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Santiago Alvarez-Blaser

Inflation and Price Dispersion: New Cross-sectoral and International Evidence

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Inflation and price dispersion: new cross-sectoral and international evidence*

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Very preliminary, please do not circulate

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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 40,000 restaurants and supermarkets across 16 countries facing high and low inflation periods, I uncover new evidence of a significant positive correlation between inflation and price dispersion. My findings reveal that the average weekly inflation, ranging between zero and 15 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, significant and heterogeneous across sectors. Cross-sectionally, I find that an increase of annualized inflation from zero to 12.7 percent, increases inefficient price dispersion for restaurants by 40.5% and by 15.1% for supermarkets. Finally, my results suggest that the relation of inflation an price dispersion does not disappear or diminish even at higher levels of inflation, maintaining a distinct “V" shape around zero inflation. This indicates a more sustained impact of inflation on price dispersion than previously estimated, implying that accommodating higher inflation levels might incur greater costs than initially estimated.

Keywords: Inflation, price-setting, price distortions.

JEL Codes: E31, E58

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1. Introduction

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 demands micro-level data during periods of substantial inflation, a resource that is challenging 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 product-level web-scraped information from over 40,000 restaurants and supermarkets across 16 countries, providing new empirical evidence of the distortionary effects of inflation.

Inflation can distort desired prices, leading to increased inefficient price dispersion. When inflation does not align with the relative depreciation or appreciation of products over time, if prices are not fully flexible, it may create gaps between the product's relative desired price (as it would be without price stickiness) and the actual price. This product-level distortion then results in cross-sectional inefficient price dispersion, causing misallocation and economic costs. The challenge lies in the fact that inefficient price dispersion cannot be directly observed in the data. A portion of price dispersion, even within narrow categories, stems from variations in desired prices, which are not inefficient. To address this, I first estimate the price distortions at the product level and the marginal effect of inflation on them using the novel approach introduced by Adam et al. (2023). Subsequently, I estimate the relationship between inflation and cross-sectional price dispersion.

First, I demonstrate that the increased frequency of price adjustments during periods of exceptionally high inflation does not mitigate the distortionary effects of suboptimal inflation on product-level relative prices.[1] Second, I find that cross-sectional price dispersion significantly comoves with inflation. This comovement is particularly strong in the restaurant sector, indicating heterogeneous effects of high inflation across different sectors. Finally, my results suggest that the relationship between price dispersion and inflation exhibits a distinct "V" shape around zero inflation. This indicates that the relationship persists even at high levels of inflation, suggesting a more sustained impact of inflation on price dispersion than previously estimated.

The paper starts identifying an effect of suboptimal inflation on price distortions at the product level. For this I use the novel approach introduced in Adam et al. (2023). This approach which derives from sticky price theories allows estimating the marginal effect of suboptimal inflation on product level relative price distortions separately for each category and city. The estimated marginal effects are positive in 97% of the category-city combinations, as predicted by the theory, and significantly positive in 85% of the category-city combinations. Across sectors, the coefficients are similar but with

[1] Cavallo et al. (2023) show the dramatic rise in the frequency of price changes in recent high inflation periods.

a much higher explanatory power for restaurants.

Cross-sectionally, I identify a comovement of category-level inflation and price dispersion which is stable at high levels of inflation. For this I use either the price distortions estimated using the previously mentioned approach or controlling for products specifics using either product-retailer fixed effects or characteristics. This comovement is 0.52 in the baseline estimation. I also observe cross-sectoral heterogeneity in the estimates with a stronger comovement for the stickier sector, restaurants. An increase of week-on-week inflation from zero to 0.1% (around 5% annualized), is associated with an increase in price dispersion of 3.6% for restaurants and only of 1.5% for supermarkets. Overall the results indicate that the costs of inflation of an inflation increase of 10% is associated with a loss of over 1% of flex price consumption. However, I show that this estimate is highly sensitive to the frequency of data used, the definition of inefficient price dispersion, and its level around zero inflation.

Finally, the comovement of inflation and price dispersion seems to maintain even at high levels of inflation, indicating a more sustained impact of inflation on price dispersion than previously estimated. When plotting the category-city inflation rates and price dispersions summarized in 100 equal sized bins, one can observe how price dispersion increases with inflation in absolute terms even at high levels of inflation. In the figure, the last bins still showing this pattern have an average absolute week-on-week inflation above 1.5% (above 217% annualized). These results could partially be explained by a share of time dependent pricing observed with an increase in the absolute size of price adjustments with an increase in inflation inflation and a significant density of price adjustments situated around the zero adjustment region.

In the standard New Keynesian Model, deviations form the optimal inflation rate results in distortions of price dispersion that are associated with substantial welfare losses. Within the framework of Workhorse New Keynesian models with Calvo pricing, Nakamura et al. (2018) pointed out that the welfare loss associated with an inflation surge, similar to the currently observed, could be comparable in magnitude to the welfare loss from business cycle fluctuations in output. However, the magnitude of these costs are not clear from a theoretical point of view since they strongly depend on the assumed price setting stickiness. Despite the importance of getting a good estimate of the relation, limited research has been conducted on the connection of inefficient price dispersion and inflation. This lack in research can be attributed to two key challenges: accurately measuring inefficient dispersion and acquiring disaggregated data covering periods with elevated inflation. As highlighted in Golosov and Lucas Jr (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 heterogenity and inefficient price dispersion, might be lumped together.

I mitigate the first concern with two approaches. First, by identifying the marginal effects of suboptimal inflation on individual products prcie distortions following the approach in Adam et al. (2023). Second, adjusting prices for desired price dispersion by correcting for product specifics or by using (short-term) product-retailer fixed effects and high frequency data. Assuming that, in the short run, the desired relative prices of products within a category exhibit limited variability, product-retailer fixed effects effectively capture these dynamics. The dataset utilized in the analysis effectively overcomes the second challenge of limited (global) data availability covering periods of significant inflation, by covering the recent worldwide high inflation phase. Notably, the dataset covers diverse inflation patterns across 16 countries, with (annualized) average weekly inflation rates ranging from 3 percent to values as high as 10 and 14 percent for restaurants, and from zero percent to around 9 percent for supermarkets.

Recent research on the relationship between price dispersion and inflation usually finds a positive comovement of inflation and price dispersion. However, there is a strong contradiction on at which inflation levels this relation is stronger or weaker and most studies focus on periods of low inflation or countries with exceptional inflation like Argentina. Among related literature looking at the cost of inflation, three papers focus on the coss-sectional dispersion of prices: Alvarez et al. (2019), Sheremirov (2020) and Sara-Zaror (2021). Alvarez et al. (2019) employing Argentine CPI microdata at biweekely frequency, found that for low inflation, below 10%, the cross-sectional price dispersions varies very little with inflation but its significantly varies for higher levels. Both Sheremirov (2020) and Sara-Zaror (2021) examined price dispersion across various stores for identical products identified in US scanner data, affirming a positive correlation. While both find a postive comovement, Sara-Zaror (2021) extends the approach and, partially contradicting Alvarez et al. (2019), finds that cross-sectional price dispersion strongly rises with the absolute deviation of inflation from zero but this relation becomes flat for annualized inflation rates above two percent. A potential explanation for this pattern, calling for a detailed investigation, could be attributed to the frequency of the data employed in the analysis. Additionally, two recent studies, Adam et al. (2023) and Nakamura et al. (2018), analyze the costs of inflation but focusing more on the across-time dispersion of prices or of absolute price adjustments. Nakamura et al. (2018) argues that one look at the absolute size of price adjustments to measure how far prices are from their desired price and find no relation of this measure with inflation using US CPI micro data going back to the 70s.[2]. Finally, Adam et al. (2023) use U.K. CPI micro data and develops a novel structural approach, to estimate the across-time distortion of prices for individual products and relates it to a product-specific measure of *suboptimal* inflation. They find that sub-optimally high or low inflation is associated with distortions in relative prices.

