	-0.597***					
					(0.021)	(0.031)	(0.026)					
SD at $\pi = 0$	0.024	0.024	0.024	0.023	0.023	0.017	0.026	0.023	0.018	0.027	0.027	0.023
SD at $\pi = 5\%$	0.031	0.031	0.031	0.031	0.032	0.027	0.036	0.028	0.024	0.032	0.031	0.029
SD at $\pi = 10\%$	0.037	0.037	0.037	0.040	0.039	0.033	0.042	0.034	0.030	0.037	0.035	0.035
Change 0–5%	26.6%	26.6%	27.3%	38.1%	42.9%	59.0%	37.2%	23.1%	31.5%	19.6%	16.0%	26.7%
Change 0–10%	53.3%	53.2%	54.5%	76.2%	72.0%	95.7%	62.9%	46.2%	62.9%	39.3%	32.0%	53.3%
Restriction	Baseline ($N_{gct} \geq 50$, $\lvert\Delta p\rvert < 20\%$)	$N_{gct} \geq 20$	$N_{gct} \geq 100$	$\lvert\Delta p\rvert < 10\%$	Quadratic	Quadratic	Quadratic	Trimmed p95	Trimmed p95	Trimmed p95	Date × City	Positive
Sector	Both	Both	Both	Both	Both	Rest.	Super.	Both	Rest.	Super.	Both	Both
N	344,496	446,384	257,673	295,700	344,496	128,436	216,060	327,271	122,014	205,256	344,495	263,913
R^2	0.36	0.35	0.37	0.32	0.37	0.36	0.29	0.32	0.32	0.25	0.54	0.36
Within R^2	0.14	0.13	0.16	0.10	0.15	0.28	0.13	0.16	0.23	0.13	0.08	0.15

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 (3.3) the category-city weekly month-on-month inflation, $|\Delta p_{gct-4}|$. All specifications include category fixed-effects. Standard errors clustered at the category-city level in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

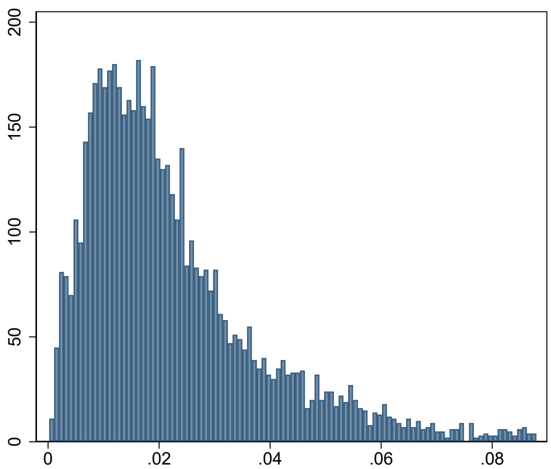
Table C.7: Price Dispersion and Inflation Comovement by City

	β	Observations	R^2	Within R^2
AM	0.062***	12,046	0.69	0.12
	(0.004)			
CI	0.046***	14,871	0.52	0.06
	(0.003)			
ES (Barcelona)	0.037***	30,323	0.79	0.04
	(0.002)			
ES (Madrid)	0.045***	29,985	0.75	0.06
	(0.002)			
ES (Valencia)	0.040***	4,226	0.73	0.07
	(0.005)			
GE	0.080***	13,792	0.63	0.09
	(0.005)			
GH	0.046***	1,344	0.64	0.05
	(0.009)			
HR	0.042***	13,865	0.57	0.03
	(0.004)			
IT (Milan)	0.040***	25,979	0.74	0.03
	(0.003)			
IT (Naples)	0.103***	1,414	0.79	0.34
	(0.013)			
IT (Rome)	0.058***	27,188	0.74	0.06
	(0.003)			
KE	0.092***	26,184	0.65	0.12
	(0.003)			
KG	0.055***	13,071	0.63	0.05
	(0.005)			
KZ	0.032***	15,943	0.61	0.01
	(0.004)			
MA	0.072***	23,344	0.69	0.10
	(0.003)			
PL (Krakow)	0.044***	2,853	0.78	0.06
	(0.005)			
PL (Warsaw)	0.041***	18,887	0.61	0.04
	(0.002)			
PT (Lisbon)	0.061***	9,031	0.85	0.06
	(0.005)			
PT (Porto)	0.044***	3,869	0.87	0.04
	(0.006)			
RO	0.046***	17,324	0.60	0.03
	(0.004)			
SI	0.061***	3,299	0.76	0.06
	(0.007)			
TN	0.068***	4,545	0.48	0.12
	(0.006)			
UA	0.044***	13,956	0.58	0.03
	(0.004)			
UG	0.062***	17,109	0.60	0.09
	(0.004)			
All (Cat.×City FE)	0.053***	344,448	0.73	0.05
	(0.001)			

