BIS Working Papers
No 1240

The granular origins of inflation

by Santiago Alvarez-Blaser, Raphael Auer, Sarah M. Lein and Andrei A. Levchenko

Monetary and Economic Department

January 2025 (revised November 2025)

JEL classification: E31, E32, L11, L16

Keywords: inflation, price setting, firm-level shocks, granular fluctuations, large firms

This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

The granular origins of inflation*

Santiago Alvarez-Blaser
Bank of Spain

Raphael Auer
Bank for International Settlements
and CEPR

Sarah M. Lein
University of Basel
CEPR, SFI, KOF ETHZ

Andrei A. Levchenko
University of Michigan
NBER and CEPR

November, 2025
Latest version

Abstract

This paper uses barcode-level price data for 16 advanced and emerging market countries over the period 2005–2022 to investigate the role of individual firms and product categories in aggregate inflation. We decompose inflation into the component due to macroeconomic shocks and the granular residuals capturing the impact of individual firms and product categories, respectively. In advanced economies, the firm granular residual accounts for 41% of the variance of overall inflation, while the product category granular residual accounts for another 15%. Most of the variation in the firm granular residual is due to idiosyncratic shocks rather than to higher sensitivity of larger firms to common shocks. In the cross-section of countries, granular residuals are less important in economies with less concentrated market shares and higher inflation, such as emerging markets. Granular forces also contributed to the post-COVID inflation surge, with the firm-level component explaining roughly one-third of the 2021–2022 inflation in advanced economies. Finally, granularities are associated with a more sluggish response of inflation to monetary policy shocks, suggesting that market concentration can influence monetary non-neutrality.

Keywords: Inflation, price setting, firm-level shocks, granular fluctuations, large firms
JEL Codes: E31, E32, L11, L16

*The views presented in this paper are those of the authors and not necessarily those of the Bank for International Settlements or the Banco de España. Access to the data is provided by AiMark (http://www.aimark.org), which is a not-for-profit foundation that supports top academic research with scanner data provided by its data partners YouGov and Kantar. We would like to extend our special thanks to Alfred Dijs and Elizabeth Ramaker from AiMark for their support with the data throughout this project. We thank Anastasia Burya, Alberto Cavallo, Saroj Bhattarai, Javier Cravino, Thomas Drechsel, Zeno Enders, Xavier Gabaix, Erwan Gautier, Gernot Mueller, Emi Nakamura, Raphael Schoenle, Jon Steinsson, Georg Strasser, and seminar participants at the ASSA, BIS, Banque de France, Barcelona Summer Forum, BdF-TSE Sectoral Inflation Dynamics Workshop, CEBRA, CEPR IMF Annual Meeting, ECB, EMMC Conference, Harvard University Macro Workshop, Inflation Drivers and Dynamics Conference, JME-SNB-SCG Conference, Konstanz Seminar on Monetary Theory and Policy, NBER IFM Spring Meetings, PSE-CEPR Policy Forum, VfS, VfS standing field committee on Monetary Economics, UC Berkeley, U Heidelberg, and U Tuebingen. Email: s.alvarez.blaser@gmail.com, Raphael.Auer@bis.org, sarah.lein@unibas.ch, and alev@umich.edu.

1. Introduction

Textbook monetary economics views inflation as fundamentally driven by aggregate shocks, such as the money supply or policy rates (Woodford, 2003; Galí, 2015).[1] While the modern literature models rich micro-level price adjustment heterogeneities, idiosyncratic firm behavior is typically integrated out, leaving no role for individual firms in aggregate inflation. At the same time, following Gabaix (2011)'s seminal contribution, an influential strand of the macro literature has modeled theoretically and documented empirically that shocks to individual (large) firms can generate aggregate fluctuations, a phenomenon termed "granularity."

However, the role of large firms in aggregate inflation, and the causes and implications of granularity in prices remain poorly understood. This paper uses detailed barcode-level price data for 16 advanced and emerging market economies over the period 2005-2022 covering 2.9 billion transactions to provide a forensic account of the contributions of individual firms and product categories to overall inflation. For each barcode-level price, we can identify the firm that produced the item, its product category, and sometimes the retail chain through which it is sold. Our sample covers a variety of inflation experiences across both countries and time. It includes low-inflation advanced economies such as the US and Germany, and higher-inflation emerging markets such as Argentina and Russia. The data span both the pre-2020 period of low and stable inflation, as well as the post-pandemic inflation surge.

By definition, aggregate inflation is an expenditure-share-weighted change in individual prices. We posit that each micro price can be written as a sum of the macroeconomic (country) component, a firm-country-specific component, and a product category-country-specific component. Aggregating up the barcode-level prices then produces an additive decomposition of the inflation rate into (i) the macro component, (ii) the firm granular residual, and (iii) the product category granular residual. The firm (resp. product category) granular residual captures the contribution of firm (resp. product category) idiosyncratic components to the overall inflation.

Our decomposition generalizes the conventional granular residual setup (e.g. Gabaix, 2011; di Giovanni et al., 2014; Gabaix and Koijen, 2024) in two dimensions. First, we allow for multiple non-nested dimensions of granularity (firms, categories, and, in an extension, retailers). Second, it has been understood since Gabaix (2011) that a granular residual can arise either from idiosyncratic shocks to large firms or from differential responses of large firms to common shocks. Our notion of granular residual explicitly allows for both of these driving forces. We document which one is more powerful in our context.

[1] This view is most famously encapsulated by Milton Friedman's emblematic quote that "inflation is always and everywhere a monetary phenomenon" (Friedman, 1963).

Our results can be summarized as follows. At the micro level, a large share of total expenditures is concentrated in a few large firms and a few large categories. The 10 largest firms account for 41% of overall sales in an average country, while the 10 largest product categories account for 48%. There is also synchronization of price changes across barcodes, within firms and within categories. Thus, the sales shares distributions and the synchronized price changes exhibit the preconditions to potentially observe granular fluctuations.

At the macro level, the firm and category granular components account for 56% of the inflation variance in advanced economies over the 2005-2020 period. The firm granular residual is relatively more important, explaining some 41% of the inflation variance. Two-thirds of this component is accounted for by the 10 largest firms alone. The category granular residual accounts for an additional 15% of inflation variance. We next decompose the granular residuals into the components due to the differential responsiveness to common shocks, and the true idiosyncratic shocks. The firm granular residual is predominantly driven by true idiosyncratic shocks. By contrast, more than half of the variability in the category granular residual is due to the categories' differential responsiveness to common shocks.

In the cross-section of countries, the granular residuals are relatively more important in economies with more concentrated market shares; and less important in higher-inflation environments. For example, in the group of emerging markets – whose inflation is substantially higher on average than in the advanced economies – the two granular residuals combined account for only 20% of inflation variance. Thus, in higher-inflation settings macro shocks tend to be a more significant driver of overall inflation. We also show that the firm granular component is relatively more important in countries with higher concentration, measured by the combined market share of the 10 largest firms or the Herfindahl index. This is sensible, as a necessary condition for the presence of granularities is that the market share distributions be highly skewed.

We next investigate the role of a third potential dimension of granularity – the retailers. This dimension can also have a notable granular component, as the retail sector is often dominated by a small number of large chains. Unfortunately, working with the retailer dimension constrains us to a significantly smaller sample as the identity of the retailer is not always recorded in our data and not all products are sold in multiple retailers. With that caveat, we also find some role for the large retailers. The retailer granular residual accounts for 17% of the aggregate inflation variance in advanced economies, and for 14% in emerging markets.

Next, we document that granularities contributed to the post-COVID inflation surge, particularly in advanced economies. Average inflation in advanced economies more than quadrupled in 2021–22 compared to 2005–2020. If anything, the relative importance of granular forces in the average inflation rate *increased* in the 2021-22 period. Up to 2020, the firm (resp. product category) granular residual accounted for an average of 22% (resp. 14%) of the rate of inflation. During the inflation surge, these shares increased to 38% (resp. 21%). The magnitudes are also significant in absolute terms: of the 3.91% average 2021–22 inflation in advanced economies, the firm granular component contributed 1.47 percentage points.[2] In the emerging economies, the relative importance of granularities is again smaller, accounting for 1.13 percentage points of a total average inflation of 10.56% during that period.

Finally, we examine how monetary policy shocks propagate through the granular and non-granular components of inflation. Following the methodology of Aruoba and Drechsel (2024) and using identified monetary policy shocks for the United States and the Euro Area, we estimate local projection impulse responses of inflation and its underlying components. Following a contractionary monetary policy shock, aggregate inflation initially rises before declining, replicating the "price puzzle" well-documented in the literature (see, for example, Christiano et al. 1999). The show that the granular components are primarily responsible, accounting for 75% of the price puzzle at the peak. The macro component acts to reduce inflation, as predicted by theory. The firm-level granular residual in particular contributes significantly to the short-run rise in inflation. These results suggest that granularities can delay the transmission of monetary policy, particularly in concentrated markets where large firms play a disproportionate role in aggregate inflation.

This paper draws from and contributes to three strands of the literature. The first one studies the micro origins of aggregate fluctuations (Long and Plosser, 1983; Jovanovic, 1987; Acemoglu et al., 2012; Carvalho and Gabaix, 2013). Gabaix (2011) argued that when the firm size distribution is fat-tailed, firm-specific idiosyncratic shocks do not average out and thus affect aggregate output, introducing the concept of granular fluctuations. Subsequent contributions have shown empirically that firm idiosyncratic shocks are important for aggregate fluctuations (e.g. di Giovanni et al., 2014), theoretically modeled granular fluctuations (e.g. Carvalho and Grassi, 2019), and studied this phenomenon in the context of international trade (di Giovanni and Levchenko, 2012; di Giovanni et al., 2018; Gaubert and Itskhoki, 2021), government policy (Gaubert et al., 2021), government spending (Cox et al., 2024), business sentiment (Jamilov et al., 2024), and banking (Amiti and Weinstein, 2018; Bremus et al., 2018; Galaasen et al., 2021), among others. The literature has for the most part neglected the implications of granularity for prices. Our paper uses micro-price data to document granularity in inflation. Conceptually, our generalizations of the granular residual decomposition (i) allow for multiple non-nested dimensions of granularity and (ii) separate true idiosyncratic shocks from differential responses to common shocks. These generalizations can be applied to other contexts in which granularity is investigated.

[2]Since we observe prices but not marginal costs, we cannot separate the observed price changes into markup adjustments vs. cost changes. Thus, our findings do not directly speak to a recent debate on whether large firms had disproportionately raised their markups during the 2021-22 inflation surge (i.e. the so-called "greedflation" or "seller's inflation" debate). Available empirical evidence suggests that markup adjustment was not a major driver in the inflation surge (see, for example Alvarez-Blaser et al., 2024).

Second, our analysis relates to the literature on price-setting in multi-product firms and in large retail chains. Consistent with our findings, there is strong evidence of synchronization of price adjustments within multi-product firms (e.g. Midrigan, 2011; Bhattarai and Schoenle, 2014; Alvarez and Lippi, 2014; Dedola et al., 2021), and retailers (e.g. DellaVigna and Gentzkow, 2019; Bonomo et al., 2022; Daruich and Kozlowski, 2023; García-Lembergman, 2025), which can be micro-founded with economies of scope in price adjustments. We show that the synchronization of prices within multi-product firms (which are also the large firms) results in a firm granular residual in aggregate inflation. The literature has also argued that price synchronization also has important implications for responses to large shocks: the aggregate price level responds disproportionately to large shocks compared to small shocks (e.g. Midrigan, 2011; Karadi and Reiff, 2019; Blanco et al., 2024) because more multi-product firms adjust prices simultaneously. Our finding that the firm granular residual increased in relative importance during the 2021–22 inflation surge aligns with these theoretical predictions.

Third, our finding that granularities contribute to the sluggish response of inflation to monetary policy shocks relates to a recent literature that departs from the standard monopolistic competition framework and shows that monetary non-neutrality is greater, and the pass-through of shocks to prices is lower, in economies with oligopolistic market structures (see, for example, Mongey, 2021; Wang and Werning, 2022; Mongey and Waugh, 2025).

The remainder of the paper is organized as follows. Section 2 presents the data along with some summary statistics. Section 3 describes the methodology and the empirical results. Section 4 concludes. Details of the data construction and additional empirical results are collected in the appendix.

2. Data and summary statistics

2.1 Data assembly

Data source. The analysis employs a homescan dataset of retail prices and expenditures from AiMark for 16 countries: Argentina, Austria, Belgium, Brazil, Chile, China, Germany, Hungary, Spain, France, Mexico, the Netherlands, Russia, Sweden, the United Kingdom and the United States. We observe most of these countries for the years 2008-2022, with Germany observed for the longest period (2005-2022), while data for Argentina, Brazil, China, Mexico, and Russia start only in 2011. The data for Russia and the US end in 2020, currently without a possibility of an update to 2022.

In each country, a participating representative sample of households logs its supermarket and drugstore purchases. Our raw data contain nearly 2.9 billion transactions. Each entry in the dataset records a purchase of a product by a household. The entry records the household identifier, product barcode (a unique item identifier), price paid, date of purchase, and retailer name. For each barcode, data include information on the associated brand and firm (producer), and barcodes are further classified into product categories and subcategories. Also recorded is a set of socioeconomic characteristics of the households purchasing the items, notably the geographic location of the household residence. To fix notation throughout the paper, product (barcode) i belongs to product category g, is sold in country c by firm f, and possibly in retailer s (for "shop").

Data preparation. For the main analysis, we compute the modal price (following Eichenbaum et al., 2014; Auer et al., 2021) and the total expenditures within country-quarter-barcode cells. We then take the year-on-year log difference in price as the measure of the inflation of a given barcode and country. Below we refer to each of these year-on-year barcode-level inflation rates as one observation.

We standardize and in some instances concord categories, firms, brands, and products across countries. First, we ensure cross-country comparability of categories, such as "Fruit Juice" or "Breakfast Cereals." For this, we establish a standardized set of 110 categories as follows. We start with the English category variable that is included in the raw data. This variable – "category name English" – is present in all datasets and is also consistent across countries, but covers only 35% of the unique barcodes in our dataset. To complete the coverage of the standardized categories, we rely on the more comprehensive "category" variable in the country language, as well as the finer "subcategory" variable that exists for most countries (also in the country language). We use manual matching of the "category" and "subcategory" information to our 110 standardized categories. In addition, we utilize product barcodes that are available in multiple countries. For example, if a given barcode is categorized as a category-subcategory combination "Fruit Juice-Apple Juice" in 90% or more transactions in all other countries, that product is assigned "Fruit Juice-Apple Juice" also in countries in which the category-subcategory information is initially missing.

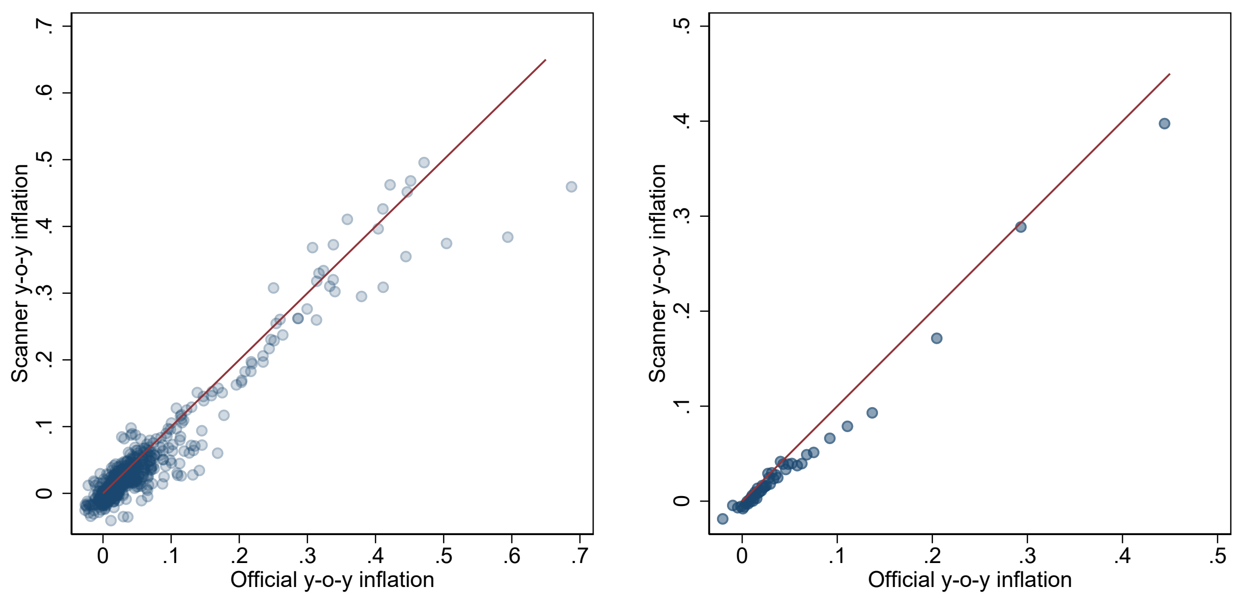
The names of firms and brands also differ across countries. We adopt a four-step procedure to harmonize firm names across countries, described in Appendix A. This appendix also provides details on the outcomes of this matching process. In the end, on average less than 2% of expenditures is on items for which the firm remains unidentified (Appendix Table A2). We provide robustness for our main results using a simpler matching process.[3]

2.2 Basic patterns

Inflation rates in our scanner data and in official sources. We start by showing that inflation rates in our data are highly correlated with official inflation rates for the same set of product categories. We calculate the price indices from the official data using only CPI categories that align with the categories

[3] See Appendix Table A7, discussed in Section 3.

Figure 1: Official vs. scanner data aggregate inflation



(a) Scatter (b) Binscatter

Notes: This figure plots the inflation computed using the scanner data on the y-axis against the inflation for the same set of categories from official sources on the x-axis. Left panel shows a scatter including all countries and time periods, and the right panel shows a binscatter of the same observations. Both panels include a 45-degree line. The sample includes all countries and years listed in Table 1, with exception of China, for which no sectoral official CPI information is available.