This paper contributes to the literature by providing new empirical evidence of a positive relation

[2] Adam et al. (2023) argues that looking at the absolute size of price adjustments might lead to misleading conclusions.

of suboptimal inflation and price distortions based on different sectors and countries during a period with high inflation worldwide. Two main reasons could justify the not flattening of the relation of inflation and price dispersion observed in previous literature. Firstly, this research leverages high-frequency weekly price data while previous research often relied on averaged data over time. As shown in Cavallo (2018), measurement bias can arise when using time-averaging in scanner data. [3] Moreover, lower frequency makes also more difficult differentiating desired from inefficient price dispersion. Second, current research underscores the synchronized pricing strategies adopted not only by retailers but also by firms, resulting in a convergence of prices for specific products even across various retailers. When focusing on specific products, if these are highly synchronized by the producing firm even across retailers, only small share of the variation of prices is left for analyzing while there might still exist large variation in price dispersion across, for example, still water brands. At the retailer level, a usually concentrated market, strong complementarity in pricing might also exist.

Section 2 presents the data that will be used together with some summary statistics. Section 3 introduces the methodology and identifies the role of suboptimal inflation for product specific price distortions. Section 4 focuses on the relation between inflation and price dispersion across products. Section 6 analyzes how the frequency and size of price adjustments change with inflation, supporting the existence of some time-dependent pricing. Finally, section 7 draws a preliminary conclusion. Future sections will provide a better understanding of the role of frequency and averaging for price dispersion, estimate possible welfare costs and analyze in detail the cross-sectoral heterogeneity, both, empirically and using a model.

2. Data and summary statistics

For the empirical analysis, I use online prices of restaurants and supermarkets webscraped from one of the largest food delivery companies in the world, present in 25 countries around the world. Prices were collected from all restaurants and retailers on a weekly basis. In addition to the price, product name, and (retailer-specific) category, I also collected the restaurant or supermarket address and rating. On a daily basis, I also collected information on the establishment's opening hours to ensure that the restaurant or supermarket was open in a given week. For each country, data were retrieved for the city with the most establishments. For Italy and Spain, data were subtracted for two main cities for future robustness tests. For Italy, the cities included are Rome and Milan, and for Spain, the cities included are Madrid and Barcelona. The data were collected starting in the last week of March 2023.

[3] 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. Now, one could imagine that the same can happen with dispersion when averaging prices within one month.

They are still being collected and updated at the time of writing. [4] The products collected belong to a large extend to the CPI expenditure categories "Food and non-alcoholic beverages", "Restaurants, cafes and the like", "Alcoholic beverages", "Non-durable household goods" and "Articles for personal hygiene", which cover around 30% of the CPI basket in the European Union. [5]

Given the size of the data, the main manipulations were performed using machine learning algorithms from Google and OpenAI. In a first step I translate all product descriptions and online categories to English using Google Translate Cloud services. Then I categorize all products in narrow categories using the translated product description and category. Having non-anonymized product names is one of many benefits of using online data. Given that I have to categorize over five million products I categorize the products using AI algorithms from OpenAI which I train with a sample of over 50'000 products classified by hand. Based on the training and validation dataset, this algorithm trained specifically for the restaurant and supermarket products (separately) categorizes each product and gives me a confidence probability which I use to select products for which I am more confident that are categorized correctly. Restaurant products are categorized into 65 categories and supermarket products into 265 categories. The categories are at a much lower level of granularity than the COICOP classification used by many statistical offices, but can be matched to these categories. Examples of restaurant categories used are for example "Coke", " Burger with fries" or "Sushi" and of supermarkets categories are for example "Microfiber towel" or "Apples". This novel classification approach opens a door to new research using automatically categorized online prices.

The data used in this paper presents four main advantages. First, it is very 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, the firms existent in their platform can freely set their prices and pay a fixed fee.[6] Second, weekly webscrapped data requires no time aggregation and arguably minimum measurement error (Alvarez et al., 2022). Previous points are especially relevant when analyzing price dispersion which can be strongly affected by time and location aggregation or collection frequency. Third, an automatised categorization of products trained for this specific international data, allows for comparisons across countries reducing composition effects. Finally, the results in this paper are replicable because the data can be shared for replication.

Table 1 contains the main descriptive statistics of the data used. Across the 16 countries and sectors I observe over six million products in over 50'000 firms. The number of restaurants is, with over 48'000 restaurants, much higher than the number of supermarkets. The sample is not balanced, with some

[4]For three countries restaurant prices are available starting in August 2022, this sample will be used for robustness tests.
[5]Current results include data collected until May 2024.
[6]This fee is usually 30% if the company delivers the order and 15% for in-store pickup or if the delivery is performed by the retailer or restaurant. 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

products and establishments entering and exiting the sample. During the studied period annualized average inflation was much higher for restaurants than for supermarkets. As also shown previously in the literature, for example in Nakamura and Steinsson (2008) and Nakamura and Steinsson (2010) for the United States, the duration calculated out of the weekly frequency is much higher for restaurants than for supermarkets. Perhaps more surprising is that this is even true in during a period in which restaurants had a much higher inflation. Across countries we can also observe how countries with a higher inflation for restaurants not necessarily have shorter duration. This could already be indicative that restaurants might struggle incrementing the frequency of price setting with higher inflation in order to keep relative prices stable.

Table 1: Descriptive statistics

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	796	100,599	2.82	24.95	16.70	121	526,982	-1.38	10.09	18.11
CI	1,423	51,118	6.34	15.59	24.66	56	83,183	5.31	4.08	13.34
ES	9,621	770,638	3.90	13.11	12.37	537	397,742	5.53	1.83	9.82
GE	1,865	110,383	6.13	12.28	15.61	372	1,021,904	0.72	6.04	18.31
GH	524	20,313	15.52	11.16	16.74	24	29,388	2.79	3.38	21.91
HR	811	85,975	8.27	12.77	13.73	135	89,833	4.02	2.85	18.59
IT	9,869	881,331	3.37	26.80	16.66	643	289,951	1.74	2.40	13.17
KE	1,122	74,842	6.64	15.42	16.12	244	269,901	8.45	3.54	12.36
KG	753	71,447	8.62	9.97	12.04	97	39,755	2.90	3.49	8.83
KZ	1,598	167,832	7.86	12.24	14.01	128	137,018	0.89	1.97	16.29
MA	1,928	134,765	5.37	13.87	15.39	244	234,239	2.77	1.51	14.46
PL	3,042	254,317	8.44	8.91	12.71	150	216,429	2.60	1.54	14.13
RO	2,717	260,909	10.76	9.07	16.05	295	164,600	3.64	1.39	13.66
SI	448	24,363	5.71	20.03	11.48	49	14,595	1.87	2.18	21.47
UA	4,654	623,494	9.49	9.10	15.17	353	1,933,428	2.77	1.35	15.68
UG	1,257	70,147	11.72	15.12	20.18	211	153,018	2.16	4.98	13.24
All	48,104	3,992,260	7.48	14.40	15.63	3,953	5,791,011	2.90	3.29	15.17

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

3. Suboptimal Inflation and Product Level Price Distortions

This section identifies the marginal contribution of suboptimal inflation on price distortions at the product level and studies the heterogeneity across countries and sectors. The approach follows the novel identification proposed in Adam et al. (2023). For intuition, consider a product i sold in a specific location by a specific supermarket or restaurant. Under flexible prices the optimal relative price $p_{it} = P^*_{it}/P^*_t$ the firm would like to charge evolves according to

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

where p^*_i is the product introduction price and Π^*_i a product-specific time trend, capturing, for example, relative changes in marginal costs. Under this setting, the optimal gross inflation rate $\ln\Pi$ for product i is $\ln\Pi = \ln\Pi^*_i$ because then there is no need to adjust the nominal price as the relative price gets eroded by the desired rate. If gross inflation is above this rate the relative price shrinks too quickly and the firm has to adjust the nominal price. Due to price stickiness, these adjustments are costly or not possible, and a gap_{it} between the flexible and sticky price appears, which generates costs of suboptimal inflation due to missallocation. Under this setting the variance of gap_{it} is a function of suboptimal inflation squared. [7]

In order to test whether the theoretical prediction that suboptimal inflation induces price distortions, Adam et al. (2023) show that a two-step estimation can identify this relation from micro data. The first stage consists of the regression of relative product price $p^{igt} = P^{igt}/P^{gt}$ on a product-specific intercept and time trend,

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

where the variance of the residual of this first stage consists in

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

with the intercept being a function of the idiosyncratic shock process $\ln x_{igt}$ and the Calvo price stickiness parameter α_z,

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

[7] A longer proof and estimation description is available in Adam et al. (2023).

and

$$c_z \equiv \frac{\alpha_z}{(1-\alpha_z)^2} \tag{3.5}$$

under time dependent price-setting.[8]

From equation (3.4) one can already see that it is difficult to infer from $\text{Var}(u_{igt})$ something about the level of price dispersion since the intercept contains also efficient price components coming from idiosyncratic fundamental shocks. However, the second term in (3.3) captures how, according to the theory, suboptimal inflation affects price distortions and can be estimated with a second stage. Estimating the term c_z, linking price distortions and suboptimal inflation, will be the main goal of this section. Equation 3.4 shows how this term is related to the stickiness parameter under time dependent price setting, indicating that a higher stickiness should yield a higher effect of suboptimal inflation on relative price distortions.