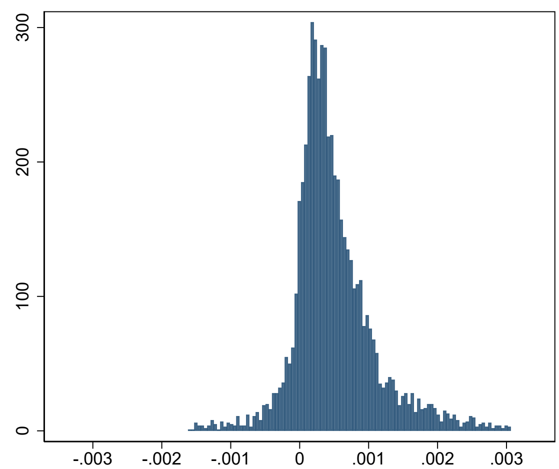
Notes: This table shows for each city separately the relation of the category-city-week standard deviation of product level residuals u_{irgct} from equation (3.3) the category-city weekly month-on-month inflation, $|\Delta p_{gct-4}|$. All specifications include category fixed-effects. Regressing the 24 city-specific estimates on the median category inflation in that city yields a coefficient of -0.588 with a standard error of 0.194, with a R^2 of 0.30. Standard errors clustered at the category level in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

D. Costs of Inflation and Model Parametrization

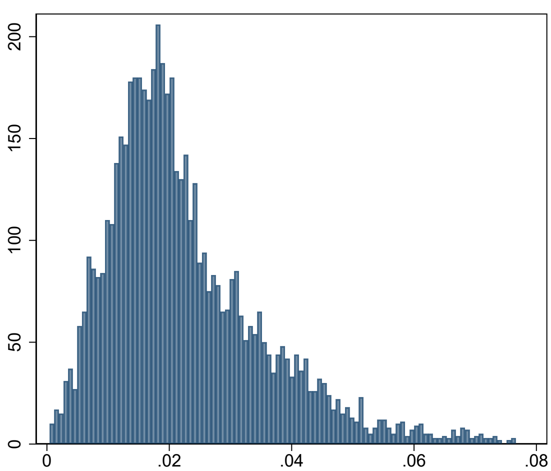
Figure C.3: Price dispersion and Sub-optimal Inflation from First-stage Regressions