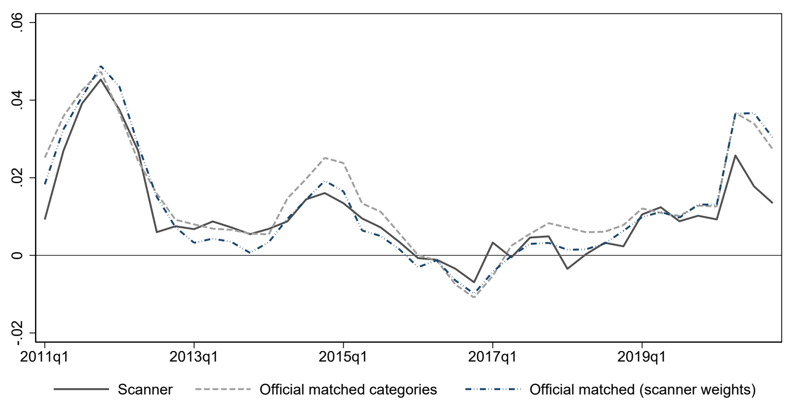
available in the scanner data. Figure 1 plots inflation computed from our scanner data against inflation for the same set of categories from official sources, for all countries and time periods, along with a 45-degree line. The overall correlation when pooling all countries is 0.96, while the average within-country correlation of scanner and official inflation is 0.89 (Appendix Table A4). The lowest correlations are in Mexico, Brazil, and Chile, at 0.71-0.73.[4] Figure 2 shows inflation computed from our scanner data alongside the official indices for underlying matched CPI categories for Germany, the US, and Argentina over time. Since some categories might be over- or under-represented in our scanner data compared to official CPI weights, we compute an official index using both scanner data weights and official weights.[5] The disparities between them are minimal. Appendix Figure A1 displays the plots for the rest of the countries.

[4]The finding that inflation rates from household scanner data closely co-move with official CPI inflation rates has been reported for various countries and time periods by, for example, Kaplan and Schulhofer-Wohl (2017), Redding and Weinstein (2019), Braun and Lein (2021), Beck and Jaravel (2021), or Beck et al. (2024).

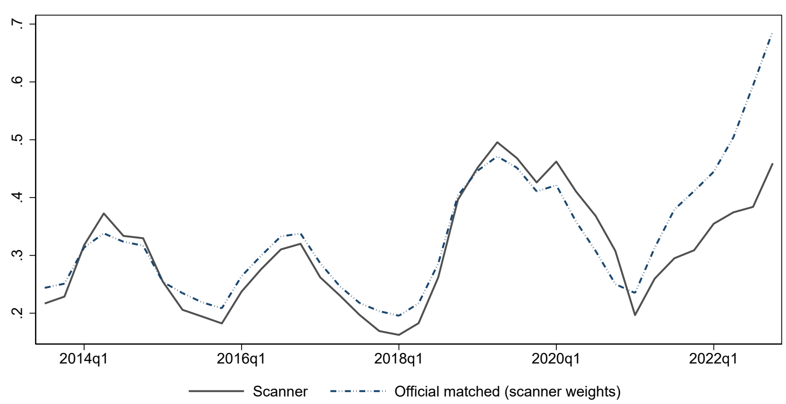
[5]In the case of Argentina, only the scanner data weights are used because we could not find official category weights at the disaggregated level. The quality of the matched categories depends on the available disaggregated data. For China no official index was constructed given that no disaggregated CPI indices were available for the period covered in this paper.

Figure 2: Official vs scanner data aggregate inflation, selected countries

(a) Germany



(b) US



(c) Argentina

Notes: All panels show the year-on-year inflation rates. “Official matched categories” use official inflation rates and weights while “Official matched (scanner weights)” weights the official inflation rate of each category with the weight observed in the scanner data for the same category. Only three out of 16 countries shown. Sources of official indices are Eurostat, Bureau of Labor Statistics (BLS), and the Dirección General de Estadística y Censos. The rest of the countries can be found in Appendix Figure A1.

Table 1: Descriptive statistics

	(1) Transactions (mln)	(2) N of Δp_{ifgct}	(3) N_f	(4) N_i	(5) Mean N_i^f	(6) Median N_i^f	(7) Years
AR	26.56	921,812	4,569	78,102	17	3	2011-2022
AT	31.78	1,374,433	4,849	150,993	25	3	2008-2022
BE	65.37	2,480,869	12,609	283,097	13	2	2008-2022
BR	84.95	1,451,640	13,443	129,769	7	2	2011-2022
CL	20.49	434,586	1,532	33,848	14	2	2012-2022
CN	99.50	4,178,845	93,372	598,409	5	1	2011-2022
DE	461.33	6,830,261	11,033	550,728	10	3	2005-2022
ES	127.29	3,509,722	14,870	306,100	8	2	2007-2022
FR	208.39	5,521,899	6,735	412,010	19	2	2008-2022
HU	13.70	834,542	3,798	95,691	9	3	2010-2022
MX	111.95	963,009	4,511	78,546	10	2	2011-2022
NL	194.58	3,287,757	10,867	357,903	11	2	2008-2022
RU	70.93	1,994,980	13,235	261,599	15	4	2011-2020
SE	25.84	958,897	3,622	84,256	10	2	2006-2022
UK	684.31	5,191,847	6,664	378,200	44	3	2005-2022
US	643.13	12,638,612	36,548	1,181,172	23	3	2010-2020
Total	2,870.09	52,573,711	213,052	4,594,606	22	2	2005-2022

Notes: Transactions is the number of entries in the raw data. N of Δp_{ifgct} is the number of available year-on-year inflation rates using the product-quarter aggregation. N_f and N_i are the numbers of unique firms and products that appear in the data. Mean N_i^f and median N_i^f indicate the average and median number of products produced by a firm.

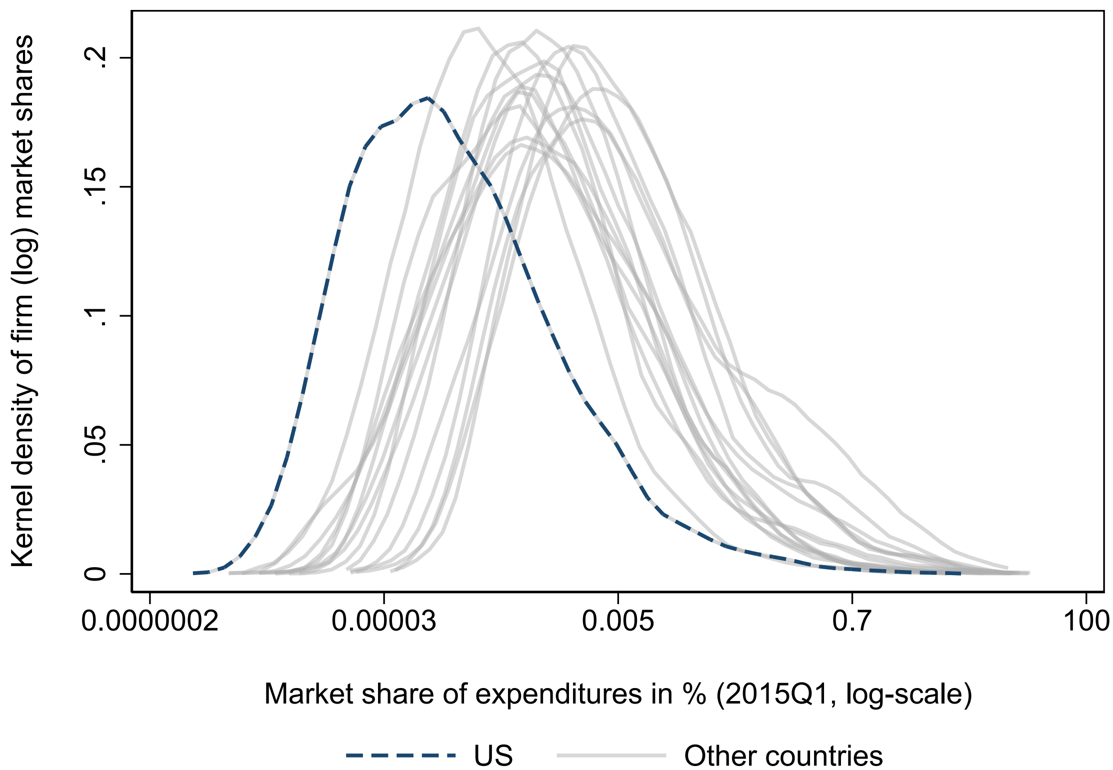
Summary statistics. Column 1 of Table 1 reports the numbers of raw entries in the data (in millions), by country. Column 2 displays the number of observations in the main sample, that is, the number of inflation observations by country, quarter, and barcode. Our baseline decomposition is based on these approximately 52 million observations.

Column 3 reports the number of firms in each country, along with the total number of distinct firms in the dataset. In total, the dataset includes approximately 213,000 distinct firms. Column 4 shows that we observe around 4.6 million unique products. Columns 5 and 6 report the mean and median number of products per firm. In total the mean (median) number of unique products one firm sells is 22 (2). Column 7 reports the years covered for each country.

Distribution of market shares. Granular fluctuations tend to arise in settings where the size distribution of the units is fat-tailed. Figure 3 shows the kernel densities of log shares of firms in country c expenditures ($\ln w_{fct}$) in the first quarter of 2015. Expenditure shares are strongly right-skewed across firms and indicative of fat tails, an important sign that underlying granularities might manifest themselves in aggregate inflation. The fat tails are visible even on logarithmic scale.

Table 2 reports the combined expenditure shares of the 10 largest and the 1% largest firms and product categories. The market share of the 10 largest firms reported in the first column is on average

Figure 3: Kernel densities of $\ln w_{fct}$



Notes: Kernel densities of firm log market shares in the first quarter of 2015. The dashed blue line represents the firm expenditure shares $\ln w_{fct}$ in the US, and each light gray line represents the kernel density of $\ln w_{fct}$ for one of the other 15 countries.

around 40%, with the highest in Mexico (60%) and the lowest in Russia (17%). When looking at the weight of the 10 largest entities, concentration is similar across the firm (column 1) and category (column 3) dimensions. However, the share of the largest 1% is much higher at the firm dimension, compared to the category dimension (column 2, compared to column 4). The reason is that the number of firms in the sample is significantly larger than the number of categories. As a result, one percent of the firms constitute more than 10 firms. This is additional evidence of fat tails that may give rise to granularities, especially at the firm level. Despite the large number of firms in the data, expenditures remain concentrated within a small proportion of them.

Table 2: Expenditure shares of top firms and categories

	Firms		Categories	
Weight of:	(1) Top 10 f	(2) Top percentile f	(3) Top 10 g	(4) Top percentile g
Advanced Economies	0.45	0.83	0.48	0.21
AT	0.48	0.85	0.52	0.23
BE	0.52	0.86	0.47	0.20
DE	0.44	0.78	0.52	0.28
ES	0.49	0.83	0.45	0.21
FR	0.40	0.83	0.44	0.19
NL	0.53	0.84	0.53	0.29
SE	0.41	0.78	0.49	0.17
UK	0.49	0.76	0.48	0.20
US	0.31	0.89	0.38	0.12
Emerging Economies	0.35	0.72	0.49	0.16
AR	0.29	0.65	0.40	0.06
BR	0.31	0.77	0.47	0.13
CL	0.41	0.67	0.48	0.16
CN	0.22	0.84	0.48	0.14
HU	0.45	0.73	0.59	0.35
MX	0.60	0.89	0.57	0.13
RU	0.17	0.48	0.46	0.15
All Countries	0.41	0.78	0.48	0.19

Notes: Top 10 weight is the total expenditure share going to the largest 10 firms and categories in each country across periods. Top percentile is the expenditure share going to the top 1% of firms or categories. Advanced economies, emerging markets and all countries means are computed as the simple average weight in each group of countries. Expenditure shares based on all expenditures, also including expenditures in not identified firms and retailers.

3. Granularity and the evolution of inflation

This section presents our main empirical results. We start with the standard granular residual and then develop our main decomposition that features multiple dimensions of granularity.

3.1 Warmup: simple granular residual

To first order, the growth rate in the aggregate price index in country c is a weighted average of barcode-level price changes:

$$\Delta p_{ct} = \sum_i w_{ifgct-4} \Delta p_{ifgct}, \tag{3.1}$$

where $w_{ifgct-4}$ is the share of barcode i in total expenditure in country c in the same quarter of the previous year, and as above, Δp_{ifgct} the year-on-year growth rate of the price of the barcode i belonging to product category g, produced by firm f, observed in country c and quarter t.

Inflation can be decomposed as follows (Gabaix, 2011; Gabaix and Koijen, 2024):

$$\Delta p_{ct} = \underbrace{\frac{1}{N_{i\in ct}} \sum_i \Delta p_{ifgct}}_{\mathcal{M}_{ct}} + \underbrace{\sum_i w_{ifgct-4} \left(\Delta p_{ifgct} - \frac{1}{N_{i'\in ct}} \sum_{i'} \Delta p_{i'fgct} \right)}_{\Gamma_{ct}}, \tag{3.2}$$

where $N_{i\in ct}$ is the number of barcodes in country c and period t. The first term, $\mathcal{M}_{ct}$, is the simple average price change across all barcodes in the economy. The second term, Γ_{ct}, is the granular residual. The granular residual is the expenditure-share weighted deviation of the price change in barcode i from the simple average price change across all barcodes in the economy. A non-zero granular residual will arise if barcodes with larger expenditure shares have systematically higher or lower relative price changes. Indeed, it can be rewritten as a covariance between price changes and expenditure shares (di Giovanni et al., 2024). By contrast, Γ_{ct} would equal 0 if either all products had the same expenditure weight or price changes were the same for all barcodes.

Although equation (3.2) can be implemented regardless of the data generating process for the prices and expenditure weights, to build intuition for this decomposition it is helpful to posit that each barcode-level price change is the sum of a common macro shock and an idiosyncratic shock with mean zero:

$$\Delta p_{ifgct} = \delta_{ct} + \varepsilon_{ifgct},$$

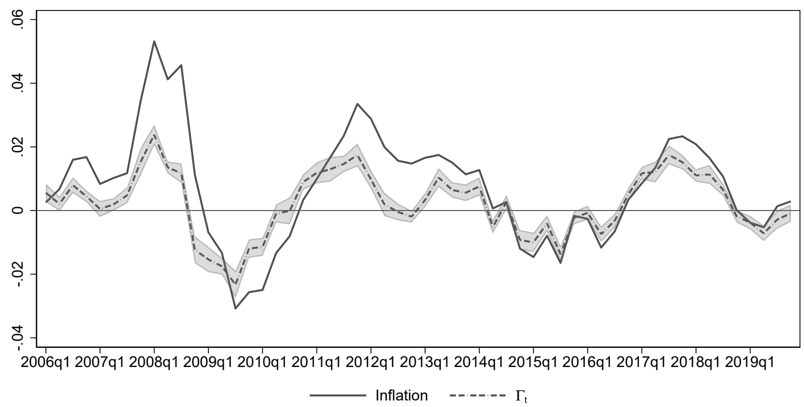
where $\frac{1}{N_{i\in ct}} \sum_i \varepsilon_{ifgct} = 0$. Then, it is immediate that in this economy, $\mathcal{M}_{ct}$ would be capturing the macro shock while Γ_{ct} would capture the weighted sum of firm idiosyncratic shocks:

$$\begin{aligned} \Delta p_{ct} &= \frac{1}{N_{i\in ct}} \sum_i \left(\delta_{ct} + \varepsilon_{ifgct}\right) + \sum_i \left(w_{ifgct-4} - \frac{1}{N_{i\in ct}} \right) \left(\delta_{ct} + \varepsilon_{ifgct}\right) \\ &= \underbrace{\delta_{ct}}_{\mathcal{M}_{ct}} + \underbrace{\sum_i w_{ifgct-4} \varepsilon_{ifgct}}_{\Gamma_{ct}} . \end{aligned}$$

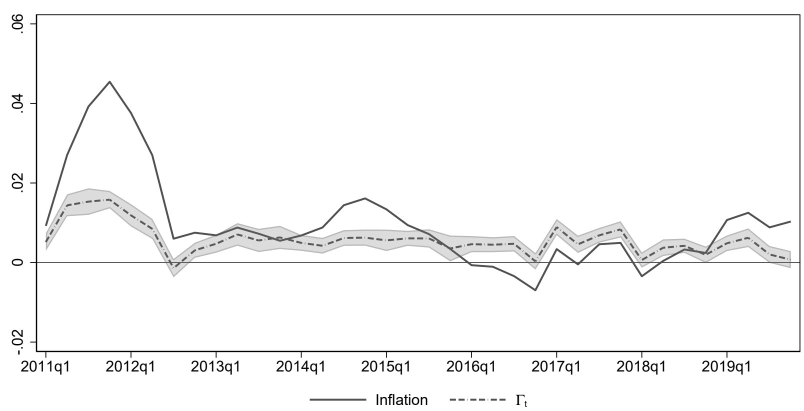
Thus, $\mathcal{M}_{ct}$ and reflects the relative importance of macro shocks, while Γ_{ct} is the contribution of idiosyncratic shocks to the aggregate inflation.

Figure 4 shows the time path of aggregate retail inflation and the simple granular component Γ_{ct} for Germany, the US, and Argentina up to 2020. We focus on the dynamics of these three countries in the main text given their size and heterogeneous inflation experiences. Appendix Figure A2

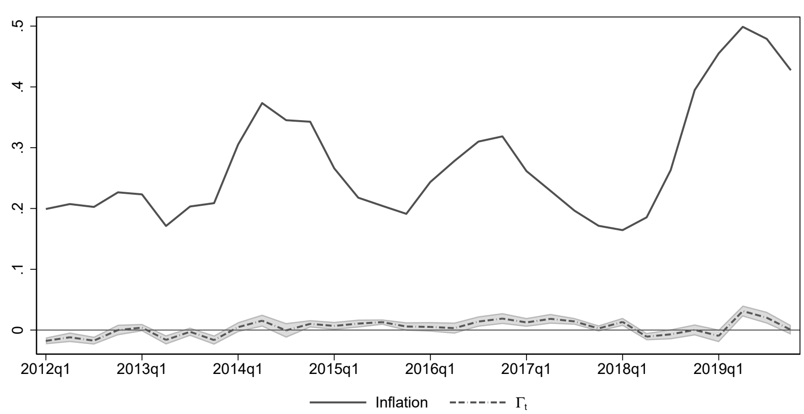
Figure 4: Aggregate retail inflation and simple granular residual



(a) Germany



(b) US



(c) Argentina

Notes: The figure displays the year-on-year overall inflation and the contribution of the simple granular residual. Only periods before 2020 included and three out of 16 countries shown. Rest of the countries and figures showing all periods can be found in Appendix Figure A2.

displays the inflation and the granular residuals for all other economies included in our sample, and including data through 2022 in countries for which it is available. The granular residual is significant in magnitude for Germany and the US. In contrast, in Argentina Γ_{ct} has about the same absolute magnitude as it does in the US and Germany, but is a much less significant component of overall inflation, which in Argentina appears driven by macroeconomic shocks in that country.

The simple granular residual exercise reveals the presence of granularities in the inflation data but is not informative on the underlying sources. In particular, each barcode i has multiple overlapping characteristics. For example, it belongs to a firm that produced it, and it belongs to a broader product category. (Below, we will also add the retailer dimension.) Thus, there are multiple distinct reasons Γ_{ct} can arise: multi-product firms adjust prices of different products simultaneously; and price changes are synchronized within categories, due to either common supply shocks or complementarities in pricing. These forces could coexist, and thus must be analyzed jointly. This is what we turn to next.