Before turning into the estimation of the second stage, note that we also need a measure for $\ln\Pi_g - \ln\Pi^*_{ig}$. This last right-side variable can be estimated using a separate first-stage

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

where P_{igt} is the nominal product price.

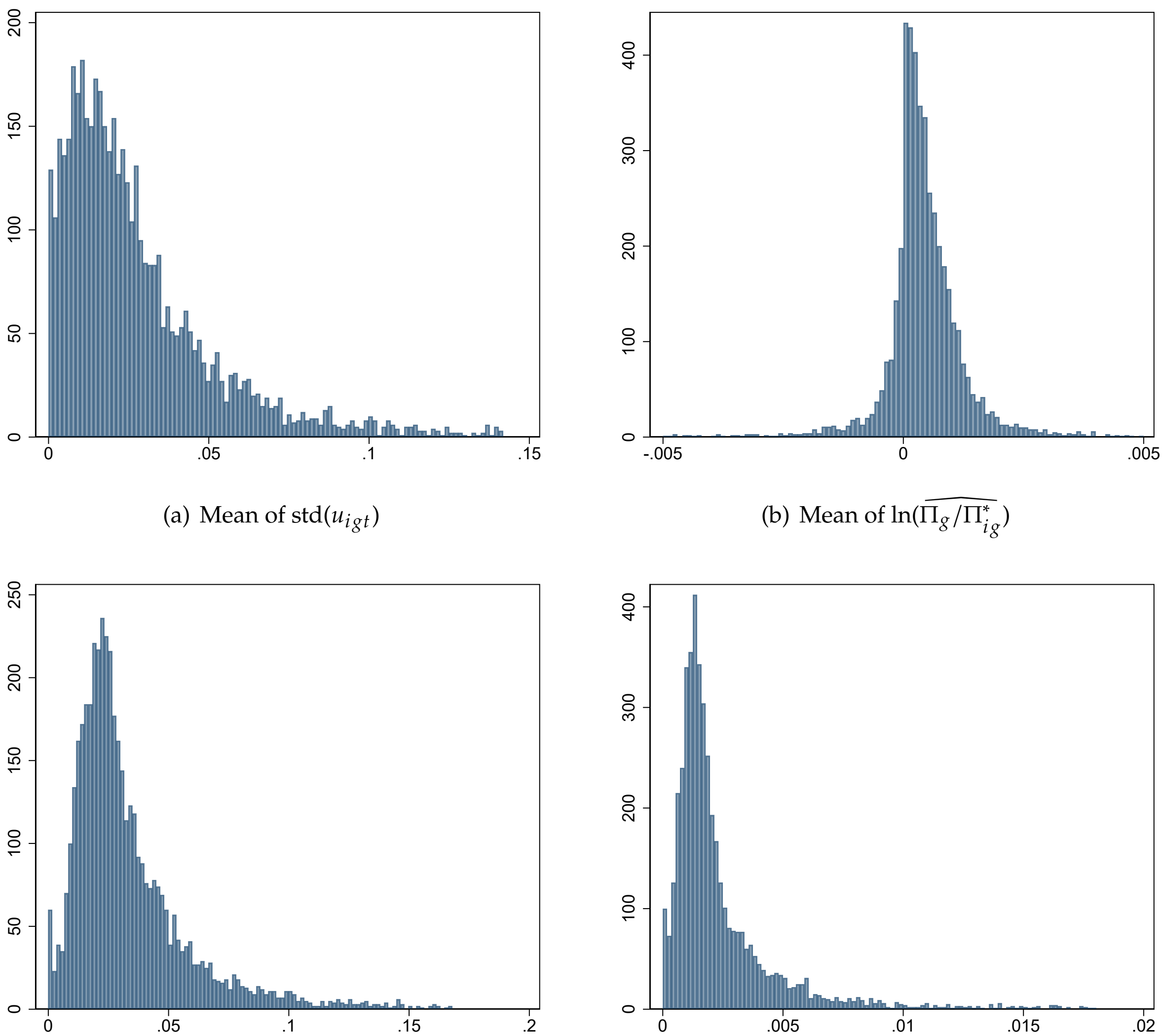
Now the second stage consists on estimating for each category g the effects of suboptimal category inflation on price distortions at the product level, by estimating c_g in the following OLS regression

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

where $\widehat{\text{Var}}(u_{igt})$ is the variance of the first-stage residuals for product i belonging to category g and $\widehat{\Pi_g/\Pi^*_{ig}}$ is the estimate of gap of product optimal inflation and category specific inflation coming from the “second" first stage.

[8] For a derivation under state dependent pricing, see Adam et al. (2023).

Figure 1: First-stage descriptive statistics



(a) Mean of std(u_{igt})

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

(c) Std of std(u_{igt})

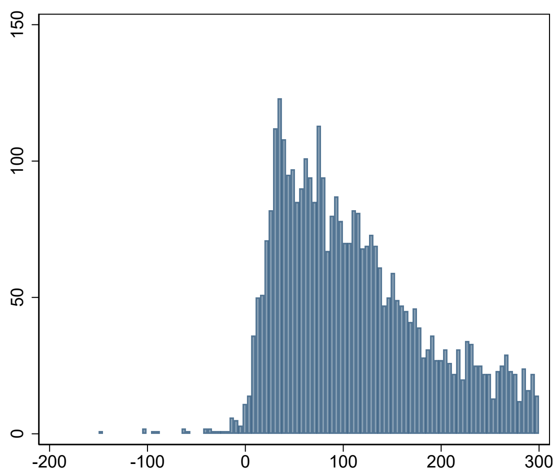
(d) Std of $\ln(\widehat{\Pi_g/\Pi^*_{ig}})$

Notes: Descriptive statistics of the first-stage resulting moments averaged within a city-category.

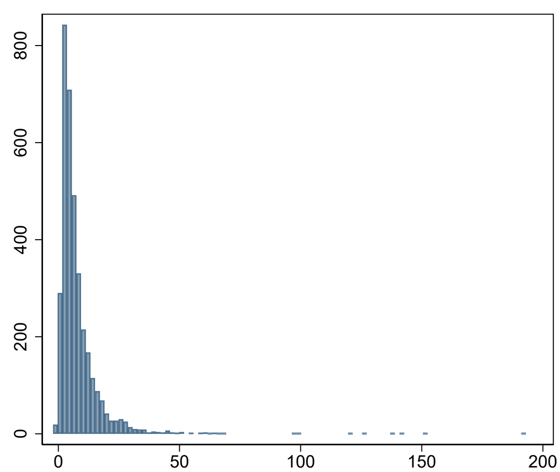
The city-category averages of std(u_{igt}) and $\ln(\widehat{\Pi_g/\Pi^*_{ig}})$ resulting from the first-stage are shown in figure 1. Excluding the top percentile of average std(u_{igt}), 4,512 city-categories are included. For the baseline estimation I only keep products observed in at least six weeks and category-city combinations with at least 20 products in order to avoid small sample bias. This leaves 4,106,177 unique products and over 150 million product-weeks for the estimation of the first stage. The top figures show the category-city mean non-squared variables entering the second-stage while the bottom figures show the standard deviation of these in order to give an overview of the variation available for the second-stage.