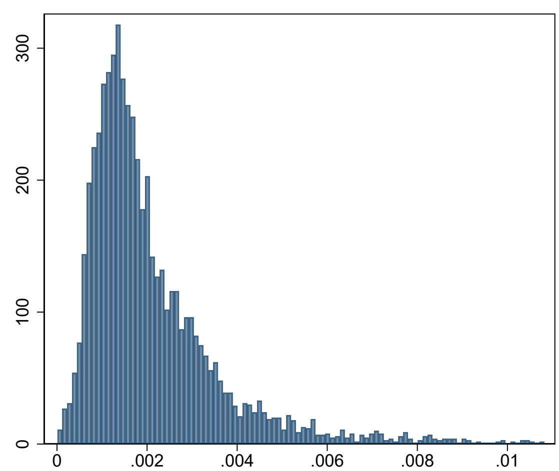
(a) Mean of $\text{std}_i(u_{igt})$



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



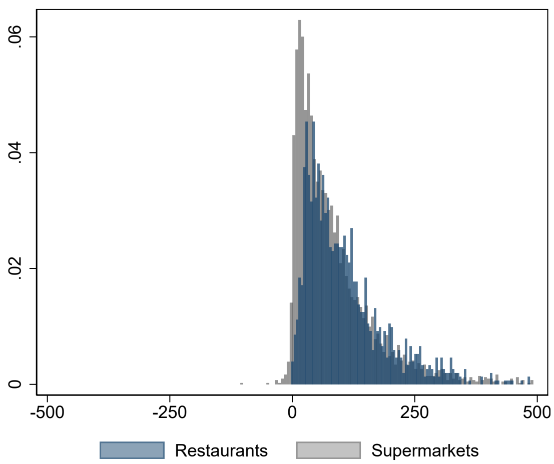
(c) Std of $\text{std}_i(u_{igt})$



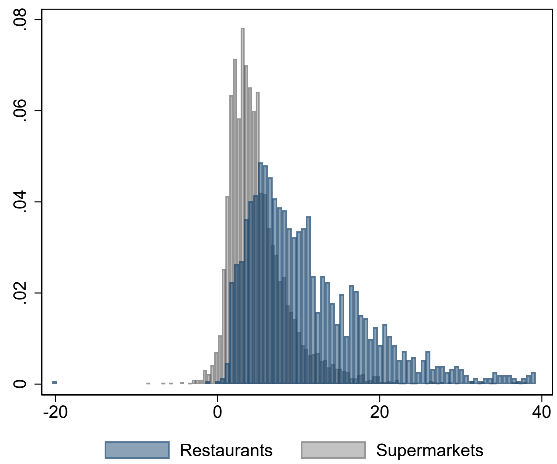
(d) Std of $\ln(\widehat{\Pi_g/\Pi^*_{ig}})$

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 5,775 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.

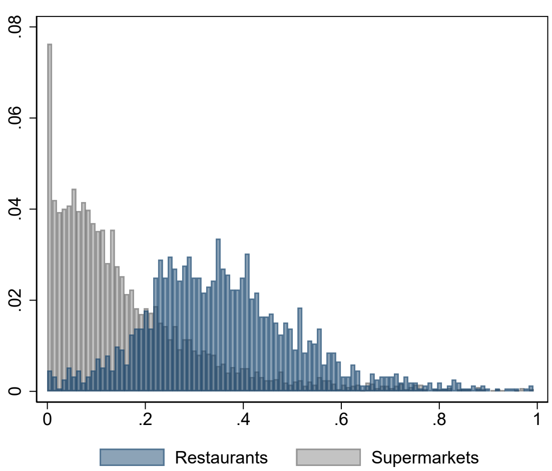
Figure C.4: Second-Stage Descriptive Statistics by Sector