3.2 Granular layers methodology

We now develop a decomposition of aggregate inflation into the macroeconomic component and granular residuals capturing the firm and category dimensions. We then describe the estimation procedure to extract all of these components from the micro price data. Assume that the growth rate in the price of barcode i in country c, approximated by a log difference, is given by:

$$\Delta p_{ifgct} = \delta_{ct} + \delta_{fct} + \boldsymbol{\lambda}_{\boldsymbol{fc}}\boldsymbol{\eta}^{\boldsymbol{f}}_{\boldsymbol{ct}} + \delta_{gct} + \boldsymbol{\lambda}_{\boldsymbol{gc}}\boldsymbol{\eta}^{\boldsymbol{g}}_{\boldsymbol{ct}} + \varepsilon_{ifgct}. \tag{3.3}$$

That is, the price change is a function of the macro shock δ_{ct}, firm(-country) shock δ_{fct}, category(-country) shock δ_{gct}, the response of firm f's prices to a vector of common shocks $\boldsymbol{\eta}^{\boldsymbol{f}}_{\boldsymbol{ct}}$, the response of category g's prices to a vector of common shocks $\boldsymbol{\eta}^{\boldsymbol{g}}_{\boldsymbol{ct}}$, and an idiosyncratic shock to the barcode ε_{ifgct}. The responses to common shocks are governed by firm- and category-specific loadings $\boldsymbol{\lambda}_{\boldsymbol{fc}}$ and $\boldsymbol{\lambda}_{\boldsymbol{gc}}$. A firm- or category-specific loading on latent common factors may be important in order to absorb heterogeneous firm/category reactions to latent aggregate time-varying variables. For example, the $\boldsymbol{\lambda}$'s might vary because firms and/or categories have different import intensities. Alternatively, variation in $\boldsymbol{\lambda}_{\boldsymbol{fc}}$ could also capture the possibility that large firms adjust prices by less following a common macro shock. Since this heterogeneous adjustment can ultimately be related to a macro source, it is potentially important to keep this separate from the firm-specific shock δ_{fct}.[6] In practice, the baseline analysis will use one common factor per dimension, so the η's and λ's are scalars, but in Appendix Table A7 we repeat the analysis using up to three common factors.

[6]Such a pricing equation could arise, for example, in a market with oligopolistic competition. See Appendix B for a theoretical motivation of our approach following Amiti et al. (2019).

Plugging (3.3) into (3.1) delivers the following decomposition:

$$\begin{aligned}\Delta p_{ct} &= \underbrace{\delta_{ct}}_{\mathcal{M}_{ct}} + \underbrace{\sum_f w_{fct-4}(\delta_{fct} + \boldsymbol{\lambda_{fc}\eta^f_{ct}})}_{\Gamma^f_{ct}} + \underbrace{\sum_g w_{gct-4}(\delta_{gct} + \boldsymbol{\lambda_{gc}\eta^g_{ct}})}_{\Gamma^g_{ct}} \\ &= \mathcal{M}_{ct} + \Gamma^f_{ct} + \Gamma^g_{ct},\end{aligned} \tag{3.4}$$

under the assumption that the idiosyncratic deviations from the firm- and category-components are mean-zero in expenditure-weighted terms, $\sum_i w_{ifgct-4}\varepsilon_{ifgct} = 0$.[7] As above, $\mathcal{M}_{ct}$ captures the macroeconomic sources of inflation: the component common to all prices. The firm granular residual Γ^f_{ct} reflects the contributions of firm-specific components to aggregate inflation, while Γ^g_{ct} reflects the contribution of category-specific components.

The decomposition (3.4) echoes the "classic" one in (3.2), but is richer in two respects. First, it allows for contributions of idiosyncratic shocks in two distinct dimensions: at the firm level Γ^f_{ct}, and at the category level Γ^g_{ct}. Second, it explicitly allows for two ways in which large firms can contribute to aggregate price fluctuations. It has been understood since Gabaix (2011) that the granular residual can arise from idiosyncratic shocks to large firms, or from a differential response of large firms to common shocks. Our granular components encompass both possibilities. The idiosyncratic firm shocks are picked up by the $\sum_f w_{fct-4}\delta_{fct}$ term. The differential response to common shocks is captured by $\sum_f w_{fct-4}\boldsymbol{\lambda_{fc}\eta^f_{ct}}$. To understand this term better, suppose for the moment that there is only one common factor, and note that we can write:

$$\sum_f w_{fct-4}\lambda_{fc}\eta^f_{ct} = \left[\text{Cov}\left(\frac{w_{fct-4}}{\overline{w}_{fct}}, \lambda_{fc}\right) + \overline{\lambda}_{fc}\right]\eta^f_{ct},$$

where $\overline{w}_{fct}$ is the average expenditure share across firms (equaling $1/N_{f\in ct}$ by construction), and $\overline{\lambda}_{fc}$ is the average firm loading on the common shock η^f_{ct}. The first term is the covariance between firm size and the loading. It shows that a common shock will induce a granular residual if larger firms are on average more reactive to these common shocks – high $\text{Cov}\left(\frac{w_{fct-4}}{\overline{w}_{fct}}, \lambda_{fc}\right)$ in absolute value. The second term is simply the unweighted average firm loading on the common shock. In practice, because we will fit the factor model on demeaned data, this term is negligible. This discussion applies equally to the category granular residual. In the empirical analysis below we will further decompose Γ^f_{ct} and Γ^g_{ct} into these subcomponents, to establish which forms of granularity matter quantitatively.

[7] The idiosyncratic shocks ε_{ifgct} could be extracted from the residuals of the fixed effects regression. However, as we estimate the regressions weighting by the initial sales share $w_{ifgct-4}$ (see below for more detail), the weighted sum of the residuals is zero by construction: $\sum_i w_{ifgct-4}\varepsilon_{ifgct} = 0$.

Shock estimation. In order to decompose aggregate inflation into these components, we must first estimate all of the objects in (3.3). We regress, separately for each period and country, p_{ifgct} on $N_{g\in ct}$ category fixed effects and $N_{f\in ct}-1$ firm fixed effects. The macro shock is then computed as the simple average of the fixed effects:

$$\delta_{ct} = \frac{1}{N_{g\in ct}} \sum_{g\in ct} \hat{\delta}_{gct} + \frac{1}{N_{f\in ct}} \sum_{f\in ct} \hat{\delta}_{fct},$$

where $\hat{\delta}_{dct}$ is the estimated fixed effect for dimension $d = f, g$, country c and quarter t.

The firm- and category-specific components are then computed as the deviations of the estimated fixed effect from the average fixed effect:

$$\tilde{\delta}_{dct} = \hat{\delta}_{dct} - \frac{1}{N_{d\in ct}} \sum_{d\in ct} \hat{\delta}_{dct}, \qquad d = f, g.$$

Using the $\tilde{\delta}_{dct}$ directly as an estimate of δ_{dct} would amount to assuming that all firm- or category-specific deviations from the unweighted average prices are due to purely idiosyncratic shocks. In order to relax this assumption and allow $\tilde{\delta}_{dct}$ to be potentially driven by differential sensitivities to a latent common shock, we estimate up to three latent common factors $\boldsymbol{\eta}^{\boldsymbol{d}}_{\boldsymbol{ct}}$ for the two dimensions $d = f, g$ using Principal Component Analysis on the demeaned fixed effects:

$$\tilde{\delta}_{fct} \quad = \quad \boldsymbol{\lambda}_{\boldsymbol{fc}} \boldsymbol{\eta}^{\boldsymbol{f}}_{\boldsymbol{ct}} + \delta_{fct} \text{ and } \tilde{\delta}_{gct} = \boldsymbol{\lambda}_{\boldsymbol{gc}} \boldsymbol{\eta}^{\boldsymbol{g}}_{\boldsymbol{ct}} + \delta_{gct}. \tag{3.5}$$

Since the panel is unbalanced, we use the iterative Expectation Maximization algorithm as in Galaasen et al. (2021) and Gabaix and Koijen (2024). This algorithm starts by estimating the principal components based on a balanced panel. It then repeatedly regresses $\tilde{\delta}_{fct}$ on $\boldsymbol{\eta}^{\boldsymbol{f}}_{\boldsymbol{ct}}$ and then $\tilde{\delta}_{fct}$ on $\boldsymbol{\lambda}_{\boldsymbol{fc}}$ until convergence.[8] We implement the same procedure for categories, though there the panel is almost balanced. We use the residuals δ_{fct} and δ_{gct} as our firm- and category-specific idiosyncratic shocks.

The baseline results use one common factor, so $\boldsymbol{\eta}^{\boldsymbol{f}}_{\boldsymbol{ct}}$ and $\boldsymbol{\eta}^{\boldsymbol{g}}_{\boldsymbol{ct}}$ are scalars. In robustness, we report results using two and three factors in $\boldsymbol{\eta}^{\boldsymbol{f}}_{\boldsymbol{ct}}$ and $\boldsymbol{\eta}^{\boldsymbol{g}}_{\boldsymbol{ct}}$. From a statistical standpoint, adding more factors will attribute more of the variation in firm prices to common components and less to idiosyncratic ones. Conceptually, when there are strategic complementarities in large firms' pricing decisions, the estimated idiosyncratic components for large firms may become positively correlated even in the absence of a truly exogenous common component to firm price changes. Appendix B lays out

[8] We define convergence and stop the iterations for a specific country c when $0.01 > \frac{1}{N_f} \sum_f |\frac{(\hat{\lambda}^{\mathcal{N}}_{fc} \hat{\eta}^{f,\mathcal{N}}_{ct} - \hat{\lambda}^{\mathcal{N}-1}_{fc} \hat{\eta}^{f,\mathcal{N}-1}_{ct})}{\hat{\lambda}^{\mathcal{N}-1}_{fc} \hat{\eta}^{f,\mathcal{N}-1}_{ct}}|$, where $\mathcal{N}$ is the iteration number. That is, when the average percentage change in the contribution of the factor $\hat{\lambda}^{\mathcal{N}}_{fc} \hat{\eta}^{f,\mathcal{N}}_{ct}$ across firms has changed by less than one percent between the current iteration ($\mathcal{N}$) and the previous iteration ($\mathcal{N}-1$).

a pricing model following Amiti et al. (2019) and shows that under oligopolistic competition large firms (i.e. those with non-negligible market share) react to both their own marginal costs and also to their competitors' price adjustments. These reactions to other firms' pricing decisions will correlate the idiosyncratic components of the large firms more than those of small firms. At the same time, these reactions will be picked up to some extent by the second and third common factors. It is a judgment call whether strategic complementarities of this type should be considered common factors or idiosyncratic shocks. Thus, in the paper, we report results with both 1 and 2-3 factors. Additional common factors have minimal impact on the main results.

All singletons or observations without a defined firm are removed from the analysis. Barcodes belonging to product categories that in one specific period and country contain less than ten barcodes or five firms were reclassified into the category "other retail products."

3.3 Main results

Micro level. We first document the importance of firm and category components in accounting for the variation in prices at the micro level. In the absence of detectable firm and category common components in product-level prices, the firm and category granular residuals would not arise, as there would not be such a thing as a firm or category shock. We report partial R^2's of the firm and category fixed effects, as well as the total R^2 that would give a sense of how much cross-sectional variation in price changes is due to idiosyncratic factors. The partial R^2 associated with dimension $d = f, g$ and country c is as follows:

$$Partial\ R^2_d \quad = \quad 1 - \frac{RSS^F}{RSS^P_d},$$

where RSS^F is the sum of squared residuals from the full model (including all fixed effects), and RSS^P_d is the sum of squared residuals from the partial model that include the other (non-d) fixed effects only. We estimate this statistic for each country separately and also pooling across countries. When doing this for each country c separately, we use the definition of $RSS^{M,c} = \sum_t \sum_i w_{ifgct-4}(p_{ifgct} - \hat{p}^M_{ifgct})^2$ where $M = \{F, P\}$ is the model (that is, either the full model or the partial model excluding one dimension). When pooling countries, we also sum the squared residuals across countries $RSS^M = \sum_c \sum_t \sum_i w_{ifgct-4}(p_{ifgct} - \hat{p}^M_{ifgct})^2$. We estimate the fixed effects and the resulting partial R^2 from a weighted regression in which each observation is weighted by its respective expenditure share in the previous year, and from an unweighted regression in which all barcodes in a given country-period have the same weight.[9] The R^2 for each country is computed with the usual formula.

[9] Note that the "unweighted" regressions also contain an implicit weight equal to $1/N_{i\in ct}$ because we give every period the same weight and the weight of each observation is defined by the number of products observed in a given country-period

Table 3: Explanatory power at the micro level

	Unweighted			Weighted		
	Partial R^2			Partial R^2		
Country	Firm	Category	R^2	Firm	Category	R^2
Advanced Economies	0.058	0.009	0.077	0.080	0.038	0.146
AT	0.059	0.009	0.077	0.079	0.034	0.137
BE	0.068	0.009	0.089	0.092	0.046	0.163
DE	0.062	0.011	0.090	0.102	0.079	0.217
ES	0.081	0.009	0.101	0.114	0.054	0.217
FR	0.045	0.005	0.057	0.051	0.018	0.097
NL	0.058	0.006	0.071	0.087	0.028	0.136
SE	0.062	0.011	0.086	0.093	0.040	0.169
UK	0.042	0.015	0.067	0.061	0.034	0.119
US	0.047	0.004	0.054	0.052	0.018	0.079
Emerging Economies	0.085	0.007	0.126	0.122	0.028	0.213
AR	0.096	0.015	0.215	0.118	0.049	0.336
BR	0.098	0.004	0.106	0.130	0.021	0.171
CL	0.052	0.011	0.089	0.138	0.030	0.225
CN	0.116	0.001	0.120	0.133	0.007	0.151
HU	0.075	0.013	0.149	0.104	0.044	0.243
MX	0.051	0.006	0.064	0.115	0.029	0.178
RU	0.087	0.005	0.124	0.116	0.016	0.177
All Countries	0.072	0.008	0.169	0.101	0.033	0.264

Notes: R^2's and partial R^2's calculated from the the sum of RSS and TSS across periods for each country. Last row shows the measures computed aggregating RSS and TSS also across countries. Unweighted columns display the R^2's resulting from an unweighted regression and weighted columns the R^2's resulting from a weighted regression using the barcode expenditure weights in the same quarter of the previous year.

Table 3 reports the resulting weighted and unweighted R^2's and partial R^2's for each country separately and for each country group. Overall, there is a clear common component, with the firm components responsible for about 10% of the variation in prices when expenditure weights are used, and 7% without expenditure weights. The product category component has smaller explanatory power, with weighted and unweighted partial R^2's in the range of 3% and 1%, respectively. Thus, at the micro level the large majority of the variation is idiosyncratic at the barcode level. This echoes the common finding in micro datasets (Haltiwanger, 1997; di Giovanni et al., 2014; Castro et al., 2015). Nonetheless, firm and category components are clearly detectable. To further explore the firm-level component in price setting, Appendix C uses a multinomial logit specification in the spirit of Bhattarai and Schoenle (2014) to document the presence of synchronization in the price changes within firms.

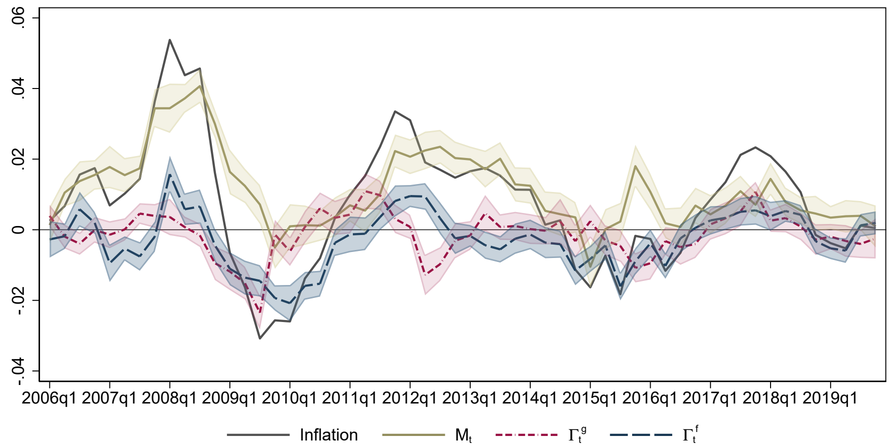
$N_{i\in ct}$. For this reason, in both cases there are weights involved in the computation of the partial R^2.

Macro level. We now present our central result: the contribution of individual firms and categories to overall inflation. In presenting the main results, we focus on the 2005-2020 period, which was a time of low and stable inflation in the AEs. Section 3.6 compares the 2021-2022 high-inflation period to the pre-2021 low-inflation period, and discusses how the main results change if we implement the granular decomposition on the full available sample of years.

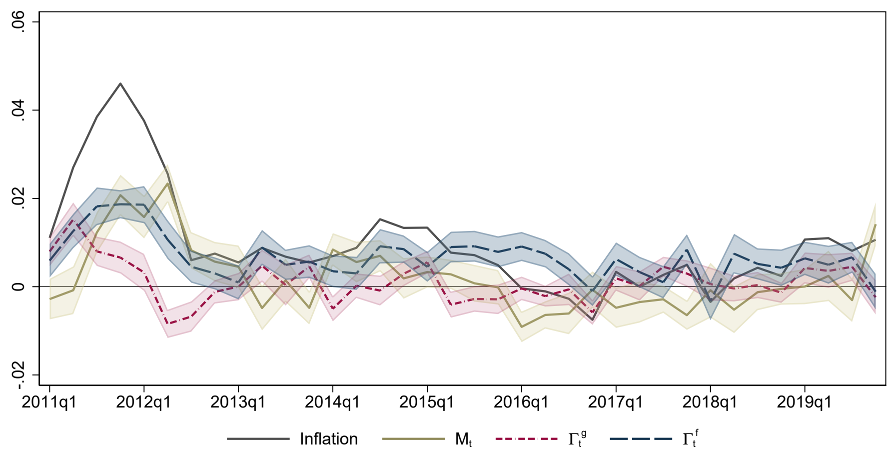
Figure 5 shows the dynamics of inflation and its components in (3.4) for Germany, the US, and Argentina (for the other countries see Appendix Figure A3). We also display 95% confidence intervals estimated using bootstrapping.[10] The firm granular component Γ^{f}_{ct} contributes significantly to aggregate retail inflation in advanced economies. The category granular component Γ^{g}_{ct} is also notable. In Argentina, where inflation is on average around 10 times higher than in the US or Germany, both granular components are relatively less important.