The figure in the top-right corner showing the distribution of product-level mean suboptimal inflation rates is particularly noteworthy. For most category-city combinations (77%), the average annualized suboptimal inflation rate was positive with a median of 1.45% across category-cities. This is a very different context as the analysed in Adam et al. (2023) where a large share of categories where in the negative region. These results are not surprising given the period of high inflation studied. This also provides me with the chance to explore the predictions of a menu cost model. In this model, during periods of high inflation, firms bear the costs of price adjustment, preventing the perpetuation of inefficient dispersion. Finally, the bottom figures show that there is a significant amount of variance entering the second-stage regression.

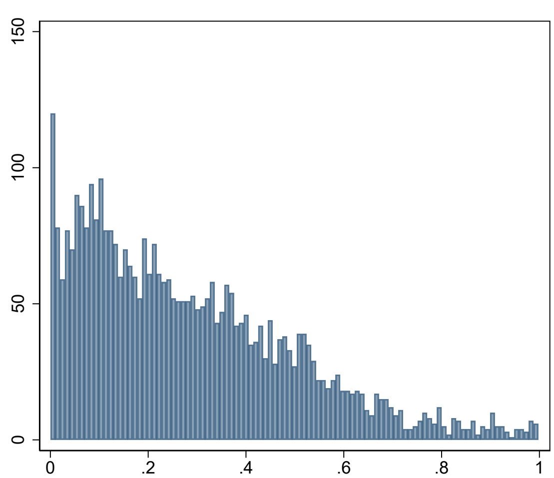
Figure 2: Baseline estimates



(a) c_g estimate



(b) c_g t-statistic



(c) Second-stage R^2

Notes: Descriptive statistics of the second-stage. Observations with an absolute c_g larger than than 300 or $t-$statistic of c_g larger 200 excluded from all figures to increase readability, this is around 10% of the sample. Included 4,043 city-category combinations.

Figure 2 reports my estimates from estimating the equation (3.7). The left panel shows the distribution c_g estimated separately for 4,555 city-category combinations. I find that 97% of the estimated coefficients are positive supporting sticky price theories. According to the distribution of t-statistics: 85% of the coefficients have a t-statistic above 2, 51% above 5 and less than 0.05% of the coefficients have a t-statistic below minus two. This provides strong support for the distortive effects of suboptimal inflation on prices at the product level. In addition, the median R^2 of the second-stage regressions is 30%. Indicating that suboptimal inflation explains a considerable share of the cross-product variance of the first-stage residuals.

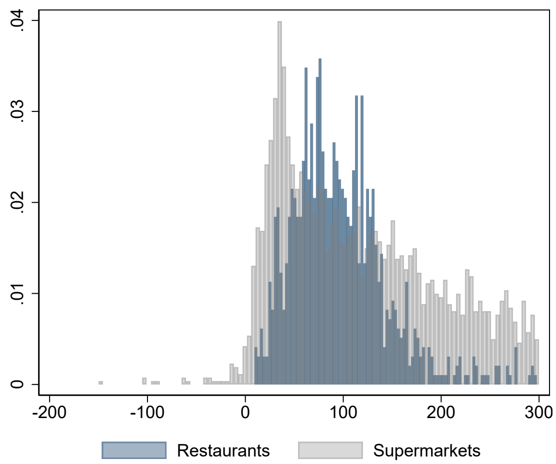
Next, I analyse cross-sectoral differences by looking at figure (3). Overall, it seems that suboptimal inflation has a much more clear effect on product-level price dispersion with a almost bell-shaped distribution of the coefficients with the median around 60. The median c_g for restaurants is higher at a value of 71 but with a very skewed distribution. The share of price distortions that can be explained by suboptimal inflation is also larger on average for restaurants with a median R^2 across category-cities of 49% for restaurants while it is 22% for supermarkets. This heterogeneity points to the importance of not only focusing on the retail sector when analysing price distortions.

Table 2: Suboptimal Inflation and Product Inefficient Price Distortions

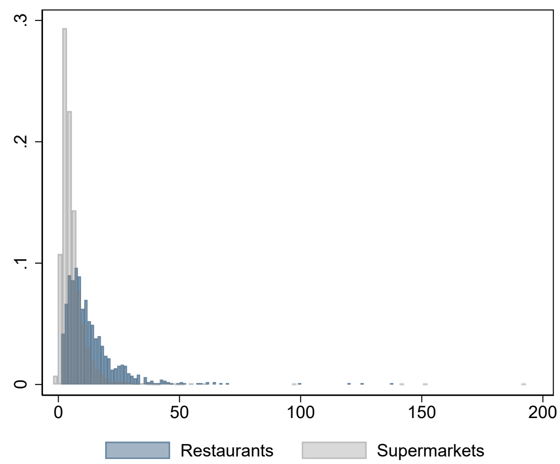
	$c_g > 0$	t-stat < -2	t-stat > 2	t-stat > 5	Median c_g	Restaurants Median c_g	Supermarkets Median c_g
AM	88%	0.00%	92%	74%	51.59	85.36	40.79
CI	96%	0.00%	84%	43%	132.76	100.93	147.81
ES (Madrid)	100%	0.00%	93%	62%	119.97	100.12	130.13
ES (Barcelona)	100%	0.00%	92%	68%	193.31	115.33	227.10
GE	99%	0.00%	90%	53%	280.83	78.71	396.32
GH	99%	0.00%	81%	37%	116.26	54.92	194.17
HR	99%	0.00%	87%	40%	136.19	121.33	152.37
IT (Rome)	97%	0.00%	87%	47%	231.80	142.73	284.15
IT (Milan)	98%	0.00%	79%	40%	168.55	124.70	212.28
KE	100%	0.00%	93%	63%	193.72	120.30	224.39
KG	99%	0.00%	93%	57%	163.43	60.07	311.88
KZ	97%	0.00%	86%	46%	114.76	78.75	141.83
MA	100%	0.00%	92%	63%	68.63	82.76	66.69
PL	97%	0.00%	87%	52%	41.64	65.73	38.29
RO	100%	0.00%	83%	38%	112.70	83.73	135.63
SI	95%	0.00%	82%	38%	243.71	112.77	516.73
UA	100%	0.00%	85%	50%	41.89	67.91	37.00
UG	99%	0.00%	87%	45%	124.85	87.13	148.38
Pooled	98%	0.00%	88%	51%	120.30	91.16	145.77

Notes: This table shows the summary statistics of costs, prices and quality statistics in the matched sample. N reports either the number of retailer-product-month observed prices in the retail data, the number of product-month observed prices in the manufacturer data or the number of products with quality information. All prices and costs are translated first in 2019m1 US Dollars. As a measure of time-series variation, we calculate the coefficient of variation for each product across time and report the average coefficient of variation across products in CV_i. Since unexpected costs have a mean close to zero, in order to help with the interpretation, for expected and unexpected costs the coefficient of variation is computed relative to the total costs. Expected and unexpected costs statistics are based on less observations because this data starts in January 2019. Data are winsorized at the 1% level. Quality information is only available for the US.

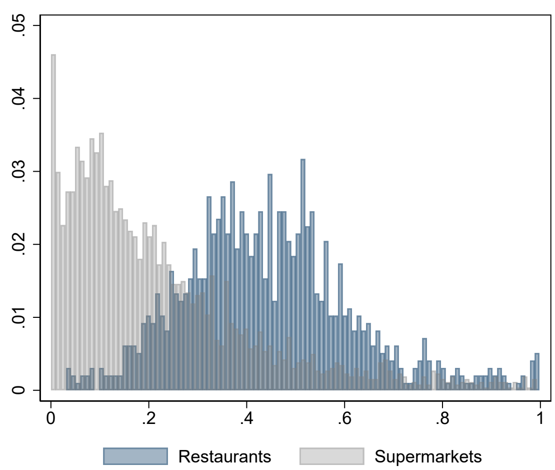
Figure 3: Baseline estimates by sector



(a) c_g estimate



(b) c_g t-statistic



(c) Second-stage R^2

Notes: Descriptive statistics of the second-stage. Observations with c_g or t−statistic of c_g larger than 200 excluded to increase readability, this is around 10% of the sample. Included 3,747 city-category combinations.

4. Inflation and Cross-Sectional Price Dispersion

In the previous section I show how inflation generates price distortions at the product level. This section now studies the comovement of inflation with price dispersion across sectors.