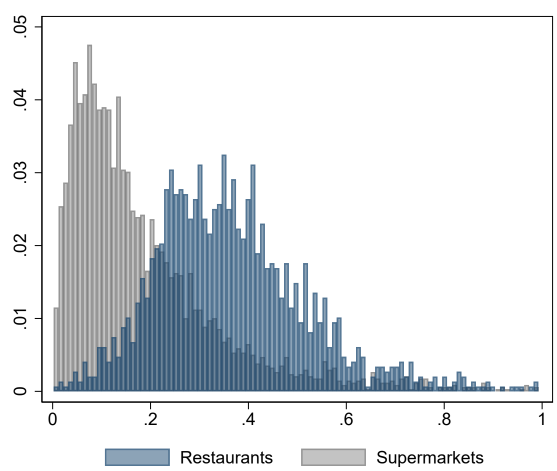
(a) c_g estimate



(b) c_g t-statistic



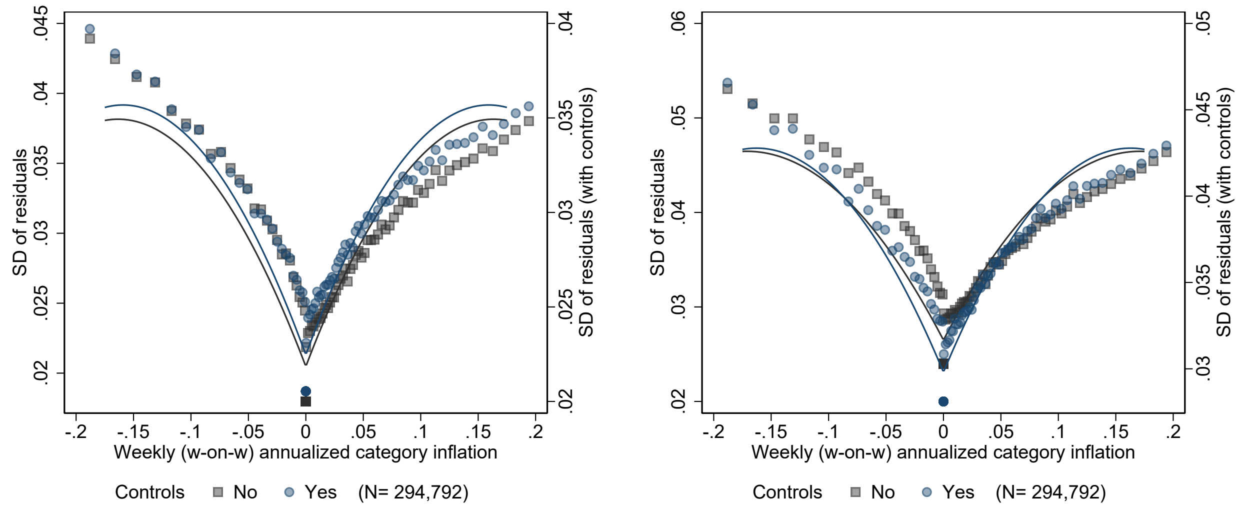
(c) Second-stage R^2



(d) Second-stage R^2 with $|t\text{-stat of } c_g| > 2$

Notes: This figure shows descriptive statistics of the second-stage regression separately by sector. Observations with $|c_g| > 500$ or $|t\text{-stat of } c_g| > 40$ are excluded for readability, around 2.5% of the sample, leaving 5,637 city-category combinations in panels (a)–(c). Panel (d) additionally drops observations with a t-statistic of $c_g < 2$.

Figure C.5: Price Dispersion and Inflation (Week-on-week)



(a) $\text{SD}_t^g(u_{irgct})$ and w-on-w inflation

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

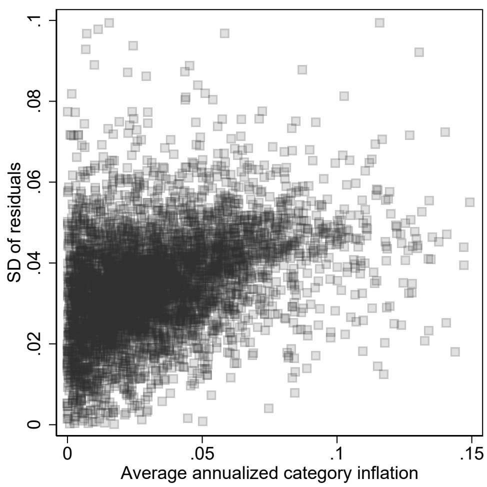
Notes: These binscatters display the relation of inflation and different measures of price dispersion. Each dot corresponds to the average price dispersion for 100 equally sized inflation bins. The unit of observation is a category × city × week. Only observations with annualized inflation below 20% included. The number of category × city × week included in panels (a) and (b) are 294,792. One bin represents around around 3,000 category × city × week combinations.

Table D.8: Variance and Welfare Cost of a Rise from Zero to 10% Annualized Inflation, by Elasticity

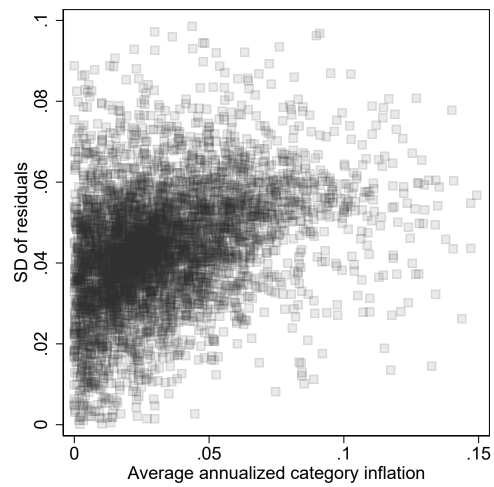
					Welfare cost ϕ (% of consumption) by elasticity σ							
Inflation measure	Disp.	$\mathbb{V}[x](0)$ ($\times 10^3$)	$\mathbb{V}[x](10)$ ($\times 10^3$)	$\Delta\mathbb{V}$ %	3	4	5	6	7	8	9	10
Week-on-week	u	0.42	1.05	+151	0.10	0.13	0.16	0.19	0.22	0.25	0.29	0.32
	ε	0.79	1.57	+98	0.12	0.15	0.19	0.23	0.27	0.31	0.35	0.39
Month-on-month	u	0.32	1.31	+314	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
	ε	0.65	1.89	+191	0.19	0.25	0.31	0.37	0.43	0.50	0.56	0.62
Category-city Average (Annualized)	u	0.35	2.33	+572	0.30	0.40	0.50	0.60	0.69	0.79	0.89	0.99
	ε	0.56	3.75	+569	0.48	0.64	0.80	0.96	1.12	1.27	1.43	1.59