[10] We first estimate the components on 30 additional period-country-specific and randomly selected (with replacement) sub-samples of the observations (Δp_{ifgct}) available within each period-country. This guarantees that we estimate the components on the same number of observations in each random sample as in the original data. We then estimate the standard deviation of the components in each period using the bootstrapped samples.

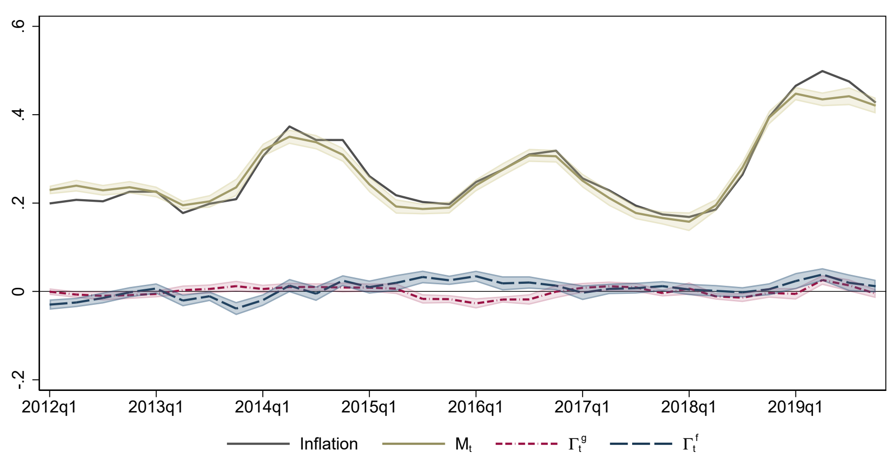
Figure 5: Aggregate retail inflation and granular components



(a) Germany



(b) US



(c) Argentina

Notes: This figure displays the aggregate year-on-year inflation and each component. Only periods up through 2020 included and three out of 16 countries shown. The rest of the countries and figures showing all available years can be found in Appendix Figure A3.

Table 4: Summary statistics and correlations of inflation components, 2005-2020

	Mean	St. Dev.	Corr.	Var(Δp_{ct}) share
Advanced Economies (N. Obs = 457)				
Δp_{ct}	0.84	1.63	1.00	1.00
$\mathcal{M}_{ct}$	0.53	1.19	0.60	0.44
Γ^{f}_{ct}	0.19	0.96	0.67	0.41
$\sum_f w_{fct-4}\delta_{fct}$	0.17	0.91	0.60	0.35
$\sum_f w_{fct-4}\lambda_{fc}\eta^{F}_{ct}$	0.02	0.37	0.27	0.07
$\Gamma^{f\in top10f}_{ct}$	*0.12*	*0.63*	*0.66*	*0.26*
$\Gamma^{f\notin top10f}_{ct}$	*0.06*	*0.49*	*0.47*	*0.15*
Γ^{g}_{ct}	0.12	0.66	0.40	0.15
$\sum_g w_{gct-4}\delta_{gct}$	0.08	0.56	0.23	0.09
$\sum_g w_{gct-4}\lambda_{gc}\eta^{G}_{ct}$	0.04	0.35	0.39	0.06
Emerging Economies (N. Obs = 252)				
Δp_{ct}	6.69	10.06	1.00	1.00
$\mathcal{M}_{ct}$	6.00	9.99	0.60	0.80
Γ^{f}_{ct}	0.66	1.39	0.67	0.20
$\sum_f w_{fct-4}\delta_{fct}$	0.69	1.35	0.60	0.20
$\sum_f w_{fct-4}\lambda_{fc}\eta^{F}_{ct}$	-0.03	0.36	0.27	0.00
$\Gamma^{f\in top10f}_{ct}$	*0.33*	*0.89*	*0.66*	*0.10*
$\Gamma^{f\notin top10f}_{ct}$	*0.33*	*0.72*	*0.47*	*0.10*
Γ^{g}_{ct}	0.03	0.92	0.40	-0.00
$\sum_g w_{gct-4}\delta_{gct}$	0.01	0.86	0.23	0.00
$\sum_g w_{gct-4}\lambda_{gc}\eta^{G}_{ct}$	-0.01	0.37	0.39	-0.01

Notes: "Mean" denotes the average inflation rate, "St. Dev." the standard deviation, "Corr." the correlation between the component in the row and aggregate inflation Δp_{ct}, and "Var(Δp_{ct}) share" denotes the share of the variance of actual inflation accounted for by each component. The top panel reports the results computed pooling nine advanced economies (Austria, Belgium, Germany, Spain, France, the Netherlands, Sweden, UK, US) and the bottom panel seven emerging markets (Argentina, Brazil, Chile, China, Hungary, Mexico and Russia). High-inflation years 2021 and 2022 excluded.

Table 4 presents the summary statistics for the macro and granular components for the advanced economies (top panel) and for the emerging markets (bottom panel) in our sample. Overall inflation has averaged 0.84% in the advanced economies over this period. Of this, the macro component contributes 0.53 percentage points, the firm granular component 0.19 percentage points, and the category component 0.12 percentage points. Large firms in our sample, therefore, experienced on average higher price increases than small firms (when controlling for category shocks). This finding dovetails with the literature on the rise of concentration and superstar firms (Autor et al., 2020; Covarrubias et al., 2020), and introduces a nuance to the evidence on the general rise in markups, such as De Loecker et al. (2020) and Döpper et al. (2025). It also relates to the observation that the rate of pass-through of cost shocks into prices depends on market structure and industry concentration (see e.g. Amiti et al., 2014; Auer and Schoenle, 2016; Brauning et al., 2022).[11] The standard deviation of the macro component is the highest at 1.19 percentage points, followed by Γ^f_{ct} at 0.96 and Γ^g_{ct} at 0.66 percentage points.

All three terms contribute notably to the variability of actual inflation in advanced economies. The correlations between actual inflation and $\mathcal{M}_{ct}$, Γ^f_{ct}, and Γ^g_{ct} are 0.60, 0.67, and 0.40, respectively. The last column of the table reports variance share of each component in the total, computed as:

$$\text{Variance Share}_d = \frac{\text{Cov}(\Delta p_{ct}, d)}{\text{Var}(\Delta p_{ct})} \quad \text{for} \quad d \in \{\mathcal{M}_{\rfloor\sqcup}, \Gamma^f_{ct}, \Gamma^g_{ct}\}.$$

This decomposition is common in finance (e.g. Campbell and Mei, 1993), and has the desirable property that the variance shares add up to 1. It is applicable in settings where the components are potentially mutually correlated.[12] The macro component $\mathcal{M}_{ct}$ accounts for 44% of inflation variance, followed by 41% for the granular firm component, and 15% for the granular category component. Thus, in the advanced economy sample, granular components account for more than half of the total variance of inflation over this period.

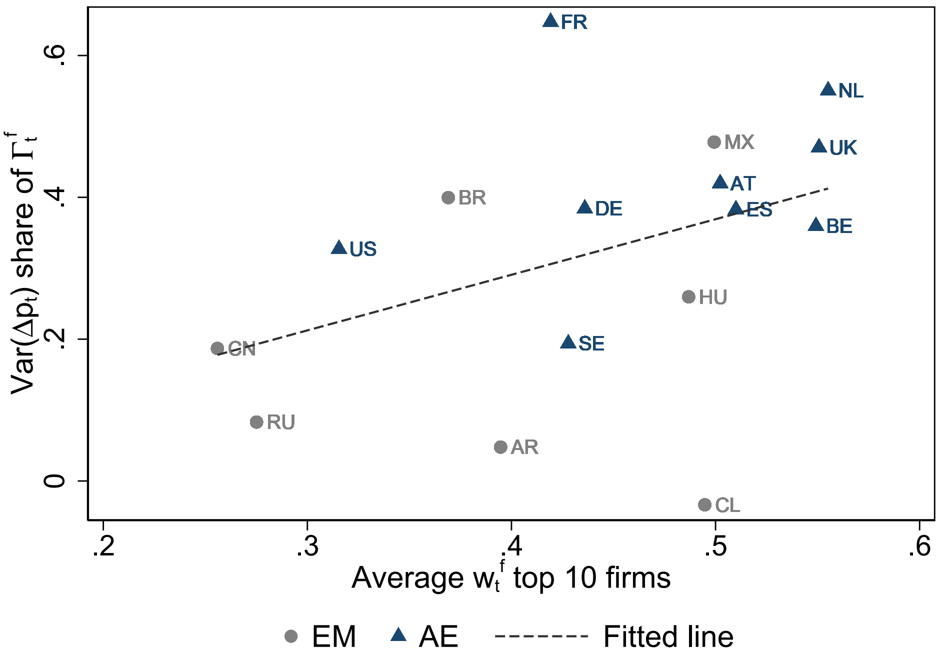
The results are quite different for the emerging markets. Here, overall inflation is much higher (6.69% on average), and the macro component is much more important, contributing 6.00 percentage points on average. While all three components have a substantial correlation with the overall inflation, the variance shares of the firm and category granular components are 20% and 0%, respectively.

Further decompositions of the granular residuals. We next undertake two further decompositions to highlight the nature of inflation granularity. First, as discussed above, Γ^f_{ct} can arise either because of idiosyncratic shocks to large firms (the $\sum_f w_{fct-4}\delta_{fct}$ subcomponent), or from higher sensitivity of large firms to common shocks (the $\sum_f w_{fct-4}\lambda_{fc}\eta^f_{ct}$ subcomponent), and similarly for the category component Γ^g_{ct}. Table 4 decomposes Γ^f_{ct} and Γ^g_{ct} into the subcomponents, as in equation (3.4). For the firm granular component, there is a clear winner: idiosyncratic shocks. This component is responsible for virtually all of the average growth in Γ^f_{ct} (0.17 percentage points of the total of 0.19), and contains nearly all of the variability of Γ^f_{ct}. Of the total of 0.41 variance share of Γ^f_{ct}, the firm idiosyncratic component accounts for 0.35 percentage points.

[11]The contributions of the granular components to mean inflation are lower bounds, as due to the intercept issue in the fixed effects regressions we renormalize the averages of firm and category fixed effects to 0. Thus, the positive averages Γ^f_{ct} and Γ^g_{ct} are entirely due to prices of larger firms/categories growing relatively faster on average.

[12]In practice, the correlations between $\mathcal{M}_{ct}$, Γ^f_{ct}, and Γ^g_{ct} are limited, and simply computing the ratios of the variances of $\mathcal{M}_{ct}$, Γ^f_{ct}, and Γ^g_{ct} to the variance of the Δp_{ct} leads to substantively similar results. When the components of the decomposition are additive (as is the case here), this variance share decomposition coincides with the Shapley (1953) value decomposition. Essentially, the Shapley value averages the contribution to the total variance of each component across all permutations of the other components.

Figure 6: Granularity and market concentration

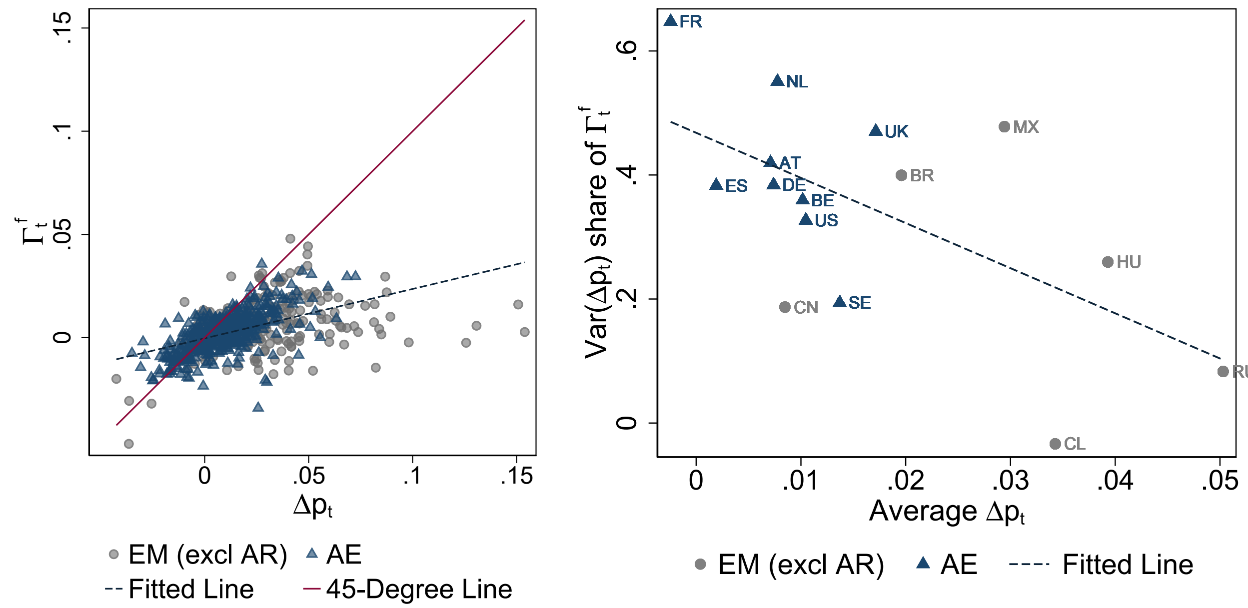


Notes: The figure displays a scatterplot of the Var(Δp_{ct}) share of Γ^f_{ct} against average share of top 10 firms $w_{ct}^{f\in top10f}$. The dashed line is a linear fit with a slope of 0.78 (robust standard error of 0.31) and a R^2 of 0.16 ($N = 16$).

The category granular component is split more evenly between idiosyncratic shocks and heterogeneous sensitivity. The idiosyncratic component accounts for 0.08 percentage points of the total of 0.12%, while the standard deviations of the two subcomponents are of similar magnitude. The contribution of the differential sensitivity to common shocks to the variability of aggregate inflation is actually slightly larger, at 9 percentage points out of the total of 15%. In emerging markets, the idiosyncratic component accounts for the entirety of the 20% contribution of the firm granular residual to the inflation variance. The category granular component is muted in those countries, and thus neither the idiosyncratic component nor the differential sensitivity to common shocks matter for the product category granular residual.

Second, we investigate the importance of the very large firms in our sample. The 10 largest firms are an important source of granular fluctuations in advanced economies. To isolate their contribution, we separate the Γ^f_{ct} additively into the components accounted for by the 10 largest firms ($\Gamma_{ct}^{f\in top10f}$ in Table 4) vs. the rest. They alone are responsible for 0.12 out of the 0.19 percentage points of the average growth in the firm granular component, and for 0.26 out of the total 0.41 variance share of Γ^f_{ct} in aggregate inflation.

Figure 7: Granularity and the inflation rate



(a) Γ^f_{ct} vs. Δp_{ct} (b) Var(Δp_{ct}) share of Γ^f_{ct} vs. average Δp_{ct}

Notes: The left panel displays a scatterplot of Γ^f_{ct} against Δp_{ct}, pooling countries and years. The solid red line is the 45-degree line, the dashed line is the linear fit. The right panel displays a scatterplot of the Var(Δp_{ct}) share of Γ^f_{ct} for country c against the average inflation of country c.

Market share concentration and inflation granularity. We next investigate the covariates of the cross-country differences in granularity of inflation. We first look at how the explanatory power of granular residuals depends on the market shares of the top firms. Figure 6 displays a scatterplot of the variance share of Γ^f_{ct} in total inflation against the average market share of the top 10 firms in each country. There is a positive and statistically significant relationship, suggesting that granular effects are stronger in countries with higher market concentration. This correlation not only reinforces our interpretation that firm-specific granular residuals should contribute more to aggregate inflation in more concentrated markets, but also suggests that trends in market concentration, as documented for example in Autor et al. (2020), may coincide with an increasing role of firm granularities in aggregate inflation dynamics.

Inflation granularity and the average inflation rate. The comparison between the advanced and the emerging economies in Table 4 suggests that in higher-inflation environments granular effects are quantitatively less important. Figure 7 investigates this more systematically. The left panel displays a scatterplot of Γ^f_{ct} against total inflation Δp_{ct} pooling countries and years. Both the 45-degree line and the linear regression line are added to the plot. Because Argentina is an outlier in terms of Δp_{ct}, we drop it from the plot (Appendix Figure A4 presents the plots including Argentina). There is a clear systematic relationship: the granular component is a smaller fraction of the overall inflation in country-years when inflation is high. The right panel displays the variance share of the Γ^f_{ct} in total inflation variance against the average inflation in the country. There is a pronounced negative relationship: the higher the average inflation, the less of its variability is accounted for by the firm granular component. Both of these patterns continue to hold if we use the combined firm and product category granular components, $\Gamma^f_{ct} + \Gamma^g_{ct}$, instead of the firm granular component alone, see Appendix Figure A4.

Robustness. Appendix Table A7 reports the results for a sample using a simplified approach for identifying missing firms, and when estimating up to three factors. The first panel uses a simpler methodology to match firms. This alternative does not change our estimates significantly.[13] The middle and right panels add more factors to the idiosyncratic shock estimation. Doing so has a minimal impact on the firm granular residual. With more factors the product category idiosyncratic shocks account for a slightly lower share of the overall variance share of Γ^g_{ct}.

In extracting the common factors in equation (3.5), we estimated separate factors $\boldsymbol{\eta}^{\boldsymbol{f}}_{\boldsymbol{ct}}$ and $\boldsymbol{\eta}^{\boldsymbol{g}}_{\boldsymbol{ct}}$ in the firm and product category fixed effects samples. Alternatively, we could fit a single common factor to both $\tilde{\delta}_{fct}$ and $\tilde{\delta}_{fct}$. Appendix Table A8 reports the results of implementing this alternative approach. They are virtually identical for the firm granular component. For the product category component, idiosyncratic shocks become more important, at the expense of the differential sensitivity to common shocks.

3.4 The retailer dimension

We next present the results taking into account the retailer dimension. As noted above, we do not adopt this decomposition as the baseline because the retailer information in these data has gaps, especially in emerging markets.

Data. Given the small number of retailers, only two adjustments were needed to add the retailer dimension. First, if one retailer has a subsidiary chain, e.g. "Carrefour Express," we assign this subsidiary to the parent chain, i.e. "Carrefour." Second, for some purchases the retailer is not identified, with the retailer field coded as "other." Relatedly, for some countries in the data some small retailers are lumped together by type of store, for example "Bakery" or "Pet store." We replaced the retailer entry with "other" in these cases. Appendix Table A2 reports the share of aggregate expenditure in retailers that could not be identified in the data. For the advanced countries, that share is only 3.24%: the vast majority of total expenditure can be attributed to named retailers. However, the unidentified retailer share is substantial emerging markets, at 31.52% on average.

[13]See Appendix A.1 for a detailed discussion of the alternative firm matching procedures.