Following Adam et al. (2023), we know that the log relative price of product i belonging to category g and retailer r in city c is

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

While so far I have shown that the variance of u_{irgct} over time for one specific product depends on the level of suboptimal inflation, I still have not focused on the cross-sectional price dispersion $\text{Var}^g(\ln p_{irgct})$. For this we can decompose the variance of p_{irgct} as follows

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

The first component captures price dispersion which results from flexible prices and would exist also without stickiness and can be computed from the first stage (3.2). The second term,

$$\text{Var}^g(u_{irgct}) = v_g + c_g E^g[(\ln \Pi_g - \ln \Pi^*_{ig})^2] \tag{4.3}$$

captures variation from the stochastic components (v_g) and price distortions induced by suboptimal inflation.

When pooling all category-city-week combinations, the median $\text{Var}^g(\ln p_{irgct})$, $\text{Var}^g(\ln p^*_{irgct} - t\ln \Pi^*_{irgct})$ and $\text{Var}^g(u_{irgct})$ are 0.23673, 0.23637 and 0.00005, respectively. This indicates that most of the price dispersion, over 99%, comes from product heterogeneity in the introduction price and trend. However, when running the following regressions,

$$\text{Var}^g_t(\ln p_{irgct}) = \alpha_{gc} + \beta \text{Var}^g_t(\ln p^*_{irgct} - t\ln \Pi^*_{irgct}) + \varepsilon_{gt} \tag{4.4}$$

and

$$\text{Var}^g_t(\ln p_{irgct}) = \alpha_{gc} + \beta \text{Var}^g_t(u_{irgct}) + \varepsilon_{gt} \tag{4.5}$$

I observe that the within R^2s, excluding the explanatory power of the fixed effects, are 0.93 and 0.05 indicating the $\text{Var}^g(u_{irgct})$ term can still explain 5% of the variation of $\text{Var}^g_t(\ln p_{irgct})$ over time.

As equation (4.3) indicates, one can expect a link between price dispersion and inflation. However, the effect of an increase in inflation $\ln \Pi_g$ depends on the average level of optimal inflation of that category. Suppose that average optimal inflation rate is zero, then an increase of $\ln \Pi_g$ from -2% to -1% will decrease the price dispersion induced by inefficient suboptimal inflation. On the other hand, an increase of $\ln \Pi_g$ from 1% to 2% is expected to increase price dispersion. This is very important when estimating the comovement of inflation with price dispersion.

In order to asses the average comovement of inflation with price dispersion, my baseline specification regresses the standard deviation of u_{irgct} in a given week and city on a category fixed effect and the absolute city-category inflation. I do so because my estimates of optimal relative inflation from the first stage (3.2) are zero or very close to zero for most of the products. Also note that as mentioned before, in the negative territory lower inflation is expected to increase price dispersion because it is also suboptimal for most categories. The estimated regression is then:

$$\mathrm{SD}_t^g(u_{irgct}) = \gamma_{gc} + \beta|\Pi_{gct}| + \varepsilon_{gct}. \tag{4.6}$$

As measures of inflation I use either the absolute weekly week-on-week inflation rate ($|\Delta p_{gct-4}|$) or the absolute weekly month-or-month inflation rate, both calculated averaging the product specific week or month inflations within each category, city and week.

I also test the comovement with other measures of price dispersion. One option is controlling for retailer or restaurant and product specific heterogeneity following Sheremirov (2020) and Alvarez et al. (2019) estimating in a first steep the equation,

$$\ln P_{irgct} = \alpha_g + \delta_{ct} + \gamma_{rct} + \eta_{irgc} + \varepsilon_{irgct} \tag{4.7}$$

where $\ln P_{irgct}$ is the log price of product i sold by restaurant or retailer r, which belongs to category g in city c and period t. Then, I estimate the standard deviation of ε_{irgct} for each category-city-week combination. Estimating this removes the variation due to retailer-products having a consistent higher price within a category and variation from specific retailers charging a higher price for all products in a given week. Additionally, I control for product specifics using product information contained in the product name or description instead of using the fixed-effects approach. For this I focus on the the beverage categories in both sectors which usually contain product size information. This includes the following categories: beer, coke, other sodas, white and red wine. In these specifications, I estimate inflation (Δp_{vgct}) and price dispersion at the ML volume-category-city-week.

In order to analyze the heterogeneity across the two sectors in my sample, the estimation (4.6) might yield misleading results. This is because the average $\mathrm{SD}_t^g(u_{irgct})$ might be different across sectors and then, even if the coefficients are the same, the marginal effect in one sector might be larger. For this reason, when analyzing the sectors separately, I also use as dependent variable the log of $\mathrm{SD}_t^g(u_{irgct})$, so that the slope will indicate percentage marginal effect of an increase in inflation.

Table 3 , report different estimated coefficents of comovement between cross-sectional price dispersion and inflation. All coefficients are significant and the coefficient is 0.638 in the baseline estimate in column (1). When beeing more restrictive with the fixed effects and controlling for category-city fixed effects in column (2), the relation seems to be less strong but still large and significant. The coefficient is larger when using the week-on-week average category inflation rate in column (3) instead of the month-on-month inflation rate. However, a one percent increase in week-on-week inflation is much larger than a one percent increase in month-on-month inflation, making the overall effect much smaller. The coefficients are higher when estimating price dispersion using dispersion of the residuals of a fixed effects regression, see column (8). Also the regressions analyzing the relation using no FEs and focusing on the dispersion of relative (log) prices with no manipulation within a product volume-category-city yield a similar sized signifficant coefficient. The variance decomposition showed earlier, indicated that a large share of the price dispersion comes from price dispersion at introduction. In order to capture this product heterogeneity, in column (10), I estimate the effect of category-inflation on the change in the standard deviation of log prices of a balanced panel of products available in periods t and $t-1$. This also yields a positive and significant coefficient.[9] In general the estimated coefficients are larger than previously estimated and seem to be closer to models mixing time and state dependent pricing with high implied costs of inflation. As reported by Appendix Table A1, including additional city × week FEs only has a small effect on the estimates. Including city × categoy FEs, aborbing for specific city-categories having over the sample a higher price dispersion, slightly diminishes the size of the coefficients, as reported in Appendix Table A1.

Across sectors columns (4) and (5) report a similar coefficient when separating the sample in the two sectors and using the baseline estimation. However, I observe that the average dispersion is significantly lower in for restaurants so that marginally, the effect is larger. This can be observed in columns (6) and (7), where we observe how an increase of inflation from zero to 1% (month-on-month), 12.7% annualized, is associated with an increase of 40.5% in $\text{SD}_t^g(u_{irgct})$ for restaurants and only of 15.1% for supermarkets. These numbers indicate a strong heterogeneity on how inflation might affect sectors and points to the importance of analyzing sectors other than supermarkets, a widely analyzed sector using scanner data.

I find that the relation of cross-sectional price dispersion persists at high levels of inflation. Under state-dependent pricing one could expect that once the gap of relative prices reaches a level, all

[9] In order to control for price outliers within a category in this last estimation, I drop the top and bottom 5 percentile in each city-category.