Notes: Each cell in the right panel reports the welfare cost of a permanent rise from zero to 10% annualized inflation, as a percentage of flex-price consumption, computed from equation (5.1) as $\phi = \frac{\sigma}{2}(\mathbb{V}[x](10) - \mathbb{V}[x](0))$ and rounded to two decimals. The cost is linear in the elasticity of substitution σ, so each row scales proportionally across columns; the baseline calibration sets $\sigma = 6$. Columns $\mathbb{V}[x](0)$ and $\mathbb{V}[x](10)$ report the variance of price gaps (the squared standard deviation of the dispersion measure, $\times 10^3$) at the bins closest to zero and to 10% annualized inflation, and $\Delta\mathbb{V}$ % is the percentage change between the two; for a given σ this percentage change equals the percentage change in the welfare cost. "Week-on-week" and "month-on-month" use the higher-frequency binscatters in Figures C.5 and 3; "cross-country average" uses the average-inflation binscatter in Figure 5. u denotes the baseline measure $\text{SD}_{gct}(u_{irgct})$, removing product-specific introduction prices and trends; ε denotes $\text{SD}_{gct}(\varepsilon_{irgct})$, removing product fixed effects only.

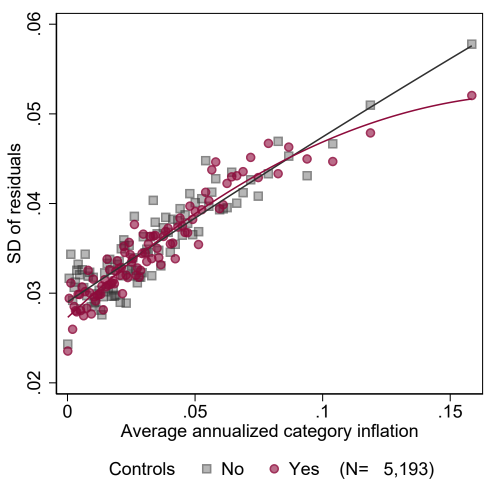
Figure D.6: Average Price Dispersion and Annualized Inflation When $N^i_{gc} > 50$



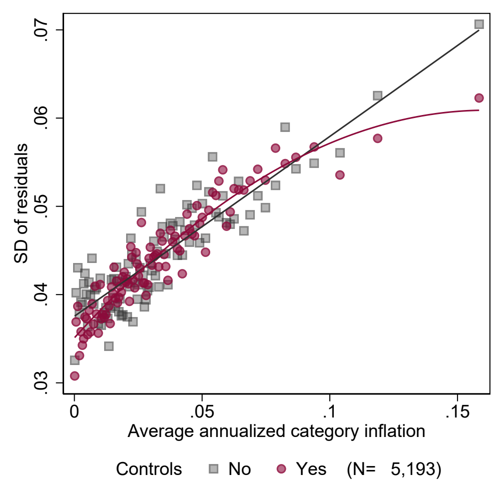
(a) $\mathrm{SD}^g_t(u_{irgct})$ and $N^i_{gc} > 50$