Column 1 of Appendix Table A3 reports the number of observations for product-level inflation rates in the sample that includes the retailer dimension. Specifically, it shows the number of inflation observations, where Δp_{ifgsct} is the inflation of barcode i, which belongs to category g and is produced by firm f, in country c and sold by retailer s. When adding the retailer dimension, the number of observations is larger, as now the same barcode-quarter can have several observations, one for each retailer (column 1). On the other hand, the set of distinct barcodes is smaller than in the baseline sample (column 2), as a product must be observed in two consecutive years in the same retailer-country-quarter cell in order to compute the corresponding price change. Column 3 reports the number of retailers in each country, along with the total number of distinct retailers in the dataset, 3,448. Columns 4 and 5 display the combined expenditure shares of the 10 largest and the 1% largest retailers. As with the firm and the product category dimensions, retailers are highly concentrated, with the top 10 accounting for 67% of total expenditure on average.

Results. Since in many of the transactions the retailer is coded as "other," we have to make a decision on how to assign a retailer component to those. We implement three versions. In the main text, we treat all unidentified retailers as a single "other" retailer. Figure 8 and Table 5 reproduce the main results with the retailer dimension. Adding the retailer component leaves the variance shares of the firm and category granular components quite similar compared to the baseline, but reduces the variance share of the macro component. The contribution to the variance of the macro component falls from 44% (c.f. Table 4) to 32%, and the difference is largely picked up by the retailer component, which accounts for 17% of the inflation variance.

To assess the role that the unidentified retailers play in the granular residual, we note that the retailer component Γ^s_{ct} is simply the sum of the contributions of each retailer. As such, we can isolate the contribution of the unidentified retailer, $w_{sct-4}\delta_{s=other,ct}$, from the rest of the retailer granular residual. The results are reported in the last 2 rows of each panel of Table 5. It turns out that the unidentified retailer's variance share contribution is nil in the advanced economies, but more than a third of the total variance share of Γ^s_{ct} in the emerging markets (0.05 out of 0.14). Since it is clearly not the case that the unidentified retailer is a single retailer in reality, this is a caveat to our ability to estimate the retailer granular residual in emerging markets.

Appendix Table A9 implements two alternative retailer decompositions. The left panel simply drops the unidentified retailer observations from the sample. The middle panel instead uses the geographic location information of households to create synthetic regional retailers. In particular, we create separate regional retailers using the region or postal code information of the households. In this approach, purchases made from the unidentified retailers in different cities in the same country are assumed to come from different retailers. The results remain unchanged. The rightmost panel of

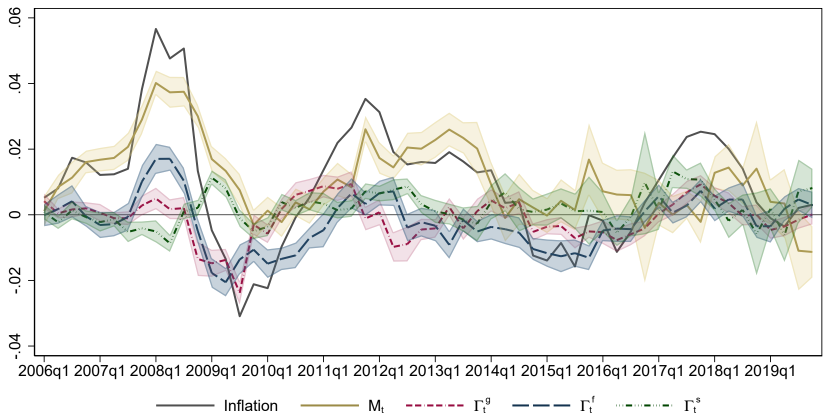
Table 5: Summary statistics and correlations of factor components: Retailer dimension

	Mean	St. Dev.	Corr.	Var(Δp_{ct}) share
Advanced Economies (N. Obs = 457)				
Δp_{ct}	1.05	1.72	1.00	1.00
$\mathcal{M}_{ct}$	0.40	1.49	0.35	0.32
Γ^f_{ct}	0.09	0.91	0.63	0.36
$\sum_f w_{fct-4}\delta_{fct}$	0.09	0.86	0.56	0.28
$\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$	-0.00	0.33	0.30	0.07
Γ^g_{ct}	0.16	0.64	0.47	0.16
$\sum_g w_{gct-4}\delta_{gct}$	0.13	0.54	0.31	0.09
$\sum_g w_{gct-4}\lambda_{gc}\eta^G_{ct}$	0.03	0.32	0.41	0.07
Γ^s_{ct}	0.41	1.16	0.27	0.17
$\sum_s w_{sct-4}\delta_{sct}$	0.42	1.12	0.28	0.17
$\sum_s w_{sct-4}\lambda_{sc}\eta^S_{ct}$	-0.01	0.33	0.01	0.00
$\Gamma^s_{ct} - w_{sct-4}\delta_{s=other,ct}$	*0.41*	*1.15*	*0.28*	*0.17*
$w_{sct-4}\delta_{s=other,ct}$	*-0.00*	*0.04*	*-0.22*	*-0.00*
Emerging Economies (N. Obs = 252)				
Δp_{ct}	6.44	9.31	1.00	1.00
$\mathcal{M}_{ct}$	5.24	8.91	0.35	0.71
Γ^f_{ct}	0.60	1.30	0.63	0.14
$\sum_f w_{fct-4}\delta_{fct}$	0.64	1.28	0.56	0.16
$\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$	-0.04	0.38	0.30	-0.03
Γ^g_{ct}	0.06	0.88	0.47	0.01
$\sum_g w_{gct-4}\delta_{gct}$	0.06	0.80	0.31	0.04
$\sum_g w_{gct-4}\lambda_{gc}\eta^G_{ct}$	-0.01	0.38	0.41	-0.02
Γ^s_{ct}	0.54	1.41	0.27	0.14
$\sum_s w_{sct-4}\delta_{sct}$	0.55	1.39	0.28	0.14
$\sum_s w_{sct-4}\lambda_{sc}\eta^S_{ct}$	-0.00	0.38	0.01	0.00
$\Gamma^s_{ct} - w_{sct-4}\delta_{s=other,ct}$	*0.39*	*0.97*	*0.28*	*0.09*
$w_{sct-4}\delta_{s=other,ct}$	*0.16*	*0.84*	*-0.22*	*0.05*

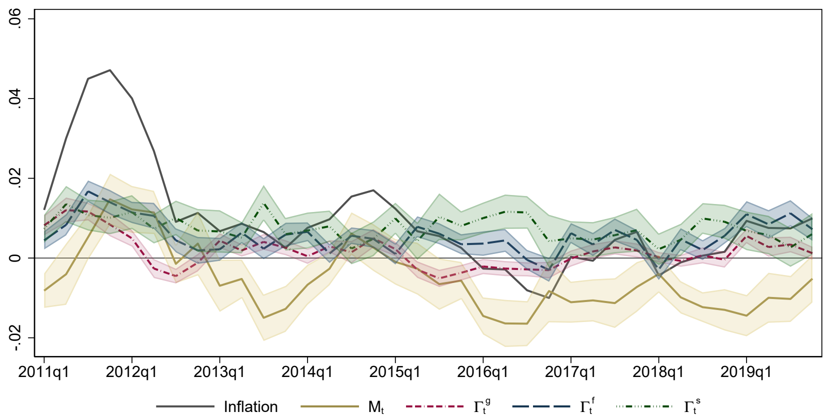
Notes: "Mean" denotes the average inflation rate, "St. Dev." the standard deviation, "Corr." the correlation between the component in the row and aggregate inflation Δp_{ct} using the product-retailer level dataset, and "Var(Δp_{ct}) share" denotes the share of the variance of actual inflation accounted for by each component. The top panel reports the results computed pooling all advanced economies and the bottom panel all emerging markets. Δp_{ct} refers to aggregate inflation computed using the retailer-country-quarter level sample, which slightly differs from the aggregate inflation in the baseline sample. The top panel reports the results computed pooling nine advanced economies (Austria, Belgium, Germany, Spain, France, the Netherlands, Sweden, UK, US) and the bottom panel seven emerging markets (Argentina, Brazil, Chile, China, Hungary, Mexico and Russia). High-inflation years 2021 and 2022 excluded.

Appendix Table A9 reports the original (retailer-less) decomposition, but on the same smaller sample of barcodes on which we estimate the retailer decompositions. The numbers are virtually the same as in the baseline in Table 4.

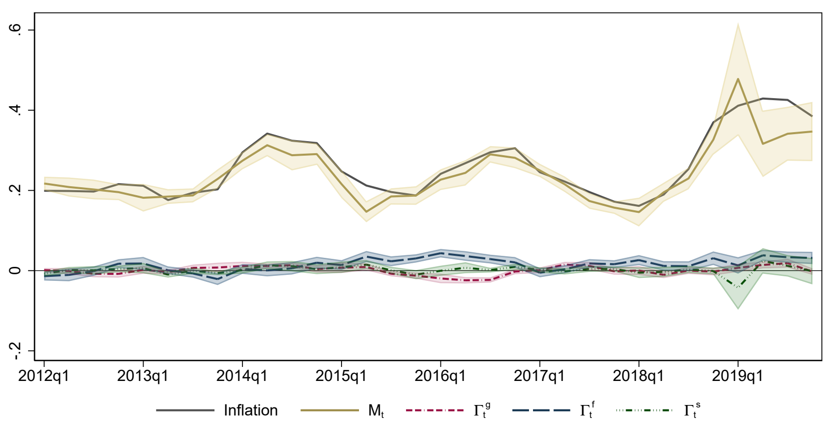
Figure 8: Aggregate retail inflation and granular components: Retailer dimension



(a) Germany



(b) US



(c) Argentina

Notes: This figure displays the aggregate year-on-year inflation and each component, including the retailer granular residual. Only periods up through 2020 included and three out of 16 countries shown. The rest of the countries and figures showing all available years can be found in Appendix Figure A5.

Table 6: Average inflation contributions Pre- and post-2021

	2008-2020		2021-2022	
	Mean	Share of $\Delta\bar{p}_{ct}$	Mean	Share of $\Delta\bar{p}_{ct}$
Advanced Economies (N. Obs = 521)				
Δp_{ct}	0.84	1.00	3.91	1.00
$\mathcal{M}_{ct}$	0.53	0.63	1.62	0.41
Γ^{f}_{ct}	0.19	0.22	1.47	0.38
$\sum_f w_{fct-4}\delta_{fct}$	0.17	0.20	1.06	0.27
$\sum_f w_{fct-4}\lambda_{fc}\eta^{f}_{ct}$	0.02	0.02	0.41	0.10
$\Gamma^{f\in top10f}_{ct}$	*0.12*	*0.15*	*1.04*	*0.27*
$\Gamma^{f\notin top10f}_{ct}$	*0.06*	*0.07*	*0.43*	*0.11*
Γ^{g}_{ct}	0.12	0.14	0.82	0.21
$\sum_g w_{gct-4}\delta_{gct}$	0.08	0.10	0.49	0.12
$\sum_g w_{gct-4}\lambda_{gc}\eta^{g}_{ct}$	0.04	0.04	0.33	0.09
Emerging Economies (N. Obs = 300)				
Δp_{ct}	6.69	1.00	10.56	1.00
$\mathcal{M}_{ct}$	6.00	0.90	8.98	0.85
Γ^{f}_{ct}	0.66	0.10	1.13	0.11
$\sum_f w_{fct-4}\delta_{fct}$	0.69	0.10	0.96	0.09
$\sum_f w_{fct-4}\lambda_{fc}\eta^{f}_{ct}$	-0.03	-0.01	0.18	0.02
$\Gamma^{f\in top10f}_{ct}$	*0.33*	*0.05*	*0.64*	*0.06*
$\Gamma^{f\notin top10f}_{ct}$	*0.33*	*0.05*	*0.49*	*0.05*
Γ^{g}_{ct}	0.03	0.00	0.45	0.04
$\sum_g w_{gct-4}\delta_{gct}$	0.01	0.00	0.43	0.04
$\sum_g w_{gct-4}\lambda_{gc}\eta^{g}_{ct}$	-0.01	-0.00	0.01	0.00

Notes: "Mean" denotes the average inflation rate. "Share of $\Delta\bar{p}_{ct}$" the ratio of the component mean to total inflation (Δp_{ct}) country mean. The top panel reports the results computed pooling nine advanced economies (Austria, Belgium, Germany, Spain, France, the Netherlands, Sweden, UK, US) and the bottom panel seven emerging markets (Argentina, Brazil, Chile, China, Hungary, Mexico and Russia).

3.5 The post-2020 inflation surge

The baseline analysis focuses on the low and stable inflation period that ended in 2020. We now compare the high-inflation period 2021-2022 to the baseline. Because this period only has two years, we do not compute time series objects such as inflation volatility and variance shares. Instead, we examine the relative importance of the granular components in overall inflation. Table 6 reports the results. The first column displays inflation and component averages for 2005-2020 (this is identical to the first column of Table 4). The third column reports the same figure but for the 2021-22 period. Columns 2 and 4 contain the ratios of each element to the average inflation.

In our data – which for the 2021-22 period does not have the US and Russia – inflation itself quadrupled in 2021-2022 compared to the 2005-2020 period in advanced economies. Along with that, the relative importance of the granular components in total inflation increased: Γ^{f}_{ct} accounted for 22% of total inflation in the low-inflation period, but almost twice that, 38%, in the high-inflation period. Similarly, the share of the product category granular component rises from 14% to 21% over this period. Evidently, the post-2020 inflation was, to a significant extent, a "granular inflation surge."

Part of the increased contribution of the firm granular component is due to a higher sensitivity of large firms to the common shocks during that period: while the differential sensitivity component ($\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$) of Γ^{f}_{ct} is negligible in normal times, it accounts for over a quarter of the firm granular residual during the inflation surge. One possible reason is that larger firms, with higher import shares in intermediate inputs, were more exposed to global supply chain bottlenecks, which contributed to the inflation surge (Amiti et al., 2014; di Giovanni et al., 2023).

In emerging markets, the average inflation increase was much more modest in relative terms, with prices increasing by 6.69% on average in the earlier period, and by 10.56% in 2021-22. The relative importance of the granular residuals stayed remarkably stable across both periods, with the contribution of Γ^{f}_{ct} at 10-11%.[14]

Because the inflation surge period is short (and, as of the time of writing, appears somewhat transitory), we lack sufficient data to fully integrate the time series observations in this subsection with the cross-sectional comparisons discussed above. The period 2021–22 was exceptional in many ways—the COVID pandemic, large-scale disruptions to supply chains, and massive fiscal and monetary interventions. Nonetheless, the experience of the inflation surge indicates that granularities can be a source of salient inflation developments.

One aspect of particular relevance is the finding that the heightened sensitivity of larger firms ($\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$) amplified the underlying macro shocks. The fact that granularities took a different form during this exceptional period is consistent with the literature on pass-through of exchange rates into prices, which argues that the origin of the shock matters for the rate of pass-through (Forbes et al., 2020). This pattern also aligns with evidence from Franzoni et al. (2024), who show that supply chain shortages strengthened the competitive position of large firms, as suppliers prioritized major customers, which could therefore increase their market share.

We also investigate the contribution of granularities to inflation variability in the entire sample period 2005-2022. Appendix Table A10 replicates the main results Table 4 for the full sample of years, 2005-2022. The main conclusions about the overall size and relative importance of the granular residuals are quite similar to the baseline. One difference is that in the sample of years that includes

[14]The smaller relative role of granularities in emerging markets is influenced by Argentina, where average annual inflation in the sectors we cover averaged around 30% (with barely an uptick in the 2021-22 period), substantially affecting the group average. Without Argentina, the average share of Γ^{f}_{ct} in the emerging market group is 22% during 2005-20 and 19% in 2021-22 – still stable across the pre- and post-inflation surge periods.

the inflation surge, the relative importance of the differential sensitivity component ($\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$) to the variance share of Γ^f_{ct} is larger, 0.16 out of 0.41 (compared to 0.07 in the sample up to 2020). This higher contribution is clearly driven by these exceptional two years, and this is the reason we report the results excluding the inflation surge as the baseline.

3.6 Granularities and monetary policy shocks

What role do large firms play in the transmission of monetary policy to inflation? We showed above that granular residuals contribute to inflation volatility. Although monetary policy shocks are aggregate in nature, pricing dynamics/decisions of large firms – captured in the firm granular residuals - may still shape the overall response of inflation to monetary policy.

To this end, we document how a monetary policy shock propagates to aggregate inflation through the different inflation components identified above. We adopt the methodology of Aruoba and Drechsel (2024), which estimates local projections for disaggregated price indices and re-aggregates them, yielding correctly adjusted standard errors. We first estimate impulse responses of individual inflation components – macro and the granular residuals – to identified monetary policy shocks. In the second step, we re-aggregate responses of the components to obtain the impulse response of overall inflation. More precisely, we estimate local projections for each component by means of the following regression separately for each horizon h:

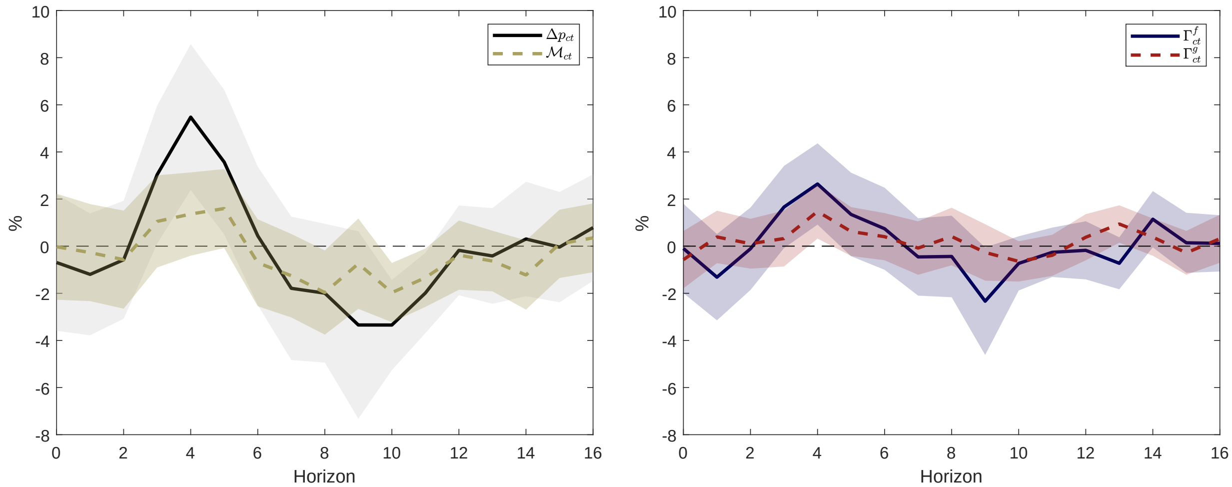
$$\ln Z_{dc,t+h} = \alpha_{dc,h} + \beta_{d,h}\hat{\varepsilon}^m_{ct} + \gamma_{dc,h}X_{c,t} + \delta_{i,h}\ln Z_{dc,t-1} + u^h_{dc,t+h}, \tag{3.6}$$

where $Z_{dc,t+h}$ is the (cumulative) contribution level of inflation component $d \in \{\mathcal{M}_{ct}, \Gamma^f_{ct}, \Gamma^g_{ct}\}$ and country c, $\hat{\varepsilon}^m_{ct}$ is an identified monetary policy shock and $X_{c,t}$ are additional controls. We construct contribution levels $Z_{dc,t+h}$ by normalizing the first observation to 100 and defining them so that their year-on-year log differences reproduce the respective components ($\mathcal{M}_{ct}, \Gamma^f_{ct}, \Gamma^g_{ct}$), i.e. $\Gamma^d_{ct} = \Delta \ln Z_{dc,t}$. Working with $\Delta \ln Z_{dc,t}$, is not only more convenient – since we already have the contributions of the components – but also required for an exact decomposition of the aggregate impulse response into the responses of its individual components.[15]

Because identified monetary policy shocks are not available for all countries in our sample, we restrict the analysis to the United States and the Euro Area. For Austria, Belgium, Germany, Spain, France, and the Netherlands, we use the Euro Area monetary policy shocks from Jarociński and

[15]The estimation procedure closely follows Aruoba and Drechsel (2024). In a first step, the local projections are run using only control variables, excluding the monetary policy shock. In the second step, local projections are estimated on the residuals from the first stage, with the shock as the sole explanatory variable. Regressions on the controls are estimated separately country by country, to allow for country-specific coefficients. The residuals are then stacked across countries to increase the number of observations, and the local projections are estimated on the shocks. Finally, the component estimates and their standard errors are re-aggregated, accounting for cross-component dependence within a seemingly unrelated regression (SUR) framework. We thank the authors for sharing their code.