Table 3: Price Dispersion and Inflation Comovement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\|\Delta p_{gct-4}\|$	0.638***	0.353***		0.645***	0.559***	15.088***	40.535***	0.779***		
	(0.00)	(0.00)		(0.01)	(0.01)	(0.27)	(3.24)	(0.01)		
$\|\Delta p_{gct}\|$			0.810***							0.647***
			(0.01)							(0.03)
$\|\Delta p_{vgct-4}\|$									0.808***	
									(0.09)	
Dep. variable	$\text{SD}_t^g(u_{irgct})$	$\text{SD}_t^g(u_{irgct})$	$\text{SD}_t^g(u_{irgct})$	$\text{SD}_t^g(u_{irgct})$	$\text{SD}_t^g(u_{irgct})$	$\log(\text{SD}_t^g(u_{irgct}))$	$\log(\text{SD}_t^g(u_{irgct}))$	$\text{SD}_t^g(\varepsilon_{irgct})$	$\text{SD}_t^{vg}(\ln p_{irgct})$	$\Delta\text{SD}_t^g(p_{irgct})$
Sector	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants	Both	Both	Both
Category FEs	Y	N	Y	Y	Y	Y	Y	Y	Y	N
Category × City FEs	N	Y	N	N	N	N	N	N	N	N
N	257959	255926	270459	197871	60088	199140	59907	261108	14678	143597
R^2	0.28	0.51	0.27	0.25	0.10	0.10	0.07	0.18	0.56	0.04

Notes: This table shows the relation of different weekly measures of cross-sectional price dispersion and inflation at the category-(product volume)-city level. The measures of price price dispersion considered are the category-city-week standard deviation of product level price gaps ($\text{SD}_t^g(u_{irgct})$), the category-city-week standard deviation of product level residualized log-prices, the category-product volume-city-week standard deviation of log prices ($\text{SD}_t^{vg}(\ln p_{irgct})$) calculated for beverages that tend to be more homogeneous and the change in the category-city-week standard deviation of log prices based on a balanced sample of products available in t and $t-1$ ($\Delta\text{SD}_t^g(p_{irgct})$). The explanatory variables are either the category-city weekly month-on-month or week on week inflation, $|\Delta p_{gct-4}|$ and $|\Delta p_{gct}|$ respectively, and the category-product volume-city weekly month-on-month inflation ($|\Delta p_{vgct-4}|$). Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

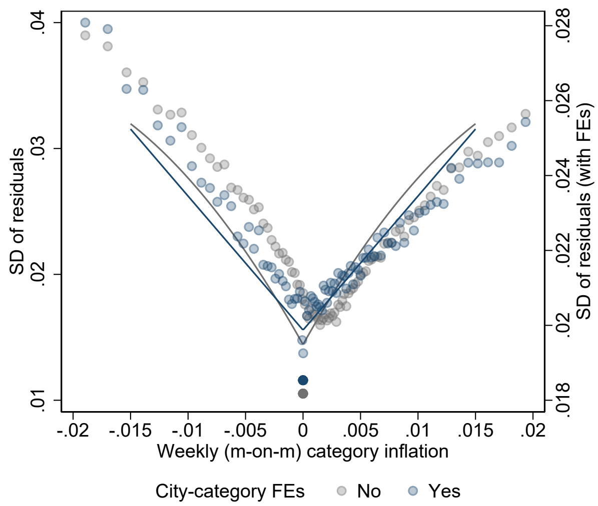
products pay the adjusting cost and reduce the gap (Nakamura et al., 2018). Sara-Zaror (2021) finds that cross-sectional price dispersion strongly rises with the absolute deviation of inflation form zero but that this relation becomes flatter for high inflation rates and rationalises the results with a menu-cost model with consumer search. [10] I follow her empirical approach and construct the following binned scatterplot: divide category-city weekly inflation into 100 equally sized bins and obtain an average price dispersion within each inflation bin. In order to control for product-specific optimal inflation rate or heterogeneity in product specifics within a category, I use as dispersion measure the previously described $\text{SD}_t^g(u_{irgct})$ and $\text{SD}_t^g(\varepsilon_{irgct})$. As inflation rates I use the weekly m-on-m (Δp_{gct-4}) and w-on-w (Δp_{gct}) inflation rates. In addition, one could argue that some categories have constantly higher dispersion on average, for example, due to a stronger idiosyncratic component in equations (3.3) and (3.4). For this reason, I also construct a binscatter from after subtracting the category-city fixed effect of the two dispersion measures.

Figure 4 shows the resulting figures separately for the two measures and two inflation rates. The figures include over 215,000 category × city × week combinations split in 100 bins so that each bin contains more than 2,000 observations. For both dispersion measures, and controlling for category-city FEs or not, one can observe that price dispersion is at its lower close to zero and increases as inflation deviates from zero towards the positiva and negative regions. From our baseline figure in Figure 4 Panel (a), it does not seem the case that the effect strongly flattens even at very high levels of month-on-month inflation of 2% (26.8% annualized). This is, one cannot observe the almost complete flattening observed in Sara-Zaror (2021) and Υ relation of the two measures, where at inflation levels

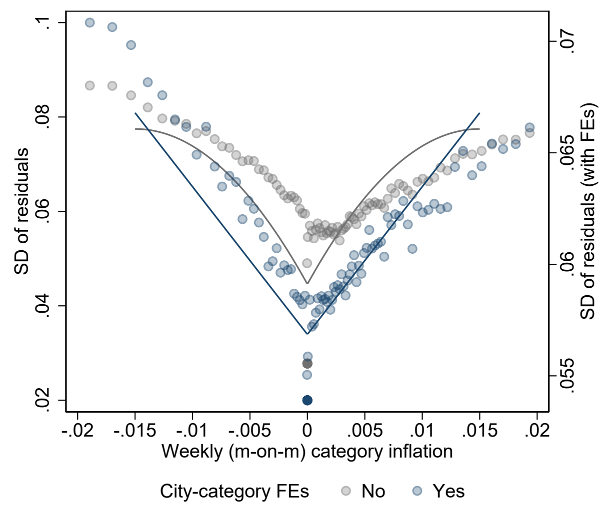
[10] Alvarez et al. (2019) empirical results suggest that price dispersion barely changes with inflation for annualized inflation rates below 10%

of 2% year-on-year price dispersion no longer increased. Using week-on-week inflation rates only results in minor changes in the figures, suggesting some persistence of price dispersion. The relation seems to despict rather a “V" shape during this period of high inflation.

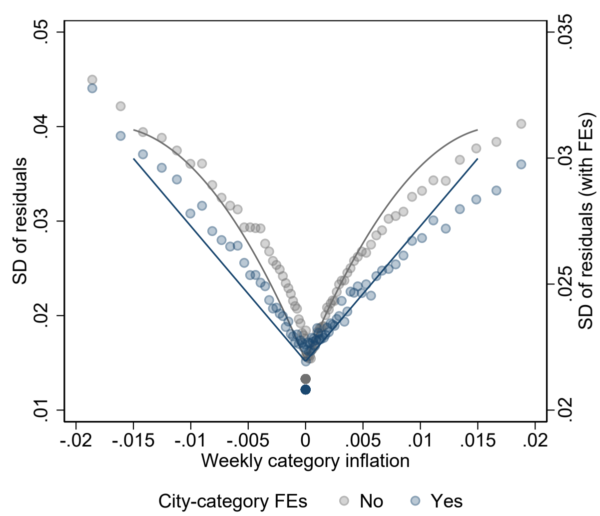
Figure 4: Price Dispersion and Inflation



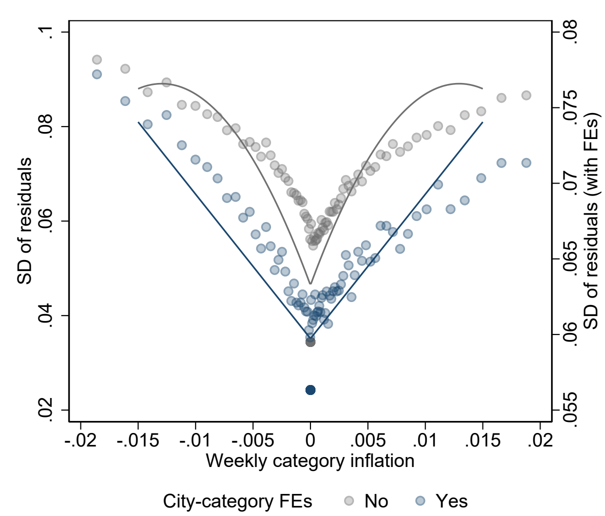
(a) $\text{SD}_t^g(u_{irgct})$ and m-on-m inflation



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



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



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

Notes: Each dot corresponds to the average price dispersion for 100 equally sized inflation bins. The unit of observation is a category × city × week. The number of category × city × week included in panels (a) to (d) are 215,623, 212,830, 243,323 and 239,919, respectively. One bin represents around over 2,100 category × city × week combinations. Panels (a) and (b) are based on weekly month-on-month average category-city inflation rates (Δp_{gct-4}) and panels (c) and (d) on weekly week-on-week average inflation rates (Δp_{gct}).