(b) $\mathrm{SD}^g_t(\varepsilon_{irgct})$ and $N^i_{gc} > 50$



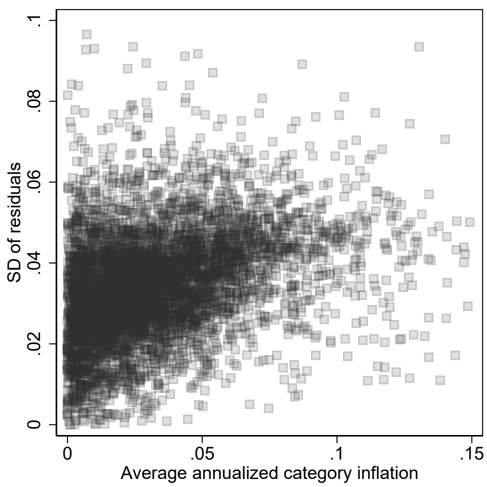
(c) $\mathrm{SD}^g_t(u_{irgct})$ and $N^i_{gc} > 50$



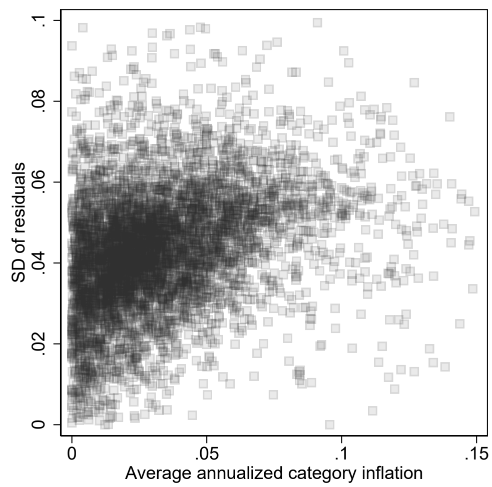
(d) $\mathrm{SD}^g_t(\varepsilon_{irgct})$ and $N^i_{gc} > 50$

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.

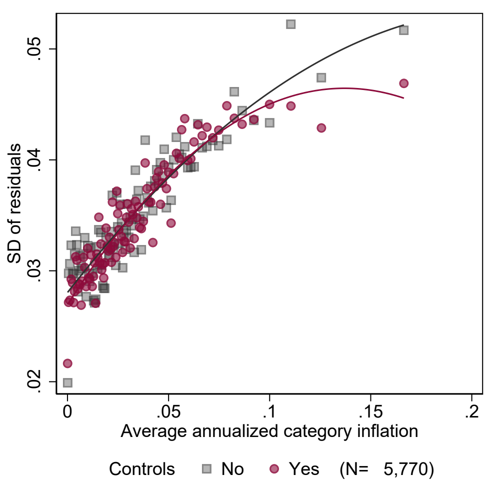
Figure D.7: Average Price Dispersion and Annualized Inflation When $N^i_{gc} > 25$



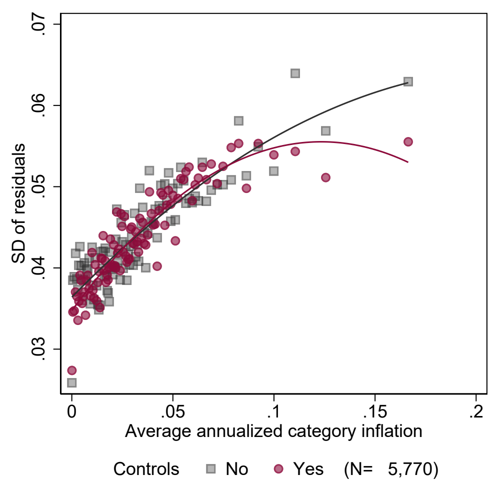
(a) $\text{SD}^g_t(u_{irgct})$ and $N^i_{gc} > 25$



(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.