Figure 9: Impulse response functions for aggregate inflation and components



(a) Aggregate inflation & macro component

(b) Granular residuals

Notes: The left panel (a) displays the quarterly results of the local projections on all components aggregated together (Δp_{ct}) and on the macro component ($\mathcal{M}_{ct}$). The right panel (b) displays the results of the local projections on the firm (Γ^f_{ct}) and category (Γ^g_{ct}) granular residuals. Shaded areas represent 90% confidence bands based on HAC standard errors.

Karadi (2020)[16] and the control variables from Aruoba and Drechsel (2024): the country-specific unemployment rate, industrial production index, nominal effective exchange rate, ECB policy rate, and the stock price index (EURO STOXX 50). For the United States, we use the Fed monetary policy shocks from the same source (Jarociński and Karadi, 2020) and similar controls: unemployment rate, industrial production index, nominal effective exchange rate, Federal Funds rate, and the stock price index (S&P 500). We include three lags for each control variable and set the maximum horizon for the local projections to 16 quarters.[17]

Figure 9 displays the impulse response functions (IRFs) to a one-percent contractionary monetary policy shock for aggregate inflation (Δp_{ct}), of the macro component ($\mathcal{M}_{ct}$), and of the granular residuals Γ^f_{ct} and Γ^g_{ct}. The figure shows the responses, in percentage points, for each series. The IRF for aggregate inflation (panel (a)) first rises before declining in response to a contractionary monetary policy shock. This resembles the well-known price puzzle documented in the macroeconomics

[16]We use the updated series provided by the authors (`https://github.com/marekjarocinski`) and aggregate them to quarterly frequency by summing within each quarter, as suggested by Wong (2021) and applied, for example, by Ottonello and Winberry (2020).

[17]For the Euro Area control variables, we use the following data sources: seasonally adjusted unemployment for each country from Eurostat, seasonally adjusted industrial production index for each country from Eurostat, daily nominal effective exchange rate (NEER) of the euro against 41 trading partners from the European Central Bank (ECB), main refinancing operations rate from the ECB, EURO STOXX 50 equity index closing value monthly average from the ECB. For the US control variables, we use the following data sources: seasonally adjusted unemployment from Eurostat, industrial production total index and Federal Funds Effective Rate from the Board of Governors of the Federal Reserve System, retrieved from FRED, daily NEER of the US dollar against 64 economies from the Bank for International Settlements (BIS), S&P closing value daily from Stooq (https://stooq.com/q/d/?s=%5Espx). Variables originally reported at monthly or daily frequency were aggregated by taking their quarterly averages.

literature (see, for example, Christiano et al. 1999). In contrast, the IRF for the macro component follows the pattern we would expect from theory, showing negative responses after roughly six quarters without a significant initial increase in inflation. The initial increase in inflation is due to the two granular residuals (panel (b)), which contribute positively and significantly during the first few quarters in which the aggregate inflation IRF exhibits the price puzzle. This suggests that the granular components may be primarily responsible for the temporarily positive response of aggregate inflation to monetary contractions. At the peak of the price puzzle (4 quarters out), 75% of the aggregate inflation response is due to the granular residuals.

Appendix Figure A6 further decomposes the firm granular component into the idiosyncratic subcomponent ($\sum_f w_{fct-4}\delta_{fct}$) and the sensitivity subcomponent ($\sum_f w_{fct-4}\lambda_{fc}\eta^f_{ct}$). The figure shows a noisy response of $\sum_f w_{fct-4}\delta_{fct}$, consistent with δ_{fct} capturing firm-specific shocks, whereas $\sum_f w_{fct-4}\lambda_{fc}\eta^f_{ct}$ exhibits a smoother and significantly positive IRF over the horizon of the price puzzle. This suggests that the reaction of large firms to monetary policy shocks tends to contribute to the price puzzle. One possible explanation is that large firms may amplify cost-channel effects, which have been proposed as one of the main mechanisms behind the price puzzle (see, for example, Ravenna and Walsh, 2006). As tighter monetary policy increases financing costs for working capital or imported inputs, the largest firms firms with greater market power can raise prices rather than reduce margins. Large firms are particularly relevant in this context because their size and market concentration allow them to adjust prices strategically and pass on higher financing or input costs more easily than smaller firms, thereby reinforcing short-run inflationary pressures after a contractionary policy shock. Moreover, strategic complementarity in price setting among dominant firms could further delay the disinflationary effects of monetary tightening. This aligns with theoretical models of pricing behavior in concentrated markets (Mongey, 2021; Wang and Werning, 2022; Mongey and Waugh, 2025), which suggest that the aggregate price level responds more sluggishly to monetary policy shocks in more concentrated markets.[18]

4. Conclusion

A sizable and growing literature has established that large firms play an important role in the economy, and that idiosyncratic shocks to these firms contribute substantially to aggregate fluctuations. However, there has been little to no empirical evidence on whether, and to what extent, inflation is affected by this phenomenon.

This paper uses barcode-level data for 16 advanced and emerging market countries and an extension of the granular residual methodology of Gabaix (2011) to study the role of individual firms and

[18] Interpreting the contribution of the category-level granular residual is more challenging, as the IRFs may capture heterogeneity in underlying characteristics within large categories, such as variation in their import content.

categories in the overall inflation. Indeed, we find that in advanced economies, idiosyncratic firm components explain a substantial share – 41% – of inflation variance. Shocks to product categories explain an additional 15%, implying that most of the variability of inflation in advanced economies is due to granular sources. The picture is quite different in the emerging markets, where the average level of inflation is higher, and the firm granular component contributed only 20% to the variation in inflation. We also examine the role of large retailers for fluctuations in overall inflation, finding that they play a moderate yet distinct role. In the cross-section of countries, the granular residuals are more important in countries with more concentrated product markets and lower average inflation.

Our methodology allows us to decompose the overall granular residuals into the parts due to truly idiosyncratic shocks, and due to the greater responsiveness of large firms to common shocks. We find that the former is more important for the firm granular residuals, especially prior to 2021. Furthermore, we find that in advanced economies, the granular components increased in importance post-2020, implying that in these countries the higher inflation was in part a "granular inflation surge."

Finally, we show that granularities contribute to a more sluggish and initially inverted response of aggregate inflation to contractionary monetary policy shocks. This finding suggests that market concentration may be an important factor in shaping monetary non-neutrality. While our analysis provides reduced-form empirical evidence on this channel, further research is needed to better understand the implications of granularity for monetary transmission and the design of monetary policy.

References

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012): "The network origins of aggregate fluctuations," *Econometrica*, 80, 1977–2016.

Alvarez, F. and F. Lippi (2014): "Price setting with menu cost for multiproduct firms," *Econometrica*, 82, 89–135.

Alvarez-Blaser, S., A. Cavallo, A. MacKay, and P. Mengano (2024): "Markups and Cost Pass-through Along the Supply Chain," Tech. rep., mimeo.

Amiti, M., O. Itskhoki, and J. Konings (2014): "Importers, Exporters, and Exchange Rate Disconnect," *American Economic Review*, 104, 1942–78.

——— (2019): "International shocks, variable markups, and domestic prices," *The Review of Economic Studies*, 86, 2356–2402.

Amiti, M. and D. E. Weinstein (2018): "How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data," *Journal of Political Economy*, 126, 525–587.

Aruoba, S. B. and T. Drechsel (2024): "The long and variable lags of monetary policy: Evidence from disaggregated price indices," *Journal of Monetary Economics*, 148, 103635.

Auer, R., A. Burstein, and S. M. Lein (2021): "Exchange Rates and Prices: Evidence from the 2015 Swiss Franc Appreciation," *American Economic Review*, 111, 652–86.

Auer, R. A. and R. S. Schoenle (2016): "Market structure and exchange rate pass-through," *Journal of International Economics*, 98, 60–77.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. V. Reenen (2020): "The Fall of the Labor Share and the Rise of Superstar Firms," *Quarterly Journal of Economics*, 135, 645–709.

Beck, G. W., K. Carstensen, J.-O. Menz, R. Schnorrenberger, and E. Wieland (2024): "Nowcasting consumer price inflation using high-frequency scanner data: Evidence from Germany," ECB Working Paper Series No 2930.

Beck, G. W. and X. Jaravel (2021): "Prices and Global Inequality: New Evidence from Worldwide Scanner Data," Tech. rep.

Bhattarai, S. and R. Schoenle (2014): "Multiproduct firms and price-setting: Theory and evidence from US producer prices," *Journal of Monetary Economics*, 66, 178–192.

Blanco, A., C. Boar, C. J. Jones, and V. Midrigan (2024): "Non-Linear Inflation Dynamics in Menu Cost Economies," Working Paper 32094, National Bureau of Economic Research.

Bonomo, M., C. Carvalho, O. Kryvtsov, S. Ribon, and R. Rigato (2022): "Multi-Product Pricing: Theory and Evidence from Large Retailers," *The Economic Journal*, 133, 905–927.

Braun, R. and S. M. Lein (2021): "Sources of Bias in Inflation Rates and Implications for Inflation Dynamics," *Journal of Money, Credit and Banking*, 53, 1553–1572.

Brauning, F., J. L. Fillat, and G. Joaquim (2022): "Cost-Price Relationships in a Concentrated Economy," Working paper.

Bremus, F., C. M. Buch, K. N. Russ, and M. Schnitzer (2018): "Big Banks and Macroeconomic Outcomes: Theory and Cross-Country Evidence of Granularity," *Journal of Money, Credit and Banking*, 50, 1785–1825.

Burya, A. and S. Mishra (2022): "Variable markups, demand elasticity and pass-through of marginal costs into prices," Mimeo, University of Bern and Bank of America.

Campbell, J. Y. and J. Mei (1993): "Where Do Betas Come From? Asset Price Dynamics and the Sources of Systematic Risk," *The Review of Financial Studies*, 6, 567–592.

Carvalho, V. and X. Gabaix (2013): "The great diversification and its undoing," *American Economic Review*, 103, 1697–1727.

Carvalho, V. M. and B. Grassi (2019): "Large Firm Dynamics and the Business Cycle," *American Economic Review*, 109, 1375–1425.

Castro, R., G. Clementi, and Y. Lee (2015): "Cross-Sectoral Variation in The Volatility of Plant-Level Idiosyncratic Shocks," *Journal of Industrial Economics*, 63, 1–29.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999): "Monetary policy shocks: What have we learned and to what end?" *Handbook of Macroeconomics*, 1A, 65–148.

Covarrubias, M., G. Gutiérrez, and T. Philippon (2020): "From Good to Bad Concentration? US Industries Over the Past 30 Years," *NBER Macroeconomics Annual*, 34, 1–46.

Cox, L., G. Müller, E. Pasten, R. Schoenle, and M. Weber (2024): "Big G," *Journal of Political Economy*, 132, 3260–3297.

Daruich, D. and J. Kozlowski (2023): "Macroeconomic Implications of Uniform Pricing," *American Economic Journal: Macroeconomics*, 15, 64–108.

De Loecker, J., J. Eeckhout, and G. Unger (2020): "The Rise of Market Power and the Macroeconomic Implications," *The Quarterly Journal of Economics*, 135, 561–644.

Dedola, L., M. Strøm Kristoffersen, and G. Zullig (2021): "The extensive and intensive margin of price adjustment to cost shocks: Evidence from Danish multiproduct firms," Mimeo, University of Copenhagen.

DellaVigna, S. and M. Gentzkow (2019): "Uniform Pricing in U.S. Retail Chains," *The Quarterly Journal of Economics*, 134, 2011–2084.

di Giovanni, J., Kalemli-Özcan, A. Silva, and M. A. Yildirim (2023): "Pandemic-Era Inflation Drivers and Global Spillovers," Working Paper 31887, National Bureau of Economic Research.

di Giovanni, J. and A. A. Levchenko (2012): "Country size, international trade, and aggregate fluctuations in granular economies," *Journal of Political Economy*, 120, 1083–1132.

di Giovanni, J., A. A. Levchenko, and I. Mejean (2014): "Firms, destinations, and aggregate fluctuations," *Econometrica*, 82, 1303–1340.

——— (2018): "The micro origins of international business-cycle comovement," *American Economic Review*, 108, 82–108.

——— (2024): "Foreign shocks as granular fluctuations," *Journal of Political Economy*, 132, 391–433.

Döpper, H., A. MacKay, N. H. Miller, and J. Stiebale (2025): "Rising Markups and the Role of Consumer Preferences," *Journal of Political Economy*, 133, 2462–2505.

Eichenbaum, M., N. Jaimovich, S. Rebelo, and J. Smith (2014): "How Frequent Are Small Price Changes?" *American Economic Journal: Macroeconomics*, 6, 137–55.

Forbes, K., I. Hjortsoe, and T. Nenova (2020): "International Evidence on Shock-Dependent Exchange Rate Pass-Through," *IMF Economic Review*, 68, 721–763.

Franzoni, F., M. Giannetti, and R. Tubaldi (2024): "Supply Chain Shortages, Large Firms' Market Power, and Inflation," University of Lugano, Working Paper.

Friedman, M. (1963): *Inflation: Causes and Consequences*, New York: Asia Publishing House.

Gabaix, X. (2011): "The granular origins of aggregate fluctuations," *Econometrica*, 79, 733–772.

Gabaix, X. and R. S. J. Koijen (2024): "Granular Instrumental Variables," *Journal of Political Economy*, 132, 2274–2303.

GALAASEN, S., R. JAMILOV, R. JUELSRUD, AND H. REY (2021): "Granular Credit Risk," Working Paper 27994, National Bureau of Economic Research.

GALÍ, J. (2015): *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and Its Applications*, Princeton, NJ: Princeton University Press.

GARCÍA-LEMBERGMAN, E. (2025): "Multi-establishment Firms, Pricing and the Propagation of Local Shocks: Evidence from US Retail," Forthcoming, *Review of Economics and Statistics*.

GAUBERT, C. AND O. ITSKHOKI (2021): "Granular comparative advantage," *Journal of Political Economy*, 129, 871–939.

GAUBERT, C., O. ITSKHOKI, AND M. VOGLER (2021): "Government Policies in a Granular Global Economy," *Journal of Monetary Economics*, 121, 95–112.

HALTIWANGER, J. C. (1997): "Measuring and Analyzing Aggregate Fluctuations: The Importance of Building from Microeconomic Evidence," *Federal Reserve Bank of St.Louis Review*, 79, 55–77.

HOTTMAN, C. J., S. J. REDDING, AND D. E. WEINSTEIN (2016): "Quantifying the sources of firm heterogeneity," *The Quarterly Journal of Economics*, 131, 1291–1364.

JAMILOV, R., A. KOHLHAS, O. TALAVERA, AND M. ZHANG (2024): "Granular sentiments," Tech. rep., University of Oxford.

JAROCIŃSKI, M. AND P. KARADI (2020): "Deconstructing monetary policy surprises—the role of information shocks," *American Economic Journal: Macroeconomics*, 12, 1–43.

JOVANOVIC, B. (1987): "Micro shocks and aggregate risk," *The Quarterly Journal of Economics*, 102, 395–409.

KAPLAN, G. AND S. SCHULHOFER-WOHL (2017): "Inflation at the household level," *Journal of Monetary Economics*, 91, 19–38.

KARADI, P. AND A. REIFF (2019): "Menu Costs, Aggregate Fluctuations, and Large Shocks," *American Economic Journal: Macroeconomics*, 11, 111–46.

LONG, J. B. AND C. I. PLOSSER (1983): "Real business cycles," *Journal of Political Economy*, 91, 39–69.

MIDRIGAN, V. (2011): "Menu costs, multiproduct firms, and aggregate fluctuations," *Econometrica*, 79, 1139–1180.

MONGEY, S. (2021): "Market structure and monetary non-neutrality," NBER Working Paper 29233.

Mongey, S. and M. E. Waugh (2025): "Pricing Inequality," Tech. Rep. 33399, National Bureau of Economic Research.

Ottonello, P. and T. Winberry (2020): "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 88, 2473–2502.

Ravenna, F. and C. E. Walsh (2006): "Optimal monetary policy with the cost channel," *Journal of Monetary Economics*, 53, 199–216.

Redding, S. J. and D. E. Weinstein (2019): "Measuring Aggregate Price Indices with Taste Shocks: Theory and Evidence for CES Preferences," *The Quarterly Journal of Economics*, 135, 503–560.

Shapley, L. S. (1953): "A Value for N-Person Games," in *Contributions to the Theory of Games*, ed. by A. Tucker and R. D. Luce, Princeton, NJ: Princeton University Press, 31–40.

Wang, O. and I. Werning (2022): "Dynamic oligopoly and price stickiness," *American Economic Review*, 112, 2815–2849.

Wong, A. (2021): "Refinancing and The Transmission of Monetary Policy to Consumption," Working Papers 2021-57, Princeton University. Economics Department.

Woodford, M. (2003): *Interest and Prices: Foundations of a Theory of Monetary Policy*, Princeton, NJ: Princeton University Press.

ONLINE APPENDIX
(NOT FOR PUBLICATION)

A. Data construction

A.1 Identifying firms

We adopt a four-step procedure to harmonize firm names across countries. First, for the largest firms, we manually match the brands to the firms that own them and harmonize variations in their names. This helps us to fill missing firm information in instances where we have brand information but no firm information and to replace instances where the brand is listed in the firm field with the firm name. For example, we use "Unilever" as the firm name whenever the brands are "Dove," "Knorr," or "Ben & Jerry's." We also harmonize firm variations such as "Company Unilever" and "Unilever International" to the unique firm name "Unilever". Second, we fill in missing information on the firms using barcodes with the same prefix (the first eight digits).[19] To do this, we sort our data by barcode. If a product without firm information shares the same barcode prefix with both the previous and the next product in this sorted list of barcodes, and both the previous and the next product have the same firm identifier, we use the firm name also for the middle product. Third, for the remaining products with missing firm identifier, we use the most common firm name within the eight-digit prefix and country. This is motivated by the methodology used in Hottman et al. (2016) and recently in Burya and Mishra (2022) and confirmed by manual checks of the allocated barcodes and their ownerships in GS1.[20]

In the fourth step, we append the data for all countries and use information from the overlap of barcodes across countries. If we observe that a given barcode is always associated with the same firm in some countries, we also use this firm name in countries in which the firm name was missing in the original data. Specifically, if firm "X" from a country was matched in N barcodes from another country and it was always matched to the same firm "Y," we populate the firm name with "X" in this country for all barcodes identified to the firm "Y," and also all the barcodes identified with firm "Y" without a barcode match. We do this bilaterally for all countries and barcodes that had so far not been matched with a firm in the previous bilateral combination.[21]

Table A1 reports summary statistics before and after the matching process for firms. Panel A summarizes the original data.[22] Panel A shows that many of the national datasets have a large share of observations without identified firm, and most of the firms are national only (ie observed on one market only).

[19]Typically, a barcode has eight to 13 digits. It is assigned to products by GS1, a global collaboration platform, that assigns unique barcodes to products. Firms have to apply for these barcodes with GS1 and are usually identified in the first seven to eleven digits of the barcode, which is what we refer to as "prefix", as described also in Hottman et al. (2016).

[20]For these manual checks, we relied on the GS1 search tool (https://gepir.gs1.org/index.php/search-by-gtin) to retrieve firm information for a subset of barcodes lacking these data and also on the adjacent barcodes in the sorted data with available firm information as explained in the main text. The website was accessed in March 2023.

[21]On the other hand, if firm "X" from a country was matched N times but to different firms, we do not replace it for the barcodes which did not have a match. This step helps to fill missing information and to match differently labelled firms especially in countries sharing European Article Number (EAN) barcodes, since those are unique across countries.

[22]The observations included in table A1 and throughout the analysis already contain some minor adjustments on the barcodes of some countries that had an extra digit or prefix. For example, in the French data, the barcodes had a prefix with either zeros or a digit denoting products from a specific shop. In addition, for finding missing firms we had to find all the country-specific labels for "other" firms and replace them with "other".

Table A1: Firms before vs after matching procedure in quarterly data

		A: Firms in original data			B: Firms after matching			
	Obs	Missing	Number	Int.	Missing	Number	Int.	Years
AR	921,812	0.19	3,076	0.11	0.05	4,569	0.16	2011-2022
AT	1,374,433	0.00	5,089	0.48	0.00	4,849	0.65	2008-2022
BE	2,480,869	0.02	15,526	0.47	0.01	12,609	0.59	2008-2022
BR	1,451,640	0.13	11,377	0.06	0.02	13,443	0.07	2011-2022
CL	434,586	0.01	1,327	0.21	0.00	1,532	0.21	2012-2022
CN	4,178,845	0.00	94,507	0.02	0.00	93,372	0.03	2011-2022
DE	6,830,261	0.02	9,728	0.32	0.01	11,033	0.50	2005-2022
ES	3,509,722	0.01	14,516	0.12	0.00	14,870	0.22	2007-2022
FR	5,521,899	0.15	3,526	0.41	0.04	6,735	0.66	2008-2022
HU	834,542	0.01	3,892	0.35	0.00	3,798	0.40	2010-2022
MX	963,009	0.01	4,493	0.12	0.01	4,511	0.12	2011-2022
NL	3,287,757	0.08	12,881	0.53	0.03	10,867	0.62	2008-2022
RU	2,063,858	0.03	13,533	0.10	0.02	13,310	0.15	2011-2020
SE	958,897	0.01	3,890	0.29	0.01	3,622	0.39	2006-2022
UK	5,191,847	0.11	6,694	0.21	0.09	6,664	0.19	2005-2022
US	12,638,612	0.01	36,530	0.05	0.00	36,548	0.05	2010-2020
Total	52,642,589	0.05	219,672	0.06	0.02	213,124	0.07	2005-2022

Notes: Obs are the number of product-country-YoY differences available using quarterly frequency. Missing is the share of these observations for which the manufacturer could not be found. Number is the number of different firms available and Int. (international) is the share of these different firms which is also observed in at least one other country.

Panel B of Table A1 reports the same descriptive statistics as in Panel A after the matching procedure described in the main text. From comparison of the country-specific statistics in panel A with panel B of Table A1, it is evident that the number of observations with missing firms strongly declines. This is mainly because we found the information in another country using the same unique barcode or because we used available brand information instead. The later step results in a larger number of firms available in some countries after the matching procedure. Second, we can see that from the available firms in each country, the share of those that appear in at least a second country strongly increases. For most European countries this number is well above 50%. Finally, when looking at the pooled numbers, the total amount of unique firms across countries declines by around 10% and the share of observations with missing firm information declines from 10% to zero.

Appendix Table A7 also provides the estimates from the empirical analysis without implementing the last step of our matching procedure.

Table A2: Share of expenditures on unidentified retailers

Weight of unidentified:	Firms (in %)	Firms in retailer dataset (in %)	Retailers in retailer dataset (in %)
Advanced Economies	1.72	1.69	3.24
AT	0.00	0.00	0.80
BE	0.66	0.66	2.80
DE	0.22	0.21	9.76
ES	0.04	0.04	4.11
FR	0.95	0.83	0.36
NL	1.06	0.97	1.83
SE	0.72	0.66	0.69
UK	11.75	11.81	2.75
US	0.06	0.05	6.02
Emerging Economies	1.39	1.49	31.52
AR	7.75	8.46	50.27
BR	1.11	1.05	60.47
CL	0.08	0.08	14.15
CN	0.02	0.02	57.71
HU	0.01	0.01	2.05
MX	0.41	0.40	3.17
RU	0.36	0.43	32.85

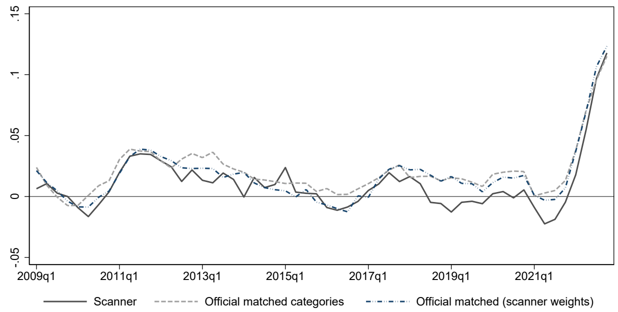
Notes: weight of unidentified firms and retailers defined as the average $\sum_{f=other} w_{ifgct-4}$ and $\sum_{s=other} w_{ifgct-4}$, respectively, in the product-level sample or retailer sample over all periods. Advanced economies and emerging markets rows report the simple average of the statistic across the corresponding economies.

Table A3: Descriptive statistics of retailer sample

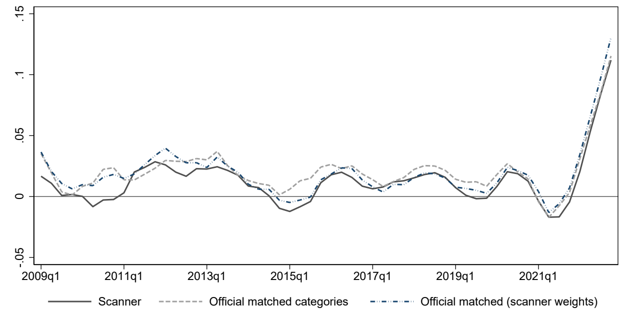
	(1)	(2)	(3)	(4)	(5)
				Expenditure Share of	
	N of Δp_{ifgsct}	N_i	N_s	Top 10 s	Top 1% s
AR	1,204,451	183,914	44	0.44	0.10
AT	2,587,427	321,368	136	0.85	0.31
BE	3,331,931	466,009	153	0.84	0.41
BR	2,587,603	569,649	430	0.18	0.12
CL	1,156,945	144,488	91	0.73	0.28
CN	5,650,157	1,295,729	489	0.26	0.16
DE	12,237,528	1,205,255	21	0.81	0.16
ES	6,149,319	866,370	203	0.76	0.54
FR	11,100,586	1,279,242	311	0.82	0.61
HU	1,207,029	190,498	85	0.83	0.16
MX	3,167,009	497,031	209	0.70	0.47
NL	6,522,967	845,916	137	0.76	0.36
RU	2,773,816	595,970	433	0.44	0.35
SE	1,709,880	203,764	124	0.93	0.64
UK	7,956,807	852,432	83	0.90	0.28
US	38,103,213	5,561,402	727	0.51	0.48
Total	107,446,668	3,913,633	3,448	0.67	0.34

Notes: Transactions refers to the number of entries in the raw data. N of Δp_{ifgsct} indicate the number of available year-on-year inflation rates using the product-retailer-quarter aggregation. N_s and N_i are the number of unique retailers and products that appear in the retailer data. Exp Share Top 10 s and Exp Share Top percentile s indicate the expenditure shares in the largest 10 retailers and in the top percentile retailers, respectively.

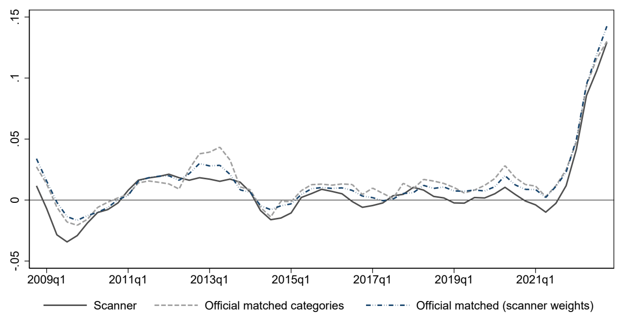
Figure A1: Official vs scanner data aggregate inflation (advanced economies)



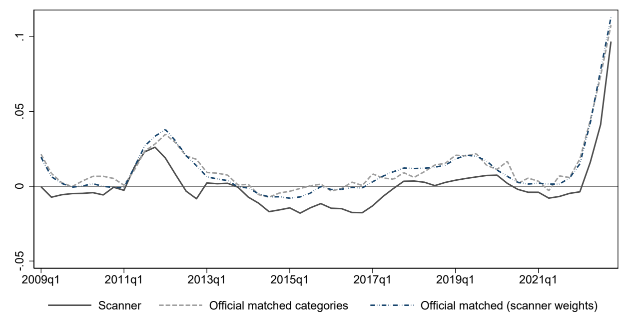
(a) AT



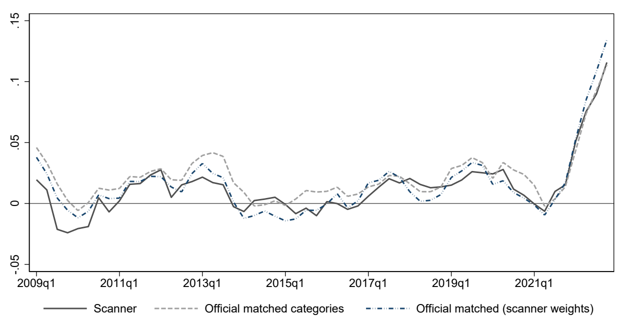
(b) BE



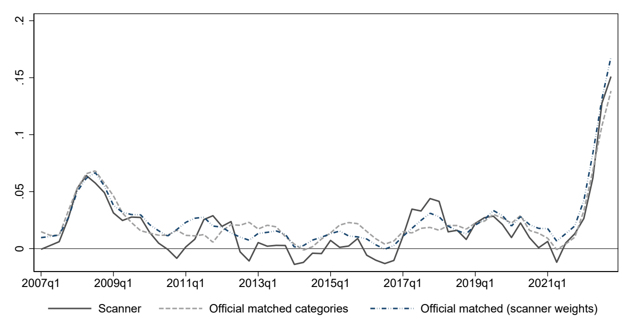
(c) ES



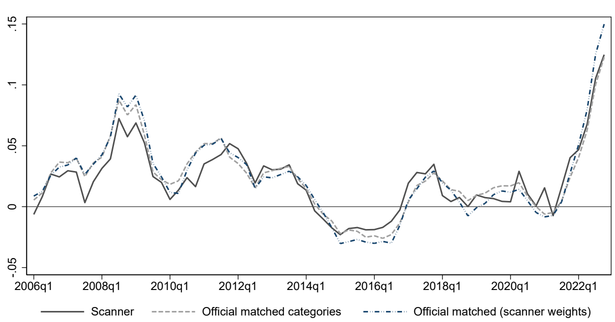
(d) FR



(e) NL

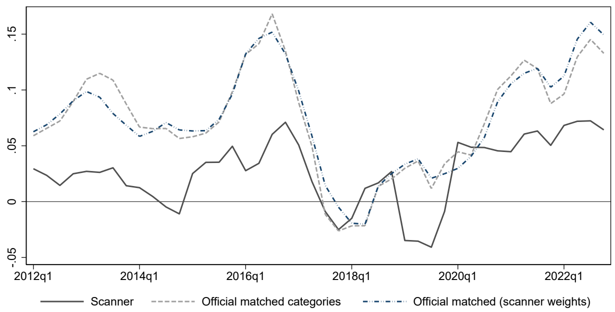


(f) SE

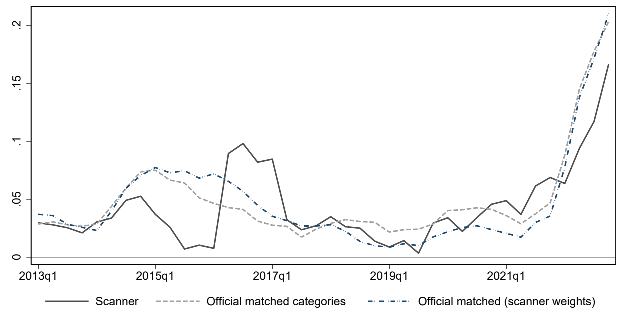


(g) UK

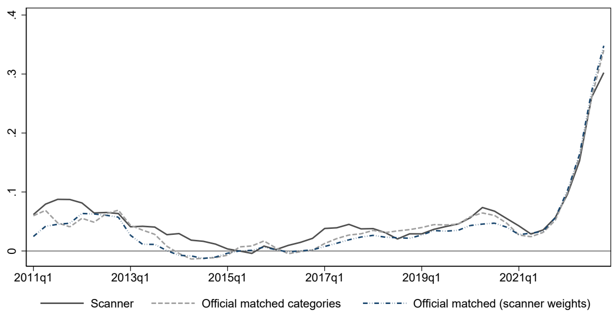
Figure A1: Official vs scanner data aggregate inflation cont. (emerging markets)



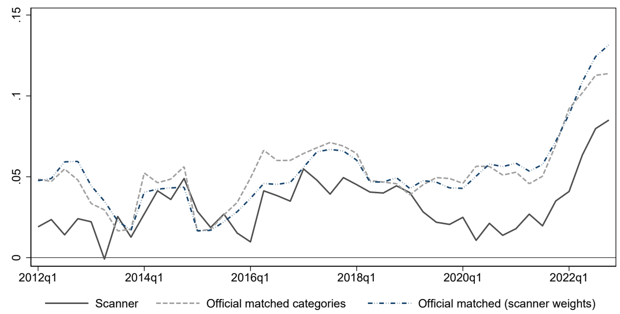
(a) BR



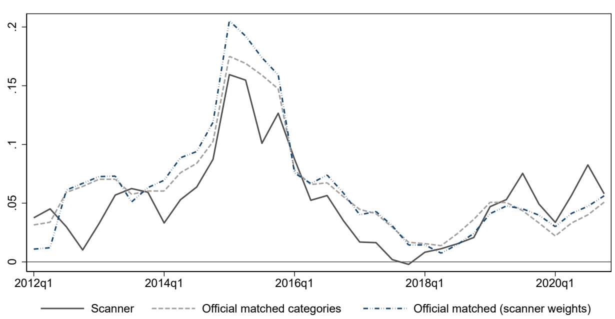
(b) CL



(c) HU



(d) MX



(e) RU

Notes: All figures show the year-on-year inflation rates. “Official matched categories” use official inflation rates and weights while “Official matched (scanner weights)” weights the official inflation rate of each category with the weight observed in the scanner data for the same category. The dynamics for Germany, the US and Argentina can be found in Figure 2 in the main text. China not displayed due to missing necessary official data.

Table A4: Correlation with official inflation

	Correlation
AR	0.84
AT	0.93
BE	0.97
BR	0.72
CL	0.73
DE	0.95
ES	0.97
FR	0.94
HU	0.97
MX	0.71
NL	0.94
RU	0.86
SE	0.95
UK	0.95
US	0.94
Average correlation	0.89
Total correlation	0.96

Notes: total correlation is measured pooling all countries.

B. Derivation of pricing equation

Motivation for keeping the number of factors low. Following Amiti et al. (2019), we start from the pricing equation of a firm f:[23]

$$p_{ft} = mc_{ft} + M_f(p_{ft}, \boldsymbol{p}_{-ft}; \boldsymbol{\xi}_t)),$$

where p_{ft} is the log price, mc_{ft} are the log marginal costs, and M_f is the log markup function which depends on the own price p_{ft}, the vector of competitors prices $\boldsymbol{p}_{-ft}$ and the vector of demand shocks of all firms $\boldsymbol{\xi}_t$.

Taking the total derivative we get

$$\Delta p_{ft} = \frac{1}{1+\Psi_{ft}}\Delta mc_{ft} + \frac{\Psi_{-ft}}{1+\Psi_{ft}}\Delta p_{-ft} + \underbrace{\frac{1}{1+\Psi_{ft}}\sum_{j=1}^{N}\frac{\partial M_f(\boldsymbol{p}_{ft};\boldsymbol{\xi}_t)}{\partial \xi_{jt}}\Delta\xi_{jt}}_{\varepsilon_{ft}\text{ effective demand shock}}, \tag{B.1}$$

where j indexes firm f's competitors, Δp_{-ft} is the Laspeyres price index of the competitors' price changes, $\Psi_{ft} \equiv -\frac{\partial M_f(p_{ft}, \boldsymbol{p}_{-ft}; \boldsymbol{\xi}_t)}{\partial p_{ft}}$ and $\Psi_{-ft} \equiv \sum_{j\neq f}\frac{\partial M_f(p_{ft}, \boldsymbol{p}_{-ft}; \boldsymbol{\xi}_t)}{\partial p_{jt}}$.

Using the assumptions in Amiti et al. (2019), $\Delta p_{-ft} = \sum_{j\neq f}\frac{S_{jt}}{1-S_{ft}}\Delta p_{jt}$ and $\Psi_{ft} = \Psi_{-ft}$, aggregating to Δp_t, replacing Δp_{-ft}, and solving yields

$$\Delta p_{ft} = \frac{1}{1+\tilde{\Psi}_{ft}}\Delta mc_{ft} + \frac{\tilde{\Psi}_{-ft}}{1+\tilde{\Psi}_{ft}}\frac{1}{\sum_{j=1}^{N}\frac{S_{jt}}{1+\tilde{\Psi}_{jt}}}\sum_{j=1}^{N}\left[\frac{S_{jt}}{1+\tilde{\Psi}_{jt}}\Delta mc_{jt} + S_{jt}\tilde{\varepsilon}_{jt}\right] + \tilde{\varepsilon}_{ft} \tag{B.2}$$

with $\tilde{\Psi}_{ft} \equiv \frac{\Psi_{ft}}{1-S_{ft}}$ and $\tilde{\varepsilon}_{jt} \equiv \frac{1}{1+\frac{S_{jt}\tilde{\Psi}_{jt}}{1+\Psi_{jt}}}\varepsilon_{jt}$.

Note that under Cournot competition and nested CES demand, with between- and within-industry elasticities of substitution ρ and η, the elasticities are:

$$\Psi_{ft} = \Psi_{-ft} = \frac{(\rho-1)S_{ft}}{1+\frac{\rho(\eta-1)}{(\rho-\eta)(1-S_{ft})}}. \tag{B.3}$$

Small firms ($S_{it} \to 0$) only react to own marginal costs while bigger firms also react strongly to competitors' shocks and less to own costs.

Assuming $\Delta mc_{ft} = \delta_t + \lambda_f\eta_t + \delta_{ft}$ (marginal costs have a common component δ_t, differential sensitivity to common shocks $\lambda_f\eta_t$, and an own idiosyncratic shock δ_{it}), we can rewrite the pricing

[23] This derivation follows closely Appendix C in Amiti et al. (2019), which can be consulted for further details.

equation as:

$$
\begin{aligned}
\Delta p_{ft} &= \delta_t + \left\{ \frac{1}{1+\tilde{\Psi}_{it}}\lambda_f + \frac{\tilde{\Psi}_{-ft}}{1+\tilde{\Psi}_{ft}} \frac{1}{\sum_{j=1}^{N} \frac{S_{jt}}{1+\tilde{\Psi}_{jt}}} \sum_{j=1}^{N} \left[\frac{S_{jt}}{1+\tilde{\Psi}_{jt}} \lambda_j \right] \right\} \eta_t \\
&+ \frac{\tilde{\Psi}_{-ft}}{1+\tilde{\Psi}_{ft}} \frac{1}{\sum_{j=1}^{N} \frac{S_{jt}}{1+\tilde{\Psi}_{jt}}} \underbrace{\sum_{j=1}^{N} \left[\frac{S_{jt}}{1+\tilde{\Psi}_{jt}} \delta_{jt} \right]}_{\eta_{2,t}} \\
&+ \frac{\tilde{\Psi}_{-ft}}{1+\tilde{\Psi}_{ft}} \frac{1}{\sum_{j=1}^{N} \frac{S_{jt}}{1+\tilde{\Psi}_{jt}}} \underbrace{\sum_{j=1}^{N} \left[S_{jt} \tilde{\varepsilon}_{jt} \right]}_{\eta_{3,t}} + \frac{1}{1+\tilde{\Psi}_{ft}} \delta_{ft} + \tilde{\varepsilon}_{ft}.
\end{aligned}
$$

In addition to the true latent factor η_t there are two additional "factors" $\eta_{2,t}$ and $\eta_{3,t}$. Then the observed correlation which we try to absorb with more factors could have a firm level idiosyncratic origin, as top firms have a high loading on $\eta_{2,t}$, $\eta_{3,t}$ and a high contribution to $\eta_{2,t}$, $\eta_{3,t}$ at the same time – e.g., the second and third factors will absorb the effect of a Unilever shock on the economy.

C. Price synchronization at the firm level

This section presents empirical results on microeconomic pricing decisions of firms and retailers, that motivate the focus on the firm dimension in the main analysis. More precisely, we document synchronization of price changes within firms and retailers, which is usually larger than the synchronization within categories.

We follow the literature on price-setting by multiproduct firms and estimate a multinomial logit model similar to the one used in Bhattarai and Schoenle (2014). The difference in our paper is that we analyze two competing synchronization forces, retailers and firms. For this reason, we use price changes aggregated at the product-retailer-country-quarter level (p_{ifgsct}). We estimate the following multinomial logit model for each country:

$$Pr(Y_{ifgst} = 1, 0, -1 | X_{ifgst} = \chi) \quad = \quad \phi(\beta X_{ifgst})$$

where Y_{ifgst} is an indicator variable for positive, no, or negative average price adjustment of product i, produced by firm f and sold by retailer s between quarter t and $t-1$. Product i belongs to category g.[24]

The main explanatory variables of interest is the share of same-signed price changes within the firm, the retailer, and the category, excluding the price change of the product i. As additional control variables we include quarter fixed effects, aggregate retail inflation and also add the average price change of products in the same firm, retailer and category as a measure of marginal costs.

Table A6 shows that synchronization of prices at the firm level is substantial and of comparable size if not larger than the synchronization driven by retailers and categories. The table reports the percentage point change in the probability of a positive or negative price change after a one-standard deviation change around the mean share of same signed price changes for each dimension.[25] For example in the US, a one standard deviation change in the fraction of positive price changes of products of the same firm is associated with a 3.88 percentage points higher probability of a positive price change.

[24] The base category of the model is no price change. We weight each product with expenditure weights.

[25] All other dimensions are left at their respective weighed averages with the exception of the quarter fixed effects which are all set equal to 0.25 in order to give each quarter the same importance.

Table A5: Marginal effect of a 1 $Std.Dev.$ on the probability of a Q-o-Q price change

	Positive change			Negative change			
	g	f	s	g	f	s	Obs
AR	5.24	6.52	6.35	0.43	2.74	3.91	926,569
AT	4.42	4.33	3.05	3.84	3.16	3.03	2,685,373
BE	3.65	7.39	3.93	3.84	3.77	4.81	3,572,527
BR	3.19	2.69	2.82	2.55	2.18	3.38	3,345,732
CN	2.29	3.37	4.46	1.94	2.68	4.68	5,789,515
DE	5.46	2.84	0.91	5.94	4.67	0.40	13,003,922
ES	3.85	5.96	3.56	2.76	4.03	5.79	6,484,983
FR	3.28	4.40	4.05	0.37	6.58	4.77	11,510,012
MX	2.55	4.69	2.04	3.64	3.27	2.65	2,811,364
NL	4.20	6.38	0.24	2.64	5.84	1.92	7,433,293
RU	4.35	4.47	5.45	4.60	3.49	3.95	3,959,745
SE	4.79	4.03	1.70	4.85	2.95	1.12	2,285,503
UK	5.28	4.25	2.20	3.27	3.71	1.42	9,741,835
US	3.77	3.88	7.40	2.40	2.44	8.81	45,738,693

Notes: Columns g, f, s report the change in the probability (in percentage points) of a positive or negative price change after a one-standard deviation change of the share of same-sign price changes around the mean in each dimension. "Obs" reports the number of observations included in the model.

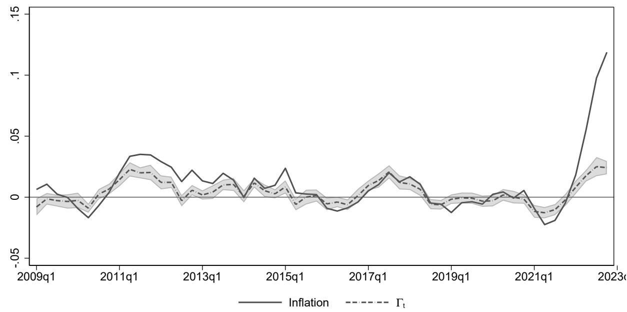
Table A6: Marginal effect of $\pm 1/2 Std.Dev.$ on the probability of a Q-o-Q price change

	Positive change			Negative change			
	g	f	s	g	f	s	Obs
AR	4.59	4.53	3.63	1.09	2.87	3.69	1,563,918
AT	5.26	5.01	3.02	3.54	3.18	2.94	3,158,861
BE	4.00	8.13	4.51	3.35	3.89	4.72	4,197,579
BR	3.82	2.16	2.86	3.00	1.80	3.31	3,865,101
CL	6.21	4.43	3.28	2.17	3.01	2.77	1,434,255
CN	2.16	3.28	4.18	2.37	3.05	4.84	7,700,815
DE	5.48	4.36	1.15	4.21	5.05	0.68	14,742,195
ES	4.71	6.37	4.55	2.30	4.09	6.47	7,539,907
FR	4.16	4.79	4.36	0.42	6.48	4.60	13,397,169
HU	8.29	4.88	3.75	2.42	3.59	3.37	1,502,777
MX	2.34	8.97	3.75	1.67	5.17	4.56	4,247,307
NL	4.55	7.07	0.70	2.21	5.89	1.94	8,575,007
RU	4.32	4.50	5.44	4.56	3.50	3.95	3,951,207
SE	6.08	4.96	1.44	4.12	2.75	1.58	2,103,656
UK	6.00	4.66	1.41	3.25	3.25	1.52	10,269,552
US	3.97	3.93	7.34	2.59	2.48	8.93	48,416,961

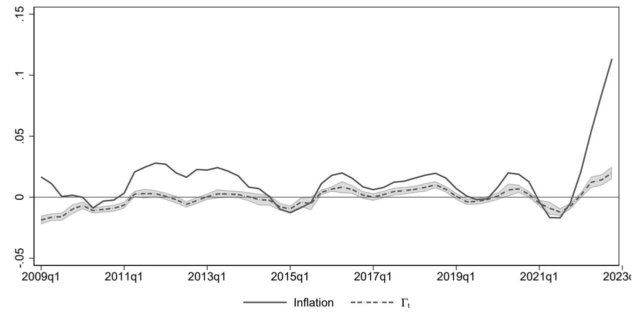
Notes: Columns g, f, s report the change in the probability (in percentage points) of a positive or negative price change after a one-standard deviation change of the share of same-sign price changes around the mean in each dimension. "Obs" reports the number of observations included in the model.

D. Additional figures and tables

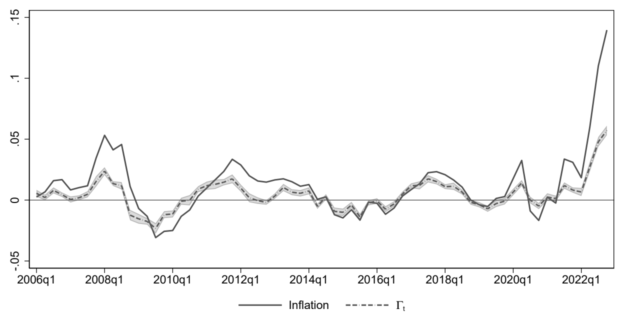
Figure A2: Aggregated retail inflation and simple granular residual (advanced economies)



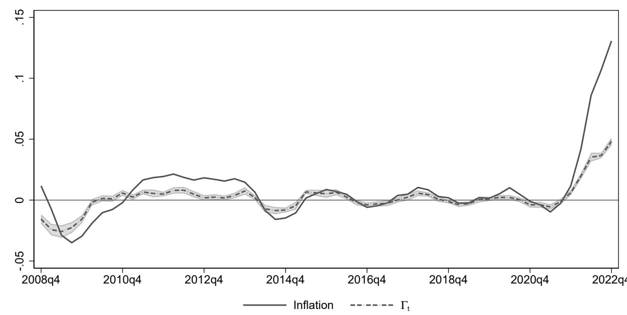
(a) AT



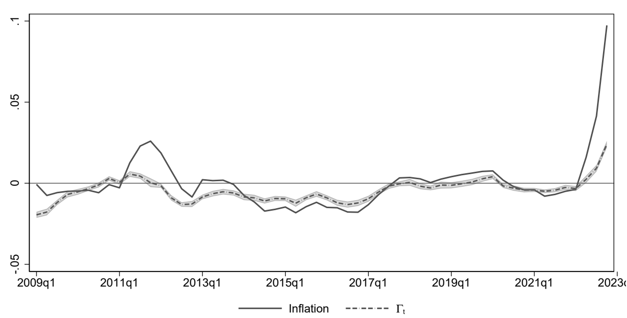
(b) BE



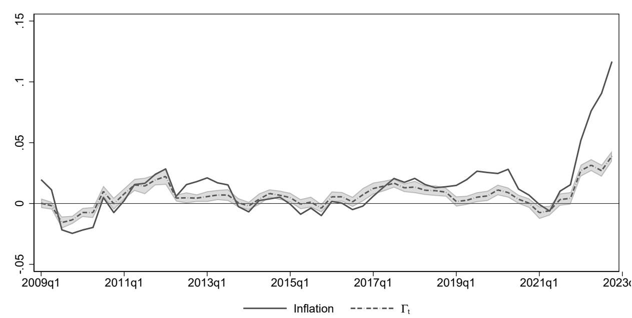
(c) DE



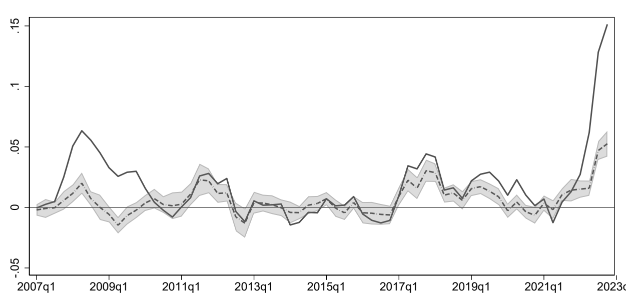
(d) ES



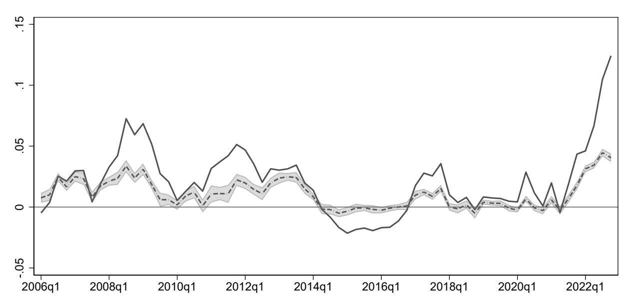
(e) FR



(f) NL

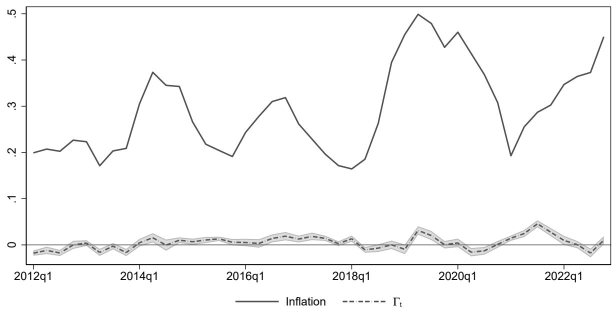


(g) SE

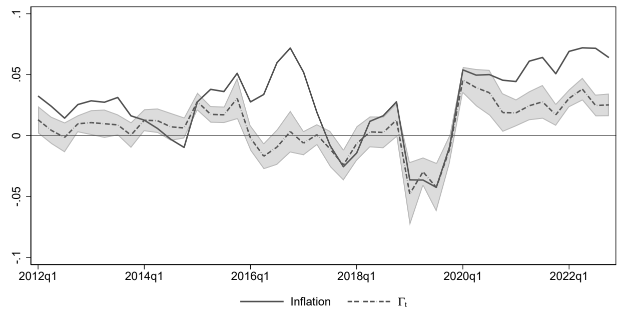


(h) UK

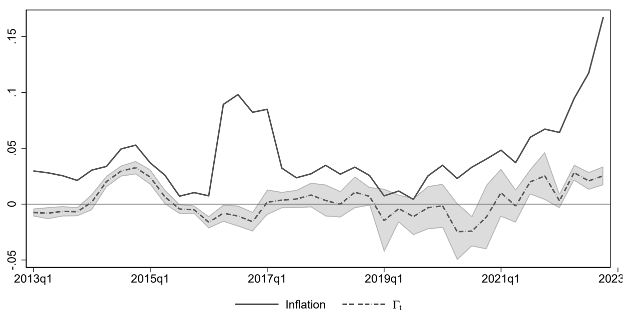
Figure A2: Aggregated retail inflation and simple granular residual cont. (emerging markets)



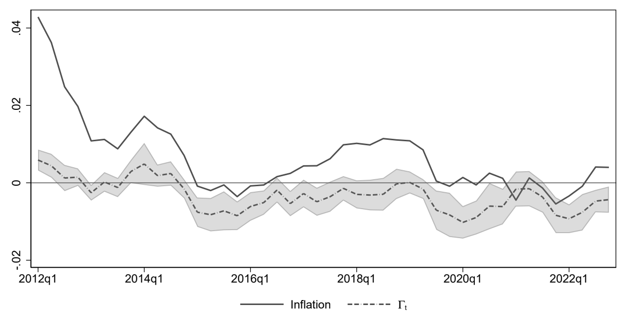
(a) AR



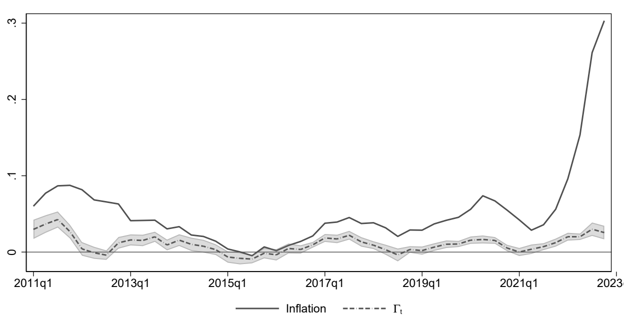
(b) BR