5. Costs of Inefficient Cross-Sectional Price Dispersion

The costs of high inflation in New Keynesian models might arise from two sources, from the missallocation due to inefficient price dispersion and from the resources used to adjust prices. This section focus on the first one that has perhaps gained more attention. This welfare cost is usually represented as the percentage loss of flex price consumption per period and it can be shown that, using a broadly used second-order approximation (Galí, 2008; Alvarez et al., 2019; Blanco et al., 2024), it equals:

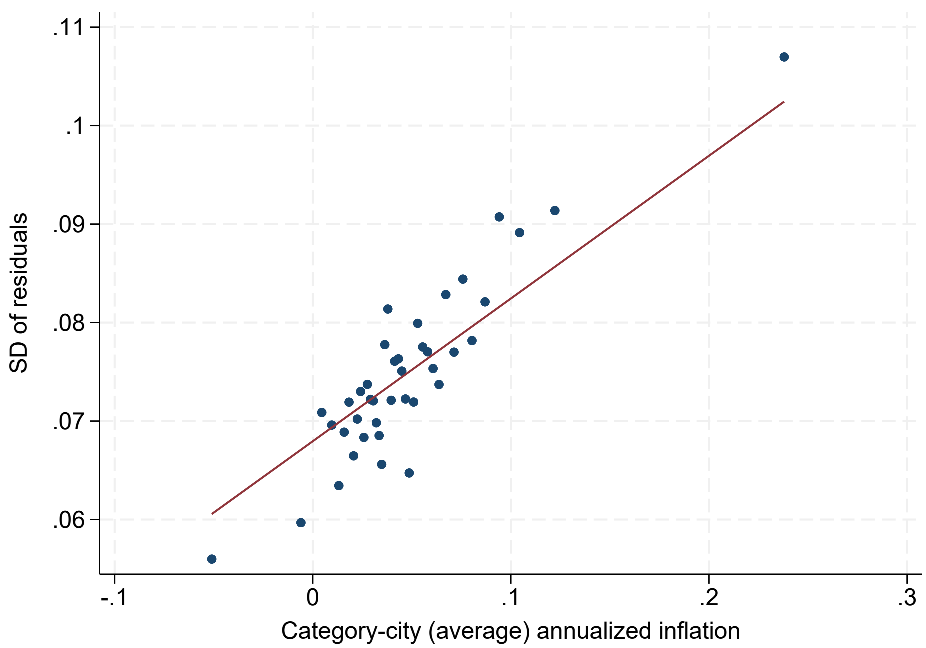
$$\phi = \frac{\sigma}{2}\mathbb{V}[x] \tag{5.1}$$

where σ is the elasticity of substitution between goods and $\mathbb{V}[x]$ is the variance of price gaps. The difficulty arises because $\mathbb{V}[x]$ is not directly observable in the data.

One option for getting an estimate of the costs of inflation is measuring how the dispersion of prices changes when we move from zero inflation to a specific inflation rate π. For example, Alvarez et al. (2019) measure price dispersion from the variance of residualized log-prices, using an regression similar to (4.7). They then calculate the cost of inflation at a certain inflation rate π by subtracting from the variance observed with π inflation ($\mathbb{V}[x](\pi)$) the variance observed around zero inflation, $\phi(\pi) = \frac{\sigma}{2}(\mathbb{V}[x](\pi) - \mathbb{V}[x](0))$. With this methodology, they find for an year-on-year inflation rate of 50% a cost of inflation of only 0.6% and almost no cost of inflation for inflation rates below 10%. Given the short period analyzed in here and the persistence of inefficient price dispersion, such an analysis is strongly sensitive to the selection of zero inflation price dispersion and how the inflation rate is measured. The results in Cavallo et al. (2023) indicate that inefficient price dispersion due to a large shock, as the recently observed, take over a year to fully dissipate. This can also be observed in Figure 4 panels (a) and (c), going from weekly week-on-week inflation to month-on-month inflation would yield a very different estimation of the costs of inflation. With an elasticity of substitution of 6, 10% annualized inflation would imply a cost of inflation of 0.24% when using m-on-m inflation and of 0.14% when using w-on-w inflation. Changing the measure of price dispersion also strongly changes the results. Focusing on the residualized relative prices instead, panel (b) and (d), results in a cost of inflation of approximately 1.56% for a 10% annualized inflation.

Taking advantage of the international dimension of the data and the narrow categorization of products using the same methodology, I last estimate the costs of inflation from the relation of the category-city (absolute) average annualized monthly inflation and the average dispersion of prices over the analyzed sample. Annualized absolute inflation was constructed by first averaging the weekly month-on-month inflation rates and then annualizing this monthly inflation and taking the absolute value. Figure 5 displays the relation of the city-category average price dispersion and the average city-category inflation across all weeks annualized for product-city combinations in a bincscatter. Only city-categories observed in at least 52 weeks and with at least 20 products included, this is 4,545 observations. The binscatter is based on the residualized variables after controlling for category fixed effects and number of products. This relation assumes that across countries the classification of products and distribution of prices is similar, within a narrow category and controlling for the number of products included, and exploits the cross-country variation. The figure shows again a positive relationship between inflation and price dispersion and annualized inflation, also at elevated levels of inflation. Making use of Equation 5.1, the costs of an inflation increase of 10% is associated with a loss of around 1-1.3% of flex price consumption.

Figure 5: Price Dispersion and Inflation



Notes: Each dot corresponds to the average price dispersion for 40. The unit of observation is a category × city. The number of category × city included is 4,545 so that one bin represents around over 100 category × city combinations. Annualized absolute inflation was constructed by first averaging the weekly month-on-month inflation rates and then annualizing this monthly inflation and taking the absolute value. Both variables were residualized controlling for category fixed effects and the number of products in the category-city combination.

6. Size and Frequency of Price Adjustments with High Inflation

This section aims to give a better understanding on the source of the results presented in the previous sections. The presence of a large share of price changes happening independently of the state of the firm, might be able to give an explanation to the results previously presented.

Under high inflation, as the one that restaurants faced in the analyzed cities and period, as pointed out in Nakamura et al. (2018), we should expect an increase in the absolute size of price adjustments if the pricing is time-dependent. In contrast, if prices are state-dependent, we would expect an increase in the frequency of price adjustments instead.

In order to understand better how the frequency and size of adjustments change with inflation, I regress either the mean absolute price adjustment (conditional on adjustment) and the frequency of adjustments measured as the share of price adjustments in a given week-city-category. This is, I run the following regressions

$$\text{mean}_{gct}(\Delta p_{igct}) = \gamma_{gc} + \beta|\Delta p_{gct}| + \varepsilon_{gct} \tag{6.1}$$

and

$$Adj.Share_{gct} = \gamma_{gc} + \beta|\Delta p_{gct}| + \varepsilon_{gct} \tag{6.2}$$

where $\text{mean}_{gct}(\Delta p_{igct})$ is the mean absolute price adjustment of price changers and $Adj.Share_{gct}$ is the share of prices that adjusted within a city, category and week. As earlier, $|\Delta p_{gct}|$ is the category-city-inflation and γ_{gc} is a city-category fixed effect.

The results are reported in table 4. The results indicate that an increase in inflation is driven by both, an increase in the size of price adjustments and in the frequency of adjustments. An increase of the weekly inflation rate from 0.25% to 0.5% increases the mean absoulute price adjustment by 0.5% on average. This number is three times significantly larger when looking at restaurants, pointing to this relevant cross-sectoral heterogeneity which is also present during the studied high inflation period. The same increase in weekly inflation, increases significantly the share of products adjusting prices by around 1.25%. I find no heterogeneity across sectors in the relation of inflation and frequency of price adjustments.