Table D.9: Calibration Moments and Parameters

City	Sector	Targeted				Untargeted (model fit)						Calibration	
		Frequency		Mean $\lvert\Delta p\rvert$		Share $\Delta p > 0$		SD Δp		Kurtosis		σ_ε	K
		Data	Model	Data	Model	Data	Model	Data	Model	Data	Model		
AM	Rest.	0.038	0.038	0.141	0.141	0.770	0.776	0.168	0.136	5.24	2.64	0.0665	0.1924
CI	Rest.	0.057	0.057	0.197	0.196	0.783	0.728	0.208	0.195	4.41	2.14	0.0897	0.2590
ES (Barcelona)	Rest.	0.055	0.055	0.132	0.133	0.730	0.734	0.169	0.129	5.29	2.19	0.0621	0.1288
ES (Madrid)	Rest.	0.071	0.071	0.135	0.135	0.700	0.682	0.167	0.134	5.02	1.76	0.0637	0.1084
ES (Valencia)	Rest.	0.052	0.053	0.134	0.134	0.752	0.722	0.166	0.132	4.61	2.06	0.0629	0.1342
GE	Rest.	0.075	0.076	0.138	0.138	0.753	0.746	0.170	0.130	5.60	2.35	0.0645	0.1119
GH	Rest.	0.147	0.147	0.154	0.154	0.890	0.877	0.154	0.106	6.33	5.82	0.0656	0.0789
HR	Rest.	0.074	0.075	0.128	0.127	0.874	0.830	0.141	0.104	7.38	3.93	0.0570	0.0995
IT (Milan)	Rest.	0.034	0.034	0.149	0.148	0.770	0.852	0.172	0.128	4.93	4.40	0.0701	0.2523
IT (Naples)	Rest.	0.034	0.034	0.155	0.155	0.746	0.780	0.172	0.151	4.40	2.68	0.0730	0.2495
IT (Rome)	Rest.	0.033	0.033	0.152	0.153	0.754	0.788	0.171	0.148	4.75	2.80	0.0721	0.2485
KE	Rest.	0.046	0.045	0.169	0.170	0.732	0.875	0.208	0.133	4.40	5.55	0.0755	0.2708
KG	Rest.	0.100	0.100	0.109	0.109	0.811	0.799	0.131	0.092	7.71	3.21	0.0496	0.0566
KZ	Rest.	0.089	0.089	0.129	0.129	0.809	0.785	0.151	0.114	6.32	2.95	0.0593	0.0869
MA	Rest.	0.067	0.067	0.151	0.151	0.696	0.703	0.180	0.150	4.25	1.92	0.0709	0.1410
PL (Krakow)	Rest.	0.079	0.079	0.119	0.119	0.785	0.701	0.144	0.116	6.11	1.91	0.0566	0.0808
PL (Warsaw)	Rest.	0.105	0.105	0.118	0.118	0.797	0.741	0.146	0.109	6.06	2.33	0.0554	0.0628
PT (Lisbon)	Rest.	0.039	0.039	0.163	0.163	0.713	0.732	0.205	0.164	4.30	2.11	0.0753	0.2305
PT (Porto)	Rest.	0.050	0.049	0.160	0.158	0.758	0.722	0.201	0.158	4.57	2.05	0.0734	0.1901
RO	Rest.	0.100	0.099	0.147	0.147	0.808	0.760	0.179	0.134	5.55	2.58	0.0684	0.1019
SI	Rest.	0.055	0.055	0.108	0.108	0.915	0.888	0.113	0.077	8.94	6.27	0.0474	0.0956
TN	Rest.	0.073	0.073	0.126	0.126	0.823	0.775	0.140	0.114	6.61	2.76	0.0583	0.0979
UA	Rest.	0.165	0.165	0.115	0.116	0.825	0.757	0.147	0.103	7.64	2.57	0.0561	0.0408
UG	Rest.	0.053	0.053	0.181	0.181	0.850	0.832	0.187	0.156	5.08	3.96	0.0807	0.2563
AM	Super.	0.094	0.095	0.130	0.130	0.574	0.548	0.174	0.133	4.57	1.24	0.0623	0.0788
CI	Super.	0.174	0.175	0.110	0.110	0.712	0.645	0.152	0.109	6.91	1.61	0.0569	0.0355
ES (Barcelona)	Super.	0.268	0.267	0.087	0.087	0.563	0.574	0.123	0.089	6.77	1.45	0.0497	0.0146
ES (Madrid)	Super.	0.284	0.283	0.086	0.086	0.566	0.587	0.122	0.088	7.03	1.51	0.0499	0.0135
ES (Valencia)	Super.	0.247	0.247	0.083	0.083	0.534	0.539	0.122	0.086	7.94	1.37	0.0467	0.0145
GE	Super.	0.213	0.213	0.193	0.192	0.570	0.573	0.243	0.199	3.16	1.44	0.1063	0.0825
GH	Super.	0.243	0.243	0.189	0.189	0.537	0.566	0.243	0.197	3.41	1.47	0.1084	0.0692
HR	Super.	0.228	0.228	0.172	0.173	0.579	0.585	0.228	0.179	3.29	1.48	0.0970	0.0637
IT (Milan)	Super.	0.247	0.247	0.141	0.141	0.546	0.557	0.190	0.146	4.31	1.42	0.0804	0.0401
IT (Rome)	Super.	0.208	0.204	0.143	0.141	0.542	0.556	0.192	0.146	3.82	1.37	0.0768	0.0489
KE	Super.	0.114	0.114	0.121	0.121	0.658	0.689	0.159	0.118	5.46	1.84	0.0587	0.0624
KG	Super.	0.210	0.209	0.096	0.096	0.586	0.603	0.132	0.097	6.72	1.47	0.0516	0.0228
KZ	Super.	0.353	0.355	0.165	0.166	0.552	0.558	0.216	0.175	3.37	1.60	0.1067	0.0343
MA	Super.	0.214	0.215	0.109	0.108	0.544	0.560	0.152	0.111	5.46	1.37	0.0592	0.0280
PL (Krakow)	Super.	0.315	0.315	0.152	0.152	0.546	0.546	0.192	0.159	3.30	1.51	0.0932	0.0344
PL (Warsaw)	Super.	0.346	0.345	0.149	0.149	0.568	0.544	0.191	0.157	3.57	1.55	0.0943	0.0295
PT (Lisbon)	Super.	0.199	0.198	0.221	0.221	0.524	0.563	0.261	0.230	2.17	1.42	0.1204	0.1113
PT (Porto)	Super.	0.267	0.267	0.216	0.216	0.549	0.553	0.262	0.227	2.26	1.50	0.1279	0.0756
RO	Super.	0.492	0.493	0.123	0.123	0.562	0.551	0.170	0.132	4.51	1.79	0.0891	0.0120
SI	Super.	0.303	0.305	0.246	0.246	0.535	0.547	0.271	0.261	1.69	1.58	0.1532	0.0741
TN	Super.	0.259	0.259	0.117	0.117	0.579	0.577	0.158	0.121	4.27	1.47	0.0669	0.0268
UA	Super.	0.534	0.535	0.149	0.149	0.598	0.554	0.197	0.161	3.55	1.89	0.1130	0.0136
UG	Super.	0.141	0.141	0.107	0.107	0.583	0.569	0.157	0.110	6.80	1.31	0.0543	0.0406
Median, restaurants		0.062	0.062	0.140	0.140	0.777	0.768	0.168	0.131	5.26	2.61	0.0650	0.1204
Median, supermarkets		0.247	0.247	0.141	0.141	0.563	0.560	0.190	0.146	4.27	1.47	0.0804	0.0355

