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

Santiago E. Alvarez-Blaser

Banco de España - CEMFI Research Workshop – 20/10/2025

Motivation

> *The crisis has shown that interest rates can actually hit the zero level [...] What we need to think about now is whether this could justify setting a higher inflation target in the future.*

Olivier Blanchard on February 12th, 2010

Motivation

The crisis has shown that interest rates can actually hit the zero level [...] What we need to think about now is whether this could justify setting a higher inflation target in the future.

Olivier Blanchard on February 12th, 2010

But a reconsideration of that objective needs to take account not only of benefits of a higher in—potential benefits of a higher inflation target, but also the potential costs that could be associated with it [...] one of the most important questions facing monetary policy around the world in the future, and we very much look forward to seeing research by economists that will help inform our future decisions on this.

Janet Yellen, FOMC Press Conference, June 2017

Motivation

The crisis has shown that interest rates can actually hit the zero level [...] What we need to think about now is whether this could justify setting a higher inflation target in the future.

Olivier Blanchard on February 12th, 2010

But a reconsideration of that objective needs to take account not only of benefits of a higher in—potential benefits of a higher inflation target, but also the potential costs that could be associated with it [...] one of the most important questions facing monetary policy around the world in the future, and we very much look forward to seeing research by economists that will help inform our future decisions on this.

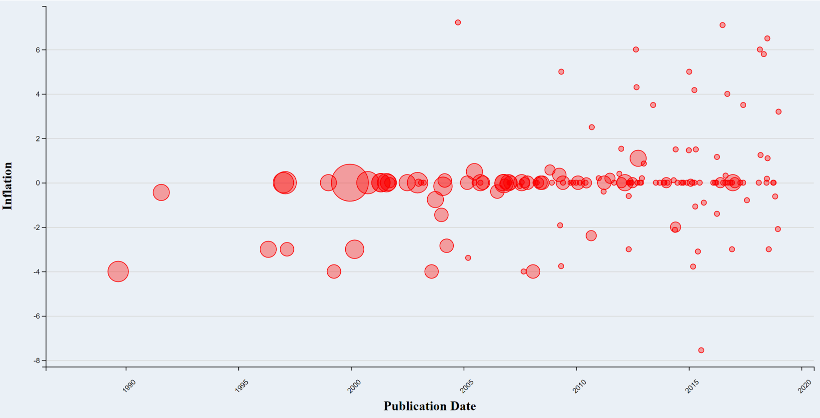
Janet Yellen, FOMC Press Conference, June 2017

First, an independent review of the level of the inflation target [...] There are risks to changing the goalposts.

Tony Yates, Financial Times, September 22, 2024

Motivation

Optimal inflation target according to the literature over years (Diercks, 2019)



Why not higher inflation targets?

Motivation

In standard New Keynesian models used by central banks

$$A_t(\bar{\pi}) = \left[\int_0^1 \left(\frac{P_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} di\right]^{-1}$$

$\uparrow$ Inflation + nominal rigidities $\rightarrow$ Price distortions $\rightarrow$ Misallocation $\rightarrow \downarrow A_t$

Motivation

In standard New Keynesian models used by central banks

$$A_t(\bar{\pi}) = \left[\int_0^1 \left(\frac{P_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} di\right]^{-1}$$

$\uparrow$ Inflation + nominal rigidities $\rightarrow$ Price distortions $\rightarrow$ Misallocation $\rightarrow \downarrow A_t$

$\hookrightarrow$ time-dependent pricing: inflation rise from 0% to 10% $\rightarrow$ welfare loss $> 2\%$

$\hookrightarrow$ fixed menu costs $\rightarrow$ almost no welfare effects

Motivation

In standard New Keynesian models used by central banks

$$A_t(\bar{\pi}) = \left[\int_0^1 \left(\frac{P_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} di\right]^{-1}$$

$\uparrow$ Inflation + nominal rigidities $\rightarrow$ Price distortions $\rightarrow$ Misallocation $\rightarrow \downarrow A_t$

$\hookrightarrow$ time-dependent pricing: inflation rise from 0% to 10% $\rightarrow$ welfare loss $>$ 2%

$\hookrightarrow$ fixed menu costs $\rightarrow$ almost no welfare effects

How does inflation empirically relate to price distortions?

Motivation

In standard New Keynesian models used by central banks

$$A_t(\bar{\pi}) = \left[\int_0^1 \left(\frac{P_{it}}{P_t}\right)^{-\theta} A_{it}^{-1} di\right]^{-1}$$

$\uparrow$ Inflation + nominal rigidities $\rightarrow$ Price distortions $\rightarrow$ Misallocation $\rightarrow \downarrow A_t$

$\hookrightarrow$ time-dependent pricing: inflation rise from 0% to 10% $\rightarrow$ welfare loss $>$ 2%

$\hookrightarrow$ fixed menu costs $\rightarrow$ almost no welfare effects

How does inflation empirically relate to price distortions?

$\hookrightarrow$ Existing empirical evidence presents mixed results (Nakamura et al., 2018; Alvarez et al., 2019; Sheremirov, 2020; Sara-Zaror, 2021; Adam et al., 2023) literature

This Paper

"How does inflation distort relative prices across different sectors and inflation environments?"

This Paper

"How does inflation distort relative prices across different sectors and inflation environments?"

- Leverage novel weekly product level big data for restaurants and supermarkets for 16 countries with average inflation rates ranging between 0% and 15%
- Use AI fine-tuned models to classify products into narrow categories

Main Findings

1. At the product level: marginal effect of suboptimal inflation on product-level price distortions is positive and significant in all countries

Main Findings

1. At the product level: marginal effect of suboptimal inflation on product-level price distortions is positive and significant in all countries

2. Across products, heterogeneous and sustained relationship of inflation and inefficient price dispersion in the two sectors:
   - an increase in annual inflation from 0% to 10% is associated with a 29.2% rise in price dispersion for restaurants and 17% for supermarkets
   - relationship between price dispersion and inflation maintains a distinct "V" shape: stable at high levels of inflation

Main Findings

1. At the product level: marginal effect of suboptimal inflation on product-level price distortions is positive and significant in all countries

2. Across products, heterogeneous and sustained relationship of inflation and inefficient price dispersion in the two sectors:

- an increase in annual inflation from 0% to 10% is associated with a 29.2% rise in price dispersion for restaurants and 17% for supermarkets
- relationship between price dispersion and inflation maintains a distinct "V" shape: stable at high levels of inflation

3. Overall the results are inconsistent with a standard menu cost model indicating a more sustained impact of inflation on inefficient price dispersion

Outline

1. Data
2. Suboptimal Inflation and Product Level Price Distortions
3. Inflation and Cross-Sectional Price Dispersion
4. Conclusion

Outline

1. **Data**
2. Suboptimal Inflation and Product Level Price Distortions
3. Inflation and Cross-Sectional Price Dispersion
4. Conclusion

Data

To investigate the distortionary effects of inflation using price data we need:
1 narrowly defined products **2** different inflation environments **3** high frequency

Data

To investigate the distortionary effects of inflation using price data we need:
1 narrowly defined products **2** different inflation environments **3** high frequency

Solution: web scraped data of restaurants and supermarkets

- weekly prices and daily opening information since March 2023 (high frequency)
- >40'000 restaurants and supermarkets (heterogeneous stickiness, many price-setters)
- 16 countries/18 cities in Africa, Asia and Europe (very different inflation levels)
  AM, CI, ES, GE, GH, HR, IT, KE, KG, KZ, MA, PL, RO, SI, UA, UG
- >9 million products and >160 million entries
- products classified into 330 narrow categories (burger with fries, coke, apples) using Google Translate Cloud and **fine-tunned OpenAI model** (narrow categories)
- tracks official inflation official comparison

Data

To investigate the distortionary effects of inflation using price data we need:
1 narrowly defined products **2** different inflation environments **3** high frequency

Solution: web scraped data of restaurants and supermarkets

- weekly prices and daily opening information since March 2023 (high frequency)
- >40'000 restaurants and supermarkets (heterogeneous stickiness, many price-setters)
- 16 countries/18 cities in Africa, Asia and Europe (very different inflation levels)
  AM, CI, ES, GE, GH, HR, IT, KE, KG, KZ, MA, PL, RO, SI, UA, UG
- >9 million products and >160 million entries
- products classified into 330 narrow categories (burger with fries, coke, apples) using Google Translate Cloud and **fine-tunned OpenAI model** (narrow categories)
- tracks official inflation official comparison

Today focus on results up to July 2024, updated findings summarized at the end

Data - descriptive statistics

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	765	95,491	2.75	27.93	14.74	116	556,100	-1.06	8.88	17.64
CI	920	42,736	6.35	19.30	19.98	47	83,989	4.75	4.02	13.34
ES	8,787	679,305	4.00	14.85	12.36	484	421,161	5.74	1.86	9.71
GE	1,573	97,550	6.31	12.61	15.09	311	1,182,042	0.83	6.37	18.52
GH	438	18,616	15.65	11.50	15.88	16	28,484	2.61	3.40	21.87
HR	778	84,334	8.59	12.70	13.19	120	544,254	3.97	2.40	18.67
IT	7,940	714,138	3.38	27.69	16.38	515	287,903	1.94	2.40	13.04
KE	1,212	82,988	6.77	18.79	16.59	198	254,815	8.08	3.83	12.51
KG	629	63,479	8.44	10.19	11.95	66	38,325	2.63	3.71	8.88
KZ	1,189	139,897	7.75	12.71	13.37	93	132,857	0.43	1.79	16.88
MA	1,528	114,333	5.47	13.93	15.32	181	297,200	3.64	1.35	14.56
PL	2,775	219,877	8.30	9.43	12.43	120	208,287	2.51	1.47	14.25
RO	2,249	223,497	10.86	9.48	15.52	247	181,691	3.43	1.43	13.74
SI	429	23,175	5.63	20.01	11.66	45	14,422	1.86	2.20	21.55
UA	4,036	576,640	10.01	8.69	14.86	330	1,850,097	3.94	1.25	16.02
UG	921	58,080	11.21	15.05	20.51	172	166,139	2.42	5.11	12.99
All	36,169	3,234,136	7.49	15.30	15.02	3,061	6,247,766	2.97	3.22	15.16

updated data additional moments

Data - descriptive statistics

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	765	95,491	2.75	27.93	14.74	116	556,100	-1.06	8.88	17.64
CI	920	42,736	6.35	19.30	19.98	47	83,989	4.75	4.02	13.34
ES	8,787	679,305	4.00	14.85	12.36	484	421,161	5.74	1.86	9.71
GE	1,573	97,550	6.31	12.61	15.09	311	1,182,042	0.83	6.37	18.52
GH	438	18,616	15.65	11.50	15.88	16	28,484	2.61	3.40	21.87
HR	778	84,334	8.59	12.70	13.19	120	544,254	3.97	2.40	18.67
IT	7,940	714,138	3.38	27.69	16.38	515	287,903	1.94	2.40	13.04
KE	1,212	82,988	6.77	18.79	16.59	198	254,815	8.08	3.83	12.51
KG	629	63,479	8.44	10.19	11.95	66	38,325	2.63	3.71	8.88
KZ	1,189	139,897	7.75	12.71	13.37	93	132,857	0.43	1.79	16.88
MA	1,528	114,333	5.47	13.93	15.32	181	297,200	3.64	1.35	14.56
PL	2,775	219,877	8.30	9.43	12.43	120	208,287	2.51	1.47	14.25
RO	2,249	223,497	10.86	9.48	15.52	247	181,691	3.43	1.43	13.74
SI	429	23,175	5.63	20.01	11.66	45	14,422	1.86	2.20	21.55
UA	4,036	576,640	10.01	8.69	14.86	330	1,850,097	3.94	1.25	16.02
UG	921	58,080	11.21	15.05	20.51	172	166,139	2.42	5.11	12.99
All	36,169	3,234,136	7.49	15.30	15.02	3,061	6,247,766	2.97	3.22	15.16

↪ almost **40’000 restaurants and supermarkets**

updated data additional moments

Data - descriptive statistics

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	765	95,491	2.75	27.93	14.74	116	556,100	-1.06	8.88	17.64
CI	920	42,736	6.35	19.30	19.98	47	83,989	4.75	4.02	13.34
ES	8,787	679,305	4.00	14.85	12.36	484	421,161	5.74	1.86	9.71
GE	1,573	97,550	6.31	12.61	15.09	311	1,182,042	0.83	6.37	18.52
GH	438	18,616	15.65	11.50	15.88	16	28,484	2.61	3.40	21.87
HR	778	84,334	8.59	12.70	13.19	120	544,254	3.97	2.40	18.67
IT	7,940	714,138	3.38	27.69	16.38	515	287,903	1.94	2.40	13.04
KE	1,212	82,988	6.77	18.79	16.59	198	254,815	8.08	3.83	12.51
KG	629	63,479	8.44	10.19	11.95	66	38,325	2.63	3.71	8.88
KZ	1,189	139,897	7.75	12.71	13.37	93	132,857	0.43	1.79	16.88
MA	1,528	114,333	5.47	13.93	15.32	181	297,200	3.64	1.35	14.56
PL	2,775	219,877	8.30	9.43	12.43	120	208,287	2.51	1.47	14.25
RO	2,249	223,497	10.86	9.48	15.52	247	181,691	3.43	1.43	13.74
SI	429	23,175	5.63	20.01	11.66	45	14,422	1.86	2.20	21.55
UA	4,036	576,640	10.01	8.69	14.86	330	1,850,097	3.94	1.25	16.02
UG	921	58,080	11.21	15.05	20.51	172	166,139	2.42	5.11	12.99
All	36,169	3,234,136	7.49	15.30	15.02	3,061	6,247,766	2.97	3.22	15.16

↪ over **9 million products** observed

updated data additional moments

Data - descriptive statistics

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	765	95,491	2.75	27.93	14.74	116	556,100	-1.06	8.88	17.64
CI	920	42,736	6.35	19.30	19.98	47	83,989	4.75	4.02	13.34
ES	8,787	679,305	4.00	14.85	12.36	484	421,161	5.74	1.86	9.71
GE	1,573	97,550	6.31	12.61	15.09	311	1,182,042	0.83	6.37	18.52
GH	438	18,616	15.65	11.50	15.88	16	28,484	2.61	3.40	21.87
HR	778	84,334	8.59	12.70	13.19	120	544,254	3.97	2.40	18.67
IT	7,940	714,138	3.38	27.69	16.38	515	287,903	1.94	2.40	13.04
KE	1,212	82,988	6.77	18.79	16.59	198	254,815	8.08	3.83	12.51
KG	629	63,479	8.44	10.19	11.95	66	38,325	2.63	3.71	8.88
KZ	1,189	139,897	7.75	12.71	13.37	93	132,857	0.43	1.79	16.88
MA	1,528	114,333	5.47	13.93	15.32	181	297,200	3.64	1.35	14.56
PL	2,775	219,877	8.30	9.43	12.43	120	208,287	2.51	1.47	14.25
RO	2,249	223,497	10.86	9.48	15.52	247	181,691	3.43	1.43	13.74
SI	429	23,175	5.63	20.01	11.66	45	14,422	1.86	2.20	21.55
UA	4,036	576,640	10.01	8.69	14.86	330	1,850,097	3.94	1.25	16.02
UG	921	58,080	11.21	15.05	20.51	172	166,139	2.42	5.11	12.99
All	36,169	3,234,136	7.49	15.30	15.02	3,061	6,247,766	2.97	3.22	15.16

↪ **wide average inflation range** covered

updated data additional moments

Data - descriptive statistics

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	765	95,491	2.75	27.93	14.74	116	556,100	-1.06	8.88	17.64
CI	920	42,736	6.35	19.30	19.98	47	83,989	4.75	4.02	13.34
ES	8,787	679,305	4.00	14.85	12.36	484	421,161	5.74	1.86	9.71
GE	1,573	97,550	6.31	12.61	15.09	311	1,182,042	0.83	6.37	18.52
GH	438	18,616	15.65	11.50	15.88	16	28,484	2.61	3.40	21.87
HR	778	84,334	8.59	12.70	13.19	120	544,254	3.97	2.40	18.67
IT	7,940	714,138	3.38	27.69	16.38	515	287,903	1.94	2.40	13.04
KE	1,212	82,988	6.77	18.79	16.59	198	254,815	8.08	3.83	12.51
KG	629	63,479	8.44	10.19	11.95	66	38,325	2.63	3.71	8.88
KZ	1,189	139,897	7.75	12.71	13.37	93	132,857	0.43	1.79	16.88
MA	1,528	114,333	5.47	13.93	15.32	181	297,200	3.64	1.35	14.56
PL	2,775	219,877	8.30	9.43	12.43	120	208,287	2.51	1.47	14.25
RO	2,249	223,497	10.86	9.48	15.52	247	181,691	3.43	1.43	13.74
SI	429	23,175	5.63	20.01	11.66	45	14,422	1.86	2.20	21.55
UA	4,036	576,640	10.01	8.69	14.86	330	1,850,097	3.94	1.25	16.02
UG	921	58,080	11.21	15.05	20.51	172	166,139	2.42	5.11	12.99
All	36,169	3,234,136	7.49	$\boxed{15.30}$	15.02	3,061	6,247,766	2.97	$\boxed{3.22}$	15.16

↪ sectors with very **heterogeneous stickiness**

updated data additional moments

Outline

1. Data
2. **Suboptimal Inflation and Product Level Price Distortions**
3. Inflation and Cross-Sectional Price Dispersion
4. Conclusion

Methodology – introduction

Assume that the optimal flexible relative price $p^*_{it} = P^*_{it}/P^*_t$, evolves according to,

$$\ln p^*_{it} = \ln p^*_i - t \ln \Pi^*_i \tag{1}$$

where p^*_i is the product introduction price and Π^*_i a product-specific time trend.

Methodology – introduction

Assume that the optimal flexible relative price $p^*_{it} = P^*_{it} / P^*_t$, evolves according to,

$$\ln p^*_{it} = \ln p^*_i - t \ln \Pi^*_i \tag{1}$$

where p^*_i is the product introduction price and Π^*_i a product-specific time trend.

- With gross inflation rate $\ln\Pi = \ln\Pi^*_i \rightarrow$ no need to adjust prices.
- With $\ln\Pi \neq \ln\Pi^*_i +$ price rigidities $\rightarrow$ a gap might arise: $\ln p_{it} = \ln p^*_i - t\ln\Pi^*_i + gap_{it}$

Methodology – introduction

Assume that the optimal flexible relative price $p^*_{it} = P^*_{it} / P^*_t$, evolves according to,

$$\ln p^*_{it} = \ln p^*_i - t \ln \Pi^*_i \tag{1}$$

where p^*_i is the product introduction price and Π^*_i a product-specific time trend.

- With gross inflation rate $\ln \Pi = \ln \Pi^*_i \to$ no need to adjust prices.
- With $\ln \Pi \neq \ln \Pi^*_i +$ price rigidities $\to$ a gap might arise: $\ln p_{it} = \ln p^*_i - t \ln \Pi^*_i + gap_{it}$

Price dispersion and price distortions:

$$\mathrm{Var}_t(\ln p_{it}) = \underbrace{\mathrm{Var}_t(\ln p^*_i - t \ln \Pi^*_{it})}_{\text{Desired } (\neq \text{ Efficient})} + \underbrace{\mathrm{Var}_t(\overbrace{gap_{it}}^{\text{Price distortions}})}_{\text{Inefficient price dispersion}} \tag{2}$$

$\hookrightarrow$ relation of inflation to (i) price distortions and to (ii) inefficient price dispersion?

Methodology – inflation and product level price distortions

We could estimate (product i, category g, city c)

$$\text{ln}p_{igct} = \text{ln}a_{igc} - (\text{ln}b_{igc})t + u_{igct} \tag{3}$$

with $\widehat{lna_{igc}} \rightarrow \text{ln}p^*_{igc}$ and $\widehat{\text{ln}b_{igc}} \rightarrow \text{ln}\Pi^*_{igc}$

Methodology – inflation and product level price distortions

We could estimate (product i, category g, city c)

$$\ln p_{igct} = \ln a_{igc} - (\ln b_{igc})t + u_{igct} \tag{3}$$

with $\widehat{ln a_{igc}} \rightarrow \ln p^*_{igc}$ and $\widehat{\ln b_{igc}} \rightarrow \ln \Pi^*_{igc}$

Issue: p^*_{it} might include idiosyncratic shocks $\rightarrow$ u_{igct} does **not** identify gap_{igct}

Methodology – inflation and product level price distortions

We could estimate (product i, category g, city c)

$$\ln p_{igct} = \ln a_{igc} - (\ln b_{igc})t + u_{igct} \tag{3}$$

with $\widehat{lna_{igc}} \to \ln p^*_{igc}$ and $\widehat{\ln b_{igc}} \to \ln \Pi^*_{igc}$

Issue: p^*_{it} might include idiosyncratic shocks $\to u_{igct}$ does **not** identify gap_{igct}

Solution: novel methodology in Adam et al. (2023)

Methodology – inflation and product level price distortions

Test if suboptimal inflation causes product level relative price distortions:

$$\widehat{\text{Var}_{(i)}}(u_{igct}) = v_{gc} + c_{gc}(\widehat{\ln\Pi_{gc}/\Pi^*_{igc}})^2 + \epsilon_{igc} \tag{4}$$

- $c_{gc} = \partial^2 \text{Var}(gap_{igct})/(\partial\Pi)^2$ at $\ln\Pi = \ln\Pi^*_i$

Methodology – inflation and product level price distortions

Test if suboptimal inflation causes product level relative price distortions:

$$\widehat{\text{Var}_{(i)}}(u_{igct}) = v_{gc} + c_{gc}(\widehat{\ln\Pi_{gc}/\Pi^*_{igc}})^2 + \epsilon_{igc} \tag{4}$$

- $c_{gc} = \partial^2 \text{Var}(gap_{igct})/(\partial\Pi)^2$ at $\ln\Pi = \ln\Pi^*_i$
- $\widehat{\ln\Pi_{gc}/\Pi^*_{igc}}$ estimated from 1st first stage $\ln P_{igct} = \ln\tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$
- $\widehat{\text{Var}_{(i)}}(u_{igct})$ estimated from 2nd first stage $\ln p_{igct} = \ln a_{igc} - (\ln b_{igc})t + u_{igct}$

Methodology – inflation and product level price distortions

Test if suboptimal inflation causes product level relative price distortions:

$$\widehat{\text{Var}_{(i)}}(u_{igct}) = v_{gc} + c_{gc}(\ln\widehat{\Pi_{gc}/\Pi^*_{igc}})^2 + \epsilon_{igc} \tag{4}$$

- $c_{gc} = \partial^2 \text{Var}(gap_{igct})/(\partial\Pi)^2$ at $\ln\Pi = \ln\Pi^*_i$
- $\ln\widehat{\Pi_{gc}/\Pi^*_{igc}}$ estimated from 1st first stage $\ln P_{igct} = \ln\tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$
- $\widehat{\text{Var}_{(i)}}(u_{igct})$ estimated from 2nd first stage $\ln p_{igct} = \ln a_{igc} - (\ln b_{igc})t + u_{igct}$

Intuitively: does the residual jump around more for products with higher suboptimal inflation?

$\hookrightarrow$ if yes: inflation is distortionary

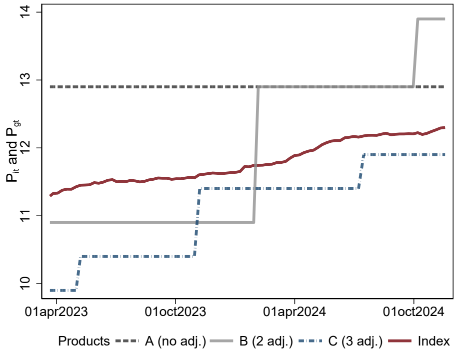
Methodology – product example

Example: Pizza Margherita in **Madrid**

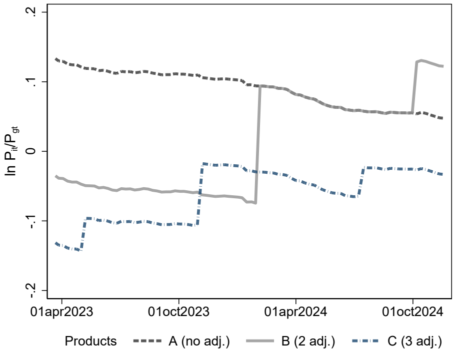
Methodology – product example

Example: Pizza Margherita in **Madrid**

Product price and category price



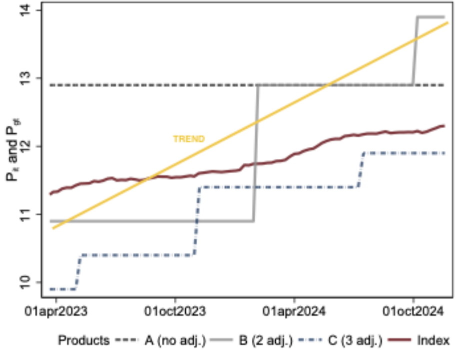
Relative prices



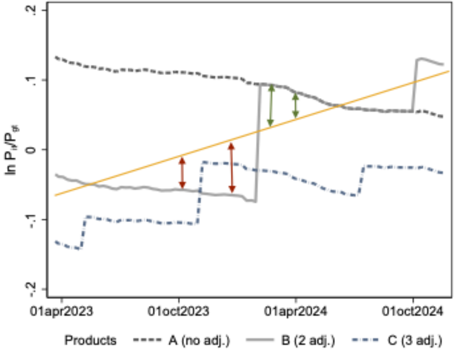
Results – product example

Example: Pizza Margherita in Madrid

Product price and category price



Relative prices



$\hookrightarrow$ use (log) nominal price to estimate suboptimal inflation $\ln\widehat{\Pi_{gc}/\Pi^*_{igc}}$

$\hookrightarrow$ use relative price to get residuals and construct $\widehat{\mathrm{Var}_{(i)}}(u_{igct})$

Results – 1st first stage regression (sub-optimal inflation)

Estimate $\widehat{\ln \Pi_{gc}/\Pi^*_{igc}}$ from: $\quad \ln P_{igct} = \ln \tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$

Results – 1st first stage regression (sub-optimal inflation)

$$\text{Estimate } \widehat{\ln \Pi_{gc}/\Pi^*_{igc}} \text{ from:} \quad \ln P_{igct} = \ln \tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$$

- $>$110 million P_{igct}
- aproximately 2.5 million products
- 4,455 category-cities

Results – 1st first stage regression (sub-optimal inflation)

Estimate $\ln\widehat{\Pi_{gc}/\Pi^*_{igc}}$ from: $\quad \ln P_{igct} = \ln\tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$

- $>$110 million P_{igct}
- aproximately 2.5 million products
- 4,455 category-cities
- display mean of $\ln(\widehat{\Pi_{gc}/\Pi^*_{igc}})$

Results – 1st first stage regression (sub-optimal inflation)

Estimate $\ln\widehat{\Pi_{gc}/\Pi^*_{igc}}$ from: $\ln P_{igct} = \ln\tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$

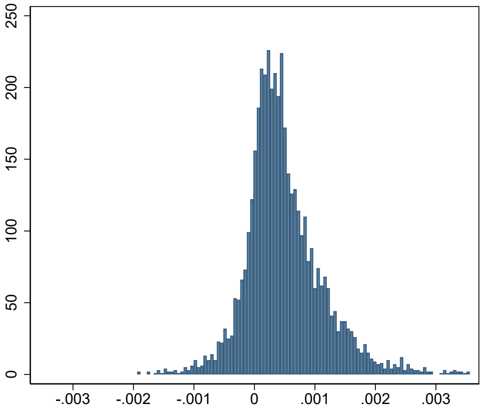
- $>$110 million P_{igct}
- aproximately 2.5 million products
- 4,455 category-cities
- display mean of $\ln(\widehat{\Pi_{gc}/\Pi^*_{igc}})$

↪ NEW:suboptimal inflation >0 for 82% of city-categories with median 2.1% (annualized)

- significant variation within a city-category combination

$\mathrm{SD}(\ln\widehat{\Pi_{gc}/\Pi^*_{igc}})$

Mean of $\ln(\widehat{\Pi_{gc}/\Pi^*_{igc}})$



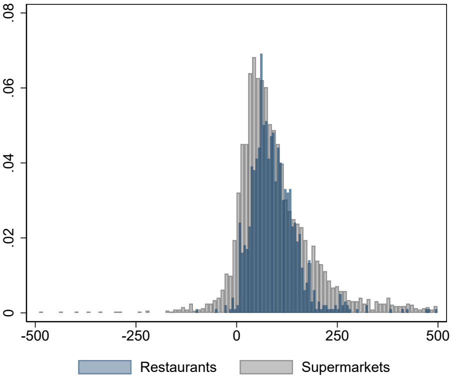
Results – second stage regression

Estimate 4,455 category-cities c_{gc}: $\widehat{\text{Var}_{(i)}}(u_{igct}) = v_{gc} + c_{gc}(\ln\widehat{\Pi_{gc}/\Pi^*_{igc}})^2 + \epsilon_{igc}$

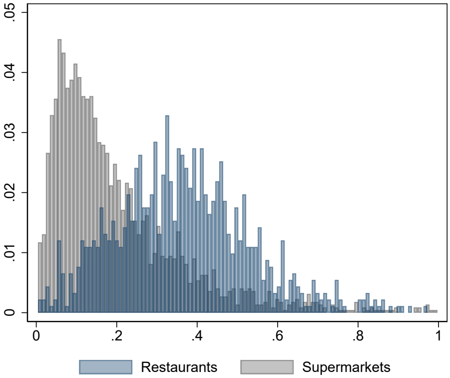
Results – second stage regression

Estimate 4,455 category-cities c_{gc}: $\widehat{\text{Var}}_{(i)}(u_{igct}) = v_{gc} + c_{gc}(\ln \widehat{\Pi_{gc}/\Pi^*_{igc}})^2 + \epsilon_{igc}$

c_{gc} estimates



Second-stage R^2



$\hookrightarrow$ c_{gc} positive for 94% category-cities, positive and significant for 74% (86% if $N_{i(gc)} > 100$)

Results – second stage regression

	$c_g > 0$	t-stat < -2	t-stat > 2	t-stat > 5	Median c_g	Restaurants Median c_g	Supermarkets Median c_g
AM	82%	5.95%	68%	42%	66.27	100.78	39.38
CI	91%	1.24%	65%	24%	93.82	125.52	79.44
ES (Madrid)	97%	0.68%	84%	47%	101.63	122.91	95.28
ES (Barcelona)	99%	0.68%	82%	40%	115.67	106.97	120.20
GE	92%	1.60%	65%	26%	83.71	66.67	109.89
GH	96%	0.00%	68%	27%	99.54	59.13	128.20
HR	92%	1.37%	71%	28%	120.00	123.25	117.94
IT (Rome)	95%	1.08%	79%	45%	153.41	149.95	157.30
IT (Milan)	96%	0.00%	74%	29%	74.51	81.72	69.76
KE	98%	0.35%	88%	48%	154.68	124.46	164.48
KG	93%	2.25%	67%	31%	77.86	67.63	95.48
KZ	90%	2.62%	75%	36%	63.05	63.05	63.05
MA	96%	0.72%	77%	42%	33.52	19.17	38.46
PL	91%	1.71%	71%	38%	32.57	58.59	27.11
RO	96%	0.65%	76%	33%	79.79	96.03	73.38
SI	91%	3.55%	71%	40%	205.06	127.88	517.12
UA	93%	1.08%	75%	38%	42.04	40.95	42.83
UG	92%	2.89%	70%	27%	79.23	84.72	77.09
Pooled	94%	1.44%	74%	36%	82.63	86.79	80.43

$\hookrightarrow$ similar pattern across all countries

update

Outline

1. Data
2. Suboptimal Inflation and Product Level Price Distortions
3. **Inflation and Cross-Sectional Price Dispersion**
4. Conclusion

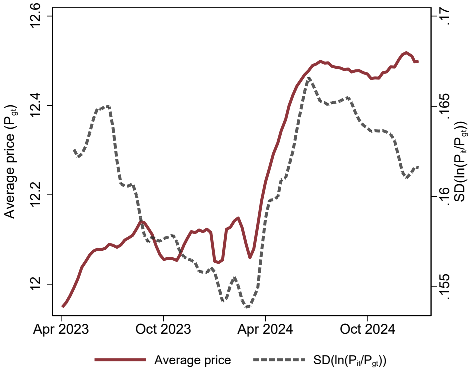
Methodology – inflation and category price dispersion

Do prices and price dispersion comove?

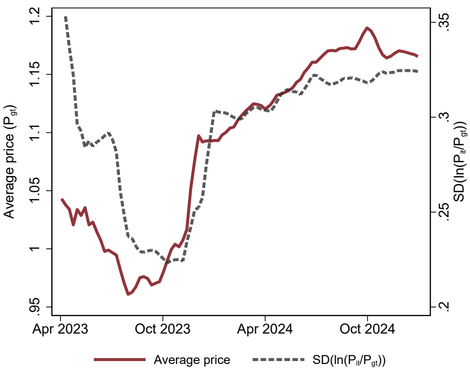
Methodology – inflation and category price dispersion

Do prices and price dispersion comove?

Pizza Margherita in Restaurant



330 ML Soda Can in Supermarket



↪ in periods of price stability price dispersion seems to stabilize or even decrease

Methodology – inflation and category price dispersion

Relation of inflation and inefficient price dispersion

$$\mathrm{SD}_t^{gc}(u_{irgct}) = \gamma_g + \beta|\Pi_{gct-4}| + \epsilon_{gct}. \tag{5}$$

$\mathrm{SD}_t^{gc}(u_{igct})$ from the estimated u_{igct} and $|\Pi_{gct-4}|$ is category-city absolute inflation

Since $\mathrm{SD}_t^{gc}(u_{igct})$ might not capture the inefficient price dispersion **level** well and similarly across city-categories:

$$\log \mathrm{SD}_t^{gc}(u_{irgct}) = \gamma_g + \beta|\Pi_{gct-4}| + \epsilon_{gct}. \tag{6}$$

Extended heterogeneity correction I Alternative tests

Results – inflation and category price dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\log \text{SD}_{gct}(u_{it})$	$\log \text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(\epsilon_{it})$	$\text{SD}_{vgct}(\ln p_{it})$	$\Delta\text{SD}_{gct}(p_{it})$
$\lvert\Delta p_{gct-4}\rvert$	0.731***	0.407***		0.730***	1.004***	21.327***	36.633***	0.704***		0.672***
	(0.00)	(0.00)		(0.01)	(0.01)	(0.19)	(0.47)	(0.00)		(0.04)
$\lvert\Delta p_{gct}\rvert$			0.920***							
			(0.00)							
$\lvert\Delta p_{vgct-4}\rvert$									0.393**	
									(0.13)	
Sector	Both	Both	Both	Super.	Rest.	Super.	Rest.	Both	Both	Both
Cat. FEs	Y	N	Y	Y	Y	Y	Y	Y	Y	N
Cat.× City FEs	N	Y	N	N	N	N	N	N	N	N
Cat.× Vol FEs	N	N	N	N	N	N	N	N	Y	N
N	231,160	231,147	231,160	171,198	59,362	169,486	59,362	231,160	11,760	162,667
R^2	0.27	0.63	0.24	0.18	0.20	0.23	0.09	0.25	0.46	0.06
Within R^2	0.17	0.09	0.13	0.17	0.16	0.06	0.07	0.14	0.00	0.06

↪ An increase in annualized inflation from 0% to 10% (12.7%) is associated with a 29.2% (36.6%) increase in price dispersion for restaurants and 17% (21.3%) for supermarkets

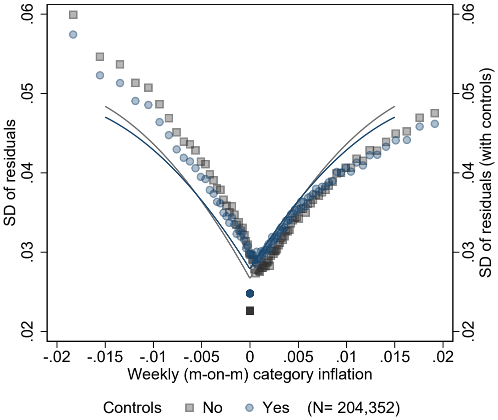
Date.× City FEs | Cat.× City FEs | Separately by country | Update

Results – inflation dispersion relation does not flatten

Binscatter: average price dispersion for 100 equally sized inflation bins

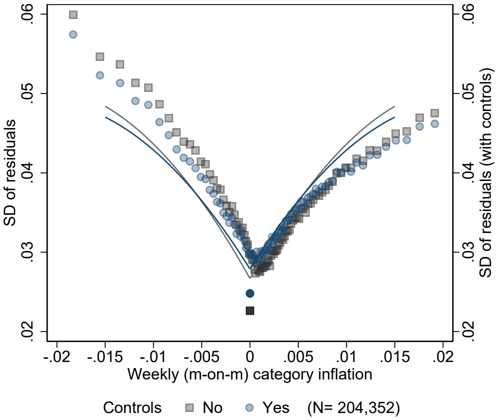
Results – inflation dispersion relation does not flatten

Binscatter: average price dispersion for 100 equally sized inflation bins



Results – inflation dispersion relation does not flatten

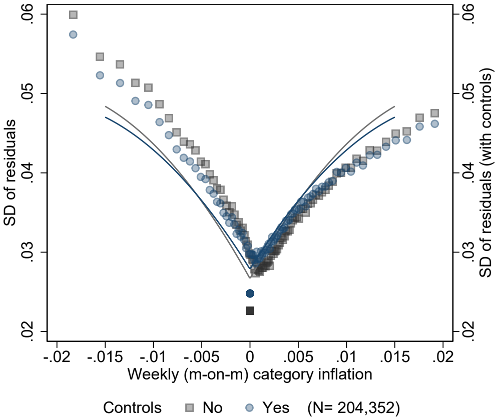
Binscatter: average price dispersion for 100 equally sized inflation bins



- ↪ 204,000 category × city × week
- ↪ each bin >2,000 obs

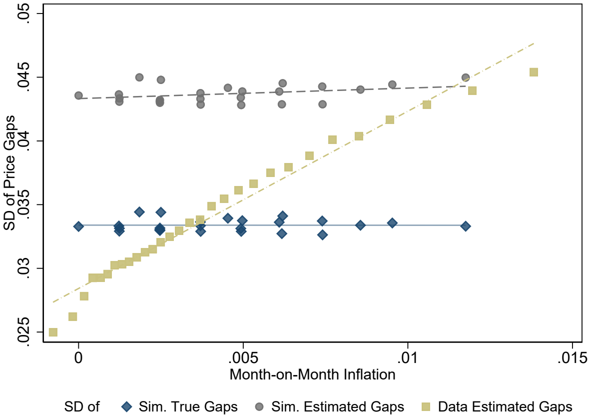
Results – inflation dispersion relation does not flatten

Binscatter: average price dispersion for 100 equally sized inflation bins



- ↪ 204,000 category × city × week
- ↪ each bin >2,000 obs
- ↪ relation seems to maintain for high inflation

Results – Comparison with Theoretical Results



Calibrate NK menu cost model, simulate data and compare:

- Simulated true gaps
- Simulated data estimated gaps
- Actual data estimated gaps

↪ The methodology might not get the level right, but it does not distort the slope

↪ Standard menu cost models fail to replicate this strong positive relation

costs | frequency-size | model moments

Results – update

	Current	Updated	Updated (N>50)
Number of weeks	70	95	95
Number of observations in 1st stages (millions)	113	168	168
Number of estimated c_g	4,455	4,498	3,704
Share $c_g > 0$	94%	98%	99%
Share t-stat > 2	74%	81%	88%
Number of week-city-categories included	231,160	317,994	241,479
Dispersion increase with 10% inflation increase			
Supermarkets	17%	25.8%	23.4%
Restaurants	29.2%	39.3%	40.0%

$\hookrightarrow$ findings remain robust, with some results showing improvement

Outline

1. Data
2. Suboptimal Inflation and Product Level Price Distortions
3. Inflation and Cross-Sectional Price Dispersion
4. **Conclusion**

Taking stock

1. Marginal effect of suboptimal inflation on product-level distortions is positive and significant

Taking stock

1. Marginal effect of suboptimal inflation on product-level distortions is positive and significant
2. An increase in annual inflation from 0% to 10% is associated with a 29.2% increase in price dispersion for restaurants and 17% for supermarkets

Taking stock

1. Marginal effect of suboptimal inflation on product-level distortions is positive and significant
2. An increase in annual inflation from 0% to 10% is associated with a 29.2% increase in price dispersion for restaurants and 17% for supermarkets
3. Relationship between price dispersion and inflation maintains a distinct “V" shape, even at higher levels of inflation

Taking stock

1. Marginal effect of suboptimal inflation on product-level distortions is positive and significant
2. An increase in annual inflation from 0% to 10% is associated with a 29.2% increase in price dispersion for restaurants and 17% for supermarkets
3. Relationship between price dispersion and inflation maintains a distinct "V" shape, even at higher levels of inflation
4. Overall the results are inconsistent with a standard menu cost model indicating a more sustained impact of inflation on inefficient price dispersion

Taking stock

1. Marginal effect of suboptimal inflation on product-level distortions is positive and significant
2. An increase in annual inflation from 0% to 10% is associated with a 29.2% increase in price dispersion for restaurants and 17% for supermarkets
3. Relationship between price dispersion and inflation maintains a distinct “V" shape, even at higher levels of inflation
4. Overall the results are inconsistent with a standard menu cost model indicating a more sustained impact of inflation on inefficient price dispersion

Thank you!

s.alvarez.blaser@gmail.com

next steps

Appendix

Results – second stage regression (updated)

	$c_g > 0$	t-stat < -2	t-stat > 2	t-stat > 5	Median c_g	Restaurants Median c_g	Supermarkets Median c_g
AM	99%	0.90%	85%	55%	62.17	92.74	48.87
CI	96%	1.19%	71%	26%	138.13	191.02	120.22
ES (Madrid)	98%	0.66%	86%	49%	142.33	164.88	137.13
ES (Barcelona)	99%	0.00%	83%	43%	187.59	214.32	170.21
GE	97%	0.39%	79%	39%	141.49	131.54	154.96
GH	100%	0.00%	74%	28%	83.74	55.92	121.40
HR	97%	0.43%	79%	38%	104.73	102.44	108.12
IT (Rome)	98%	0.00%	86%	44%	247.29	252.60	241.45
IT (Milan)	99%	0.55%	94%	73%	203.32	194.85	213.75
KE	100%	0.00%	93%	63%	180.62	144.59	195.96
KG	97%	1.09%	75%	35%	98.09	98.49	96.79
KZ	99%	0.00%	80%	42%	139.57	108.72	160.37
MA	99%	0.00%	87%	52%	53.88	25.23	59.14
PL	97%	0.34%	78%	39%	62.43	79.21	59.27
RO	97%	0.33%	76%	36%	128.18	131.36	126.48
SI	97%	0.00%	82%	40%	200.06	113.30	363.07
UA	97%	0.00%	83%	43%	47.75	49.73	47.46
UG	99%	0.40%	79%	38%	93.43	133.89	84.75
Pooled	98%	0.33%	82%	44%	120.43	120.46	120.40

back

Results – inflation dispersion relation (separately by country)

	β	Observations	R^2	Within R^2
AM	0.366***	8,715	0.36	0.09
	(0.01)			
CI	0.488***	12,561	0.47	0.16
	(0.01)			
ES (Madrid)	0.343***	16,669	0.48	0.15
	(0.01)			
ES (Barcelona)	0.376***	16,751	0.50	0.11
	(0.01)			
GE	0.602***	14,156	0.47	0.17
	(0.01)			
GH	0.460***	5,622	0.51	0.16
	(0.01)			
HR	0.403***	10,781	0.40	0.08
	(0.01)			
IT (Rome)	0.493***	15,815	0.47	0.09
	(0.01)			
IT (Milan)	0.362***	14,781	0.48	0.06
	(0.01)			

	β	Observations	R^2	Within R^2
KE	0.287***	15,509	0.49	0.09
	(0.01)			
KG	0.250***	9,327	0.44	0.07
	(0.01)			
KZ	0.419***	13,924	0.58	0.07
	(0.01)			
MA	0.566***	14,844	0.52	0.08
	(0.02)			
PL	0.394***	15,150	0.38	0.12
	(0.01)			
RO	0.332***	17,451	0.47	0.09
	(0.01)			
SI	0.426***	7,118	0.47	0.14
	(0.01)			
UA	0.266***	9,403	0.57	0.04
	(0.01)			
UG	0.377***	12,570	0.50	0.08
	(0.01)			

back

Methodology – inflation and category price dispersion

Alternative: Correct for desired price dispersion using FEs estimating (Sheremirov, 2020; Alvarez et al., 2019):

$$\ln P_{irgct} = \alpha_g + \delta_{ct} + \gamma_{rct} + \eta_{irgc} + \varepsilon_{irgct} \tag{7}$$

P_{irgct} price of product i, retailer r, category g, in city and week c and t.

- ↪ FEs capture "desired" price dispersion: η_{irgc} captures one specific product having a constantly higher price (eg larger package size), γ_{rct} captures that all products of a given firm increased prices (eg because firm shock), ε_{irgct} unexplained relative price
- ↪ partially criticised because firm idiosyncratic shocks can strongly move desired prices
  - ⋆ arguably not a big issue when using weekly data, short period, and focusing on city-specific price dispersion (no local demand shocks) back

Methodology – inflation and category price dispersion

Other tested alternatives to u_{igct}:

- $\hookrightarrow$ Δp_{vgct} where is the price dispersion for beverage category g and volume v in city c
- $\hookrightarrow$ $\Delta \text{SD}_t^{gc}(p_{igct})$ on balanced sample of products in t and $t-1$

back

Results – inflation dispersion relation (DateXCity FEs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\log \text{SD}_{gct}(u_{it})$	$\log \text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(\epsilon_{it})$	$\text{SD}_{vgct}(\ln p_{it})$	$\Delta\text{SD}_{gct}(p_{it})$
$\lvert\Delta p_{gct-4}\rvert$	0.550***	0.360***		0.617***	0.503***	22.632***	13.661***	0.704***		0.672***
	(0.00)	(0.00)		(0.01)	(0.01)	(0.60)	(0.18)	(0.00)		(0.05)
$\lvert\Delta p_{gct}\rvert$			0.715***							
			(0.00)							
$\lvert\Delta p_{vgct-4}\rvert$									-0.020	
									(0.14)	
Sector	Both	Both	Both	Restaurants	Supermarkets	Restaurants	Supermarkets	Both	Both	Both
Cat. FEs	Y	N	Y	Y	Y	Y	Y	Y	Y	N
Cat.× City FEs	N	Y	N	N	N	N	N	N	N	N
Cat.× Vol FEs	N	N	N	N	N	N	N	N	Y	N
N	231,159	231,146	231,159	59,361	171,198	59,361	169,486	231,160	11,736	162,667
R^2	0.52	0.69	0.51	0.59	0.54	0.27	0.33	0.25	0.62	0.07
Within R^2	0.13	0.08	0.11	0.09	0.11	0.02	0.02	0.14	0.00	0.05

back

Results – inflation dispersion relation (CategoryXCity FEs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(u_{it})$	$\log \text{SD}_{gct}(u_{it})$	$\log \text{SD}_{gct}(u_{it})$	$\text{SD}_{gct}(\epsilon_{it})$	$\text{SD}_{vgct}(\ln p_{it})$	$\Delta\text{SD}_{gct}(p_{it})$
$\lvert\Delta p_{gct-4}\rvert$	0.731***	0.407***		0.456***	0.409***	15.621***	10.626***	0.346***		0.672***
	(0.00)	(0.00)		(0.01)	(0.01)	(0.37)	(0.11)	(0.00)		(0.04)
$\lvert\Delta p_{gct}\rvert$			0.549***							
			(0.00)							
$\lvert\Delta p_{vgct-4}\rvert$									0.036	
									(0.03)	
Sector	Both	Both	Both	Restaurants	Supermarkets	Restaurants	Supermarkets	Both	Both	Both
Cat. FEs	Y	N	N	N	N	N	N	N	N	N
Cat.× City FEs	N	Y	Y	Y	Y	Y	Y	Y	Y	N
Cat.× City FEs× Vol FEs	N	N	N	N	N	N	N	N	Y	N
N	231,160	231,147	231,147	59,361	171,186	59,361	169,474	231,147	11,758	162,667
R^2	0.27	0.63	0.63	0.64	0.60	0.49	0.75	0.64	0.94	0.06
Within R^2	0.17	0.09	0.08	0.07	0.09	0.02	0.04	0.06	0.00	0.06

back

Results – 2nd first stage regression (residuals)

Estimate $\widehat{\text{Var}}_{(i)}(u_{igct})$ from: $\quad \ln p_{igct} = \ln a_{igc} - (\ln b_{igc})t + u_{igct}$

Results – 2nd first stage regression (residuals)

Estimate $\widehat{\text{Var}_{(i)}}(u_{igct})$ from: $\ln p_{igct} = \ln a_{igc} - (\ln b_{igc})t + u_{igct}$

- $>$110 million P_{igct}
- aproximately 2.5 million products
- 4,455 category-cities

Results – 2nd first stage regression (residuals)

Estimate $\widehat{\text{Var}}_{(i)}(u_{igct})$ from: $\ln p_{igct} = \ln a_{igc} - (\ln b_{igc})t + u_{igct}$

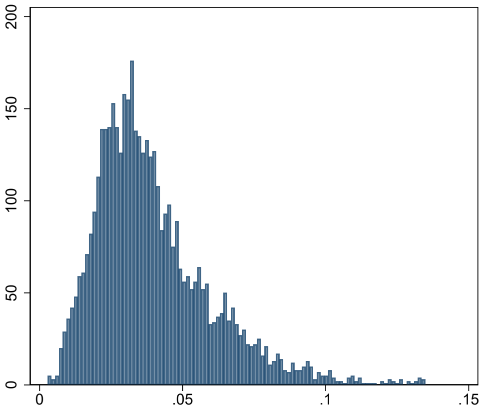
- $>$110 million P_{igct}
- aproximately 2.5 million products
- 4,455 category-cities
- display mean of $\widehat{\text{SD}}_{(i)}(u_{igct})$

$\hookrightarrow$ significant variation of u_{igct} within the lifetime of a product

- significant variation within a city-category combination

SD($\widehat{\text{SD}}_{(i)}(u_{igct})$)

Mean of $\widehat{\text{SD}}_{(i)}(u_{igct})$



back

Results – inflation dispersion relation (updated)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\text{SD}_t^{gc}(u_{irgct})$	$\text{SD}_t^{gc}(u_{irgct})$	$\text{SD}_t^{gc}(u_{irgct})$	$\text{SD}_t^{gc}(u_{irgct})$	$\text{SD}_t^{gc}(u_{irgct})$	$\log(\text{SD}_t^{gc}(u_{irgct}))$	$\log(\text{SD}_t^{gc}(u_{irgct}))$	$\text{SD}_t^{gc}(\epsilon_{irgct})$	$\text{SD}_t^{vgc}(\ln p_{irgct})$	$\Delta\text{SD}_t^{gc}(p_{irgct})$
$\lvert\Delta p_{gct-4}\rvert$	0.741***	0.456***		0.926***	1.219***	32.404***	49.296***	0.675***		0.701***
	(0.00)	(0.00)		(0.01)	(0.01)	(0.32)	(0.62)	(0.00)		(0.02)
$\lvert\Delta p_{gct}\rvert$			0.927***							
			(0.00)							
									0.729***	
									(0.08)	
Sector	Both	Both	Both	Supermarkets	Restaurants	Supermarkets	Restaurants	Both	Both	Both
Cat. FEs	Y	N	Y	Y	Y	Y	Y	Y	Y	N
Cat.$\times$ City FEs	N	Y	N	N	N	N	N	N	N	N
Cat.$\times$ Vol FEs	N	N	N	N	N	N	N	N	Y	N
N	317,994	317,989	317,994	230,652	84,161	230,613	84,152	317,994	17,903	225,405
R^2	0.31	0.63	0.27	0.26	0.26	0.10	0.09	0.27	0.50	0.08
Within R^2	0.19	0.13	0.15	0.19	0.21	0.03	0.05	0.14	0.01	0.08

back

Data - updated descriptive statistics

	Restaurants					Supermarkets				
	Firms	Products	Inflation	Duration	Mean Abs. Adj.	Firms	Products	Inflation	Duration	Mean Abs. Adj.
AM	914	97,915	2.43	24.67	17.33	109	100,068	-0.51	5.08	15.83
CI	979	47,348	4.88	17.75	25.11	70	102,019	5.20	3.35	13.66
ES	10,462	780,681	3.60	14.06	12.85	721	430,765	5.26	1.97	9.92
GE	1,950	127,982	5.56	12.32	15.58	313	122,800	1.94	4.05	19.04
GH	441	18,777	14.79	11.33	16.63	23	29,154	1.65	3.34	22.14
HR	674	40,555	8.20	10.61	14.70	129	52,180	2.71	3.69	15.98
IT	10,359	891,590	3.02	26.18	16.65	563	247,046	1.16	3.18	14.13
KE	1,314	105,318	5.38	18.64	16.53	322	344,703	6.14	5.18	12.96
KG	884	83,047	7.86	9.91	11.72	106	48,372	3.50	2.90	9.66
KZ	1,950	195,115	7.56	11.47	13.94	137	161,242	3.58	1.83	15.44
MA	2,410	170,833	4.96	13.42	15.47	285	308,373	2.75	1.59	12.77
PL	3,452	261,696	7.84	9.17	12.92	140	220,208	2.30	1.82	15.13
RO	2,931	273,903	9.54	9.42	15.68	258	196,827	2.29	1.60	13.22
SI	444	23,996	5.50	19.77	11.25	45	14,625	1.84	2.18	21.48
UA	2,969	264,436	8.68	7.81	14.31	226	266,289	7.65	0.99	17.85
UG	1,065	66,243	8.54	17.70	19.97	251	205,300	1.61	5.18	13.83
All	43,198	3,449,435	6.56	14.64	15.77	3,698	2,849,971	3.10	3.00	14.86

back

Moments for NK Calibration

I calibrate a standard NK menu cost model using empirical moments for Madrid

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

back

Results – absolute size of price adjustments and frequency

Do prices adjust in larger steps with higher inflation? Estimate:

1. $MeanAbsoluteAdj._{gct} = \gamma_{gc} + \beta_1 |\Delta p_{gct-4}| + \varepsilon_{gct}$
2. $Adj.Share_{gct} = \gamma_{gc} + \beta_2 |\Delta p_{gct-4}| + \varepsilon_{gct}$

	Cond. Mean Absolute Adjustment					Frequency				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\lvert\Delta p_{gct-4}\rvert$	1.504***	2.071***	1.455***	1.536***	1.476***	4.752***	6.034***	4.640***	5.118***	4.420***
	(0.01)	(0.06)	(0.01)	(0.02)	(0.01)	(0.05)	(0.13)	(0.05)	(0.05)	(0.05)
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	213,532	53,751	159,781	143,180	213,532	213,543	53,753	159,790	143,187	213,543
R^2	0.48	0.41	0.49	0.48	0.48	0.66	0.69	0.58	0.70	0.68
Within R^2	0.12	0.07	0.14	0.12	0.11	0.29	0.57	0.27	0.32	0.26

$\hookrightarrow$ not only they adjust in larger steps, but also heterogeneously across sectors back

Results – rough estimates of costs of inflation

Flex-price consumption loss: $\phi(\pi) = \frac{\sigma}{2}\mathbb{V}[u](\pi)$ back

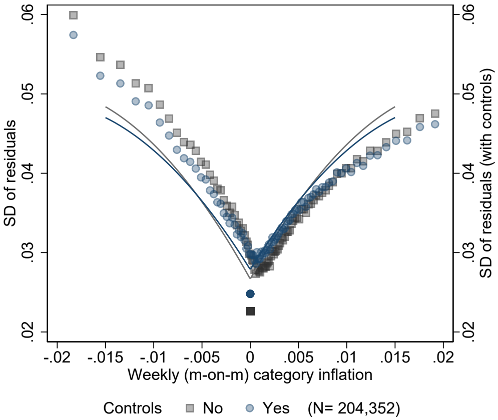
Results – rough estimates of costs of inflation

Flex-price consumption loss: $\phi(\pi) = \frac{\sigma}{2}\mathbb{V}[u](\pi)$

Cost of 10% inflation:

$\hookrightarrow$ $\phi(\pi = 10\%) - \phi(\pi = 0\%)$

Which is the right π frequency?



back

Results – rough estimates of costs of inflation

Flex-price consumption loss: $\phi(\pi) = \frac{\sigma}{2}\mathbb{V}[u](\pi)$

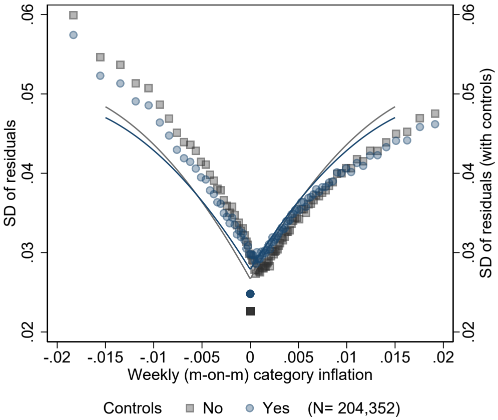
Cost of 10% inflation:

↪ $\phi(\pi = 10\%) - \phi(\pi = 0\%)$

Which is the right π frequency?

↪ m-on-m inflation cost: 0.25%

↪ w-on-w inflation cost: 0.16%



back

Results – rough estimates of costs of inflation

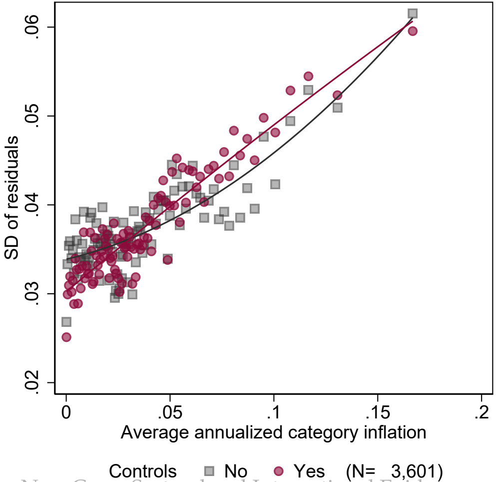
Flex-price consumption loss: $\phi(\pi) = \frac{\sigma}{2}\mathbb{V}[u](\pi)$

Cost of 10% inflation:

- $\hookrightarrow$ $\phi(\pi = 10\%) - \phi(\pi = 0\%)$

Which is the right π frequency?

- $\hookrightarrow$ m-on-m inflation cost: 0.25%
- $\hookrightarrow$ w-on-w inflation cost: 0.16%
- $\hookrightarrow$ yearly inflation cost: 0.51%



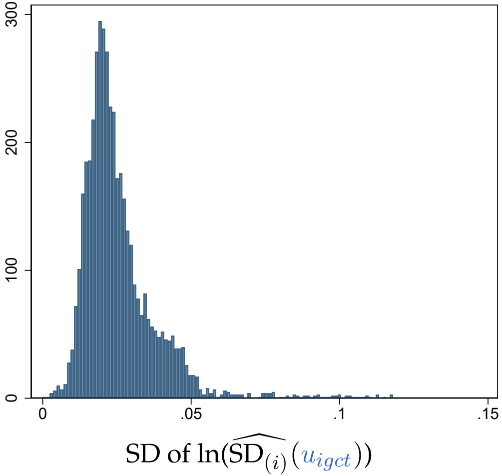
Data - additional standardized moments

Supermarkets	Mean Frac. Δp	Median Frac. Δp	Share Adj $\Delta p > 0$	Mean $\lvert\Delta p\rvert$	Median $\lvert\Delta p\rvert$	Mean Δp	std. dev. Δp	Kurtosis Δp	Mean Δp_g	std. dev. Δp_g
AM	0.054	0.035	0.487	0.140	0.110	-0.015	0.177	2.956	-0.001	0.022
CI	0.137	0.134	0.609	0.120	0.091	0.024	0.152	3.487	0.003	0.022
ES (Madrid)	0.274	0.259	0.561	0.089	0.066	0.014	0.113	3.299	0.003	0.022
ES (Barcelona)	0.212	0.195	0.563	0.096	0.073	0.012	0.122	3.326	0.002	0.019
GE	0.096	0.076	0.551	0.161	0.128	0.012	0.203	3.035	0.001	0.024
GH	0.169	0.150	0.509	0.216	0.160	-0.004	0.273	2.868	-0.001	0.030
HR	0.119	0.105	0.632	0.144	0.109	0.027	0.184	3.303	0.002	0.018
IT (Rome)	0.181	0.181	0.534	0.123	0.089	0.005	0.160	3.493	0.000	0.013
IT (Milan)	0.183	0.174	0.554	0.115	0.086	0.010	0.150	3.649	0.001	0.014
KE	0.149	0.144	0.622	0.121	0.098	0.032	0.148	3.232	0.005	0.020
KG	0.163	0.125	0.576	0.080	0.064	0.012	0.100	3.280	0.002	0.016
KZ	0.223	0.210	0.547	0.149	0.113	0.005	0.193	3.291	0.000	0.024
MA	0.232	0.207	0.534	0.151	0.107	0.007	0.204	3.713	0.000	0.025
PL	0.265	0.246	0.553	0.120	0.089	0.007	0.153	3.222	0.001	0.029
RO	0.382	0.348	0.523	0.119	0.090	0.005	0.155	3.344	0.001	0.031
SI	0.157	0.148	0.544	0.200	0.198	0.009	0.237	2.137	0.001	0.032
UA	0.245	0.235	0.587	0.146	0.110	0.012	0.191	2.950	0.002	0.023
UG	0.138	0.134	0.545	0.107	0.072	0.011	0.148	4.840	0.001	0.015
All (mean)	0.188	0.173	0.557	0.133	0.103	0.010	0.170	3.301	0.001	0.022
Restaurants	**Mean Frac. Δp**	**Median Frac. Δp**	**Share Adj $\Delta p > 0$**	**Mean $\lvert\Delta p\rvert$**	**Median $\lvert\Delta p\rvert$**	**Mean Δp**	**std. dev. Δp**	**Kurtosis Δp**	**Mean Δp_g**	**std. dev. Δp_g**
AM	0.028	0.029	0.774	0.141	0.118	0.070	0.159	3.984	0.002	0.005
CI	0.036	0.036	0.812	0.220	0.185	0.103	0.241	3.870	0.003	0.008
ES (Madrid)	0.043	0.043	0.791	0.114	0.092	0.063	0.128	4.319	0.003	0.004
ES (Barcelona)	0.039	0.038	0.793	0.129	0.100	0.074	0.147	4.509	0.003	0.004
GE	0.059	0.052	0.803	0.135	0.108	0.072	0.153	4.458	0.004	0.008
GH	0.081	0.072	0.913	0.151	0.118	0.130	0.141	4.484	0.010	0.017
HR	0.065	0.062	0.935	0.117	0.104	0.102	0.097	5.500	0.006	0.011
IT (Rome)	0.026	0.026	0.809	0.152	0.125	0.088	0.163	4.540	0.002	0.003
IT (Milan)	0.028	0.028	0.824	0.156	0.132	0.096	0.160	4.156	0.002	0.004
KE	0.051	0.030	0.889	0.139	0.110	0.100	0.144	5.360	0.005	0.010
KG	0.081	0.055	0.892	0.101	0.079	0.079	0.100	5.215	0.006	0.011
KZ	0.067	0.068	0.849	0.126	0.100	0.085	0.132	4.495	0.004	0.005
MA	0.047	0.046	0.752	0.148	0.125	0.073	0.164	3.496	0.003	0.005
PL	0.084	0.074	0.887	0.102	0.076	0.072	0.110	5.895	0.005	0.007
RO	0.081	0.076	0.865	0.138	0.106	0.093	0.148	4.749	0.007	0.009
SI	0.048	0.039	0.943	0.100	0.081	0.088	0.090	4.967	0.004	0.006
UA	0.087	0.072	0.864	0.134	0.101	0.087	0.150	5.346	0.006	0.011
UG	0.055	0.035	0.892	0.177	0.158	0.138	0.163	4.299	0.005	0.012
All (mean)	0.056	0.049	0.849	0.138	0.112	0.090	0.144	4.647	0.004	0.008

back

Results – first stage regression I, SD($\widehat{\text{SD}_{(i)}}(u_{igct})$)

Estimate $\ln\widehat{\Pi_{gc}/\Pi^*_{igc}}$ from: $\quad P_{igct} = \ln\tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$

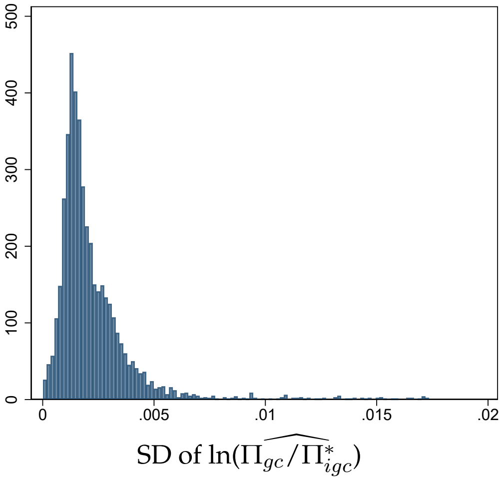


- There is significant variation to exploit within a city-category

back

Results – first stage regression II, SD($\ln\widehat{\Pi_{gc}/\Pi^*_{igc}}$)

Estimate $\ln\widehat{\Pi_{gc}/\Pi^*_{igc}}$ from: $P_{igct} = \ln\tilde{a}_{igc} + \ln(\Pi_{gc}/\Pi^*_{igc})t + \tilde{u}_{igct}$



- There is significant variation to exploit within a city-category

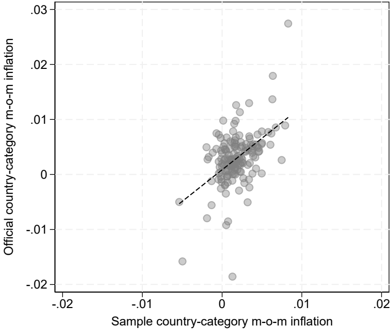
back

Correlation with official inflation

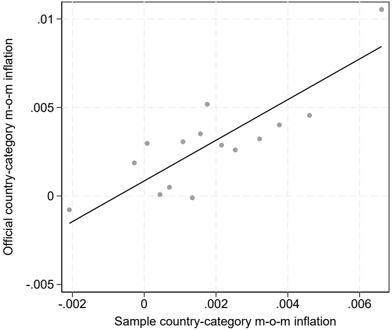
Match categories to official inflation series of 152 country-COICOPs

$\hookrightarrow$ 8 countries, April 2024-May 2024

Scatter



Binscatter



$\hookrightarrow$ slope of 1.001, R^2 of 0.226, correlation, correlation is 0.475

back

Literature

Detailed theoretical welfare analysis of price distortions: Coibion et al. (2012)

Empirical papers studying inflation induced price distortions

- ↪ Nakamura et al. (2018) US CPI micro data and looking at the absolute size of price adjustments: absolute size did not change during high inflation period
- ↪ Alvarez et al. (2019) micro-level CPI price data from Argentina, **elasticity of price dispersion is zero for inflation below 10%**
- ↪ Sheremirov (2020) using identical product across U.S. supermarkets during 2001-2011 finds **positive correlation between regular price dispersion and inflation**
- ↪ Sara-Zaror (2021) similar approach, **at inflation > 2% y-o-y this relation flattens out**
- ↪ Adam et al. (2023) U.K. CPI micro data with novel structural approach, **sub-optimal inflation is associated with relative prices distortions**

Additional literature on other costs of inflation: perceived costs, tax distortions,...

extended literature

Literature on other costs associated with inflation

Literature on other costs associated with high inflation

- mental burden and perceived costs: Shiller (1997); Stantcheva (2024); Binetti et al. (2024)
- tax distortions Feldstein et al. (1978); Altig et al. (2024)
- real wage declines Del Canto et al. (2023); Blanco et al. (2024)
- wage bargaining conflicts Afrouzi et al. (2024); Guerreiro et al. (2024)

back

Next steps

1. Follow-up project: does providing additional information to firms affect their pricing behavior?
   1.1 Do firms adjust more frequently with additional information?
   1.2 Do they react to macro information or information on competitors prices?
   1.3 Does this change the relationship of inflation and inefficient price dispersion?
2. In this paper: how big is the bias of using miss-specified hazard functions to get an estimate of the costs of inflation?
3. In this paper: two sector model that matches all moments including the relation of price dispersion and inflation?

back

References I

Adam, K., A. Alexandrov, and H. Weber (2023): Inflation Distorts Relative Prices: Theory and Evidence, Centre for Economic Policy Research.

Afrouzi, H., A. Blanco, A. Drenik, and E. Hurst (2024): "A Theory of How Workers Keep Up with Inflation," Tech. rep., mimeo.

Altig, D., A. J. Auerbach, E. F. Eidschun, L. J. Kotlikoff, and V. Y. Ye (2024): "Inflation's Impact on American Households," Tech. rep., National Bureau of Economic Research.

Alvarez, F., M. Beraja, M. Gonzalez-Rozada, and P. A. Neumeyer (2019): "From hyperinflation to stable prices: Argentina's evidence on menu cost models," The Quarterly Journal of Economics, 134, 451–505.

Binetti, A., F. Nuzzi, and S. Stantcheva (2024): "People's Understanding of Inflation," Tech. rep., National Bureau of Economic Research.

References II

Blanco, A., A. Drenik, and E. Zaratiegui (2024): "Nominal Devaluations, Inflation and Inequality," Tech. rep., National Bureau of Economic Research.

Coibion, O., Y. Gorodnichenko, and J. Wieland (2012): "The optimal inflation rate in New Keynesian models: should central banks raise their inflation targets in light of the zero lower bound?" Review of Economic Studies, 79, 1371–1406.

Del Canto, F. N., J. R. Grigsby, E. Qian, and C. Walsh (2023): "Are inflationary shocks regressive? A feasible set approach," Tech. rep., National Bureau of Economic Research.

Diercks, A. M. (2019): "The reader's guide to optimal monetary policy," Available at SSRN 2989237.

Feldstein, M., J. Green, and E. Sheshinski (1978): "Inflation and taxes in a growing economy with debt and equity finance," Journal of Political Economy, 86, S53–S70.

References III

Guerreiro, J., J. Hazell, C. Lian, and C. Patterson (2024): "Why Do Workers Dislike Inflation? Wage Erosion and Conflict Costs," Tech. rep., National Bureau of Economic Research.

Nakamura, E., J. Steinsson, P. Sun, and D. Villar (2018): "The elusive costs of inflation: Price dispersion during the US great inflation," The Quarterly Journal of Economics, 133, 1933–1980.

Sara-Zaror, F. (2021): "Expected inflation and welfare: The role of consumer search," Available at SSRN 4127502.

Sheremirov, V. (2020): "Price dispersion and inflation: New facts and theoretical implications," Journal of Monetary Economics, 114, 59–70.

Shiller, R. J. (1997): "Why do people dislike inflation?" in Reducing inflation: Motivation and strategy, University of Chicago Press, 13–70.

Stantcheva, S. (2024): "Why do we dislike inflation?" Tech. rep., National Bureau of Economic Research.