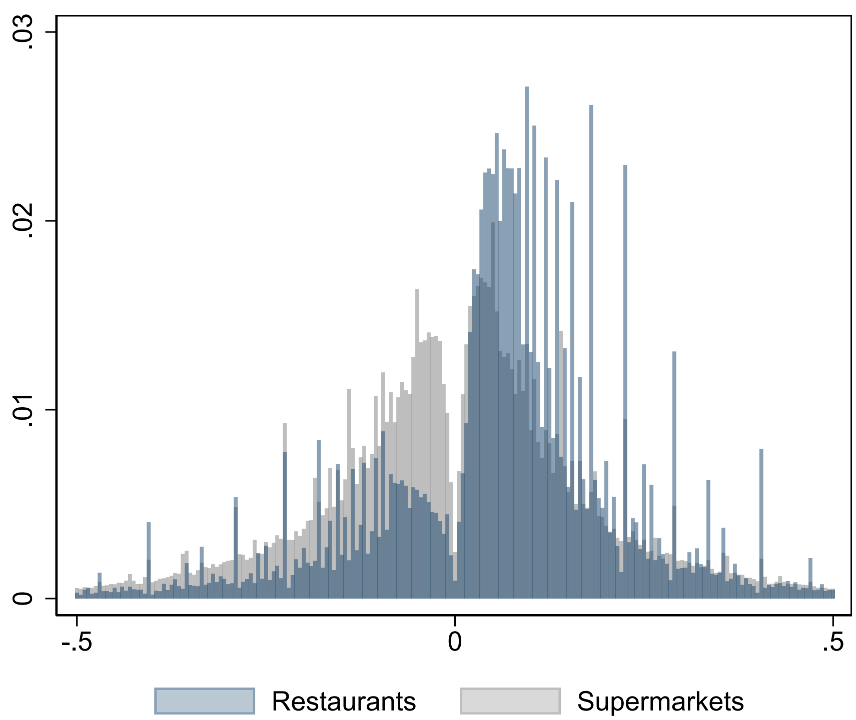
Table 4: Conditional Mean Absolute Price Adjustment, Frequency and Inflation

	Mean Absolute Adjustment					Frequency				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\lvert\Delta p_{gct}\rvert$	2.353***	5.492***	2.236***	2.399***	2.386***	5.157***	5.608***	5.137***	4.872***	4.867***
	(0.02)	(0.20)	(0.02)	(0.03)	(0.02)	(0.03)	(0.14)	(0.03)	(0.04)	(0.03)
City×Category FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Date FEs	N	N	N	N	Y	N	N	N	N	Y
$\Delta p < 0$ excl.	N	N	N	Y	N	N	N	N	Y	N
Sector	Both	Rest.	Super.	Both	Both	Both	Rest.	Super.	Both	Both
N	197019	44073	152945	115811	197019	230347	56400	173945	115828	230347
R^2	0.40	0.36	0.42	0.40	0.41	0.60	0.62	0.53	0.60	0.62

Notes: Robust standard errors in parenthesis. Only city-category combinations with non-zero inflation included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Finally, figure 6 displays the distribution of price adjustments in the two sectors. The results in previous sections could be the result of some degree of time dependent pricing. Meaning that a share of price adjustments are independent of the state. Despite the period of high inflation we still observe a large density of price adjustments around the $\Delta p_{irgct} = 0$ area. The share of price adjustmets that are smaller than one (five) percent are 2% (20%) and 4% (29%) for restaurants and supermarkets respectively, also indicating to some extend the existence of some time dependent price setting.

Figure 6: Distribution of Price Adjustments by Sector



7. Preliminary conclusion

This study provides robust evidence of the significant distortionary effects of suboptimal inflation on relative prices, using a novel approach to estimate price distortions across various sectors and countries. By analyzing extensive product-level web-scraped data from over 40,000 restaurants and supermarkets across 16 countries, the research uncovers a strong positive comovement between inflation and inefficient price dispersion.

First, the findings reveal that heightened frequency of price adjustments during periods of exceptionally high inflation does not mitigate the distortionary effects on product-level relative prices. This indicates that even with more frequent price changes, the inefficiencies induced by suboptimal inflation persists (inconsistently with the commonly used menu cost models). Second, there is a significant comovement between cross-sectional price dispersion and inflation, with a more pronounced effect observed in the restaurant sector compared to supermarkets. This sectoral heterogeneity suggests that inflation affects different sectors to varying degrees, likely due to differences in price stickiness.

The analysis also uncovers a distinct "V" shape in the relationship between inflation and price dispersion around zero inflation. This implies that the impact of inflation on price dispersion is sustained even at higher levels of inflation, contrary to some previous estimates that suggested diminishing effects. Specifically, the results show that an annualized inflation increase from zero to 12.7 percent leads to a 40.5% increase in inefficient price dispersion for restaurants and a 15.1% increase for supermarkets. This highlights the broader economic costs of inflation, which extend beyond the traditionally measured welfare losses. Furthermore, the study indicates that the cost of a 10% annualized inflation increase is associated with a loss of over 1% in flexible price consumption. However, this estimate is highly sensitive to the frequency of data used, the definition of inefficient price dispersion, and its level around zero inflation. This sensitivity underscores the complexity of accurately measuring the true costs of inflation.

This research emphasizes the significant and sustained impact of inflation on price dispersion, with notable sectoral differences. These findings support theoretical models that incorporate time-dependent nominal rigidities and suggest that the costs of accommodating higher inflation are substantial. In future research, I aim to provide with this project a better understanding on the associated welfare costs of inflation using other moments of the distribution of prices following the literature in generalized hazard functions. 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. Robustness Inflation and Cross-Sectional Price Dispersion

Table A1: Price Dispersion and Inflation Comovement with Date×City FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\lvert\Delta p_{gct-4}\rvert$	0.561***	0.312***		0.551***	0.446***	13.465***	27.691***	0.657***		
	(0.00)	(0.00)		(0.01)	(0.02)	(0.28)	(2.75)	(0.01)		
$\lvert\Delta p_{gct}\rvert$			0.705***							0.617***
			(0.01)							(0.03)
$\lvert\Delta p_{vgct-4}\rvert$									0.615***	
									(0.09)	
Dep. variable	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	log $(SD_t^g(u_{irgct}))$	log $(SD_t^g(u_{irgct}))$	$SD_t^g(\varepsilon_{irgct})$	$SD_t^{vg}(\ln p_{irgct})$	$\Delta SD_t^g(p_{irgct})$
Sector	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants	Both	Both	Both
Category FEs	Y	N	Y	Y	Y	Y	Y	Y	Y	N
Week × City FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Category × City FEs	N	Y	N	N	N	N	N	N	N	N
N	257959	255926	270459	197871	60088	199140	59907	261108	14671	143597
R^2	0.35	0.55	0.37	0.33	0.25	0.20	0.15	0.31	0.62	0.06

Notes: This table shows the relation of different weekly measures of cross-sectional price dispersion and inflation at the category-(product volume)-city level. The measures of price price dispersion considered are the category-city-week standard deviation of product level price gaps ($SD_t^g(u_{irgct})$), the category-city-week standard deviation of product level residualized log-prices, the category-product volume-city-week standard deviation of log prices ($SD_t^{vg}(\ln p_{irgct})$) calculated for beverages that tend to be more homogeneous and the change in the category-city-week standard deviation of log prices based on a balanced sample of products available in t and $t-1$ ($\Delta SD_t^g(p_{irgct})$). The explanatory variables are either the category-city weekly month-on-month or week on week inflation, $\lvert\Delta p_{gct-4}\rvert$ and $\lvert\Delta p_{gct}\rvert$ respectively, and the category-product volume-city weekly month-on-month inflation ($\lvert\Delta p_{vgct-4}\rvert$). All specifications include Date×City FEs. Robust standard errors in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A1: Price Dispersion and Inflation Comovement with Category×City FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\lvert\Delta p_{gct-4}\rvert$	0.638***	0.353***		0.357***	0.290***	7.464***	15.388***	0.437***		
	(0.00)	(0.00)		(0.01)	(0.01)	(0.20)	(1.51)	(0.01)		
$\lvert\Delta p_{gct}\rvert$			0.513***							0.647***
			(0.00)							(0.03)
$\lvert\Delta p_{vgct-4}\rvert$									0.231***	
									(0.04)	
Dep. variable	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	$SD_t^g(u_{irgct})$	log $(SD_t^g(u_{irgct}))$	log $(SD_t^g(u_{irgct}))$	$SD_t^g(\varepsilon_{irgct})$	$SD_t^{vg}(\ln p_{irgct})$	$\Delta SD_t^g(p_{irgct})$
Sector	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants	Both	Both	Both
Category FEs	Y	N	N	N	N	N	N	N	N	N
Category × City FEs	N	Y	Y	Y	Y	Y	Y	Y	Y	N
N	257959	255926	270458	197871	60088	199139	59907	261108	14677	143597
R^2	0.28	0.51	0.49	0.49	0.40	0.51	0.48	0.52	0.93	0.04

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