Notes: One menu-cost model calibrated per city-sector to its monthly frequency and (standardized) mean absolute size of price changes at its average monthly inflation. Targeted moments match by construction; untargeted moments (share of increases, SD, kurtosis of standardized price changes) are a model-fit check. Frequencies are monthly. Model moments are from the model's stationary distribution; data moments from the analysis sample (`11_additional_moments.do`). The last two rows report within-sector medians across cities.

Table D.10: Price Dispersion and Inflation Comovement: Data vs Model

	(1)	(2)	(3)
Dep. var:	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{Gct,s}(x_{it})$	$\text{SD}_{Gct,s}(u_{it})$
Source:	Data	Model (True)	Model (Estimated)
$\lvert\Delta p_{gct}^{Ann}\rvert$	0.119^{***}	-0.008^{***}	-0.013^{***}
	(0.002)	(0.001)	(0.001)
Fixed effects	City×sector (G)	City×sector (G)	City×sector (G)
N	328,022	22,503	22,503
R^2	0.39	0.97	0.98
Within R^2	0.09	0.01	0.01

Notes: This table shows the estimated slopes of the different measures of price dispersion plotted in Figure 6 on absolute annualized inflation. The three measures of price dispersion are: the baseline category-city-month price dispersion estimated from the data, the actual city-sector (G)-month-simulation (s) dispersion of price gaps from the simulation, and the dispersion city-sector (G)-month-simulation (s) dispersion of estimated price gaps from the simulated data. Standard errors clustered at the category-city level in column (1) and clustered at the sector-city-sample level for columns (2)-(3) in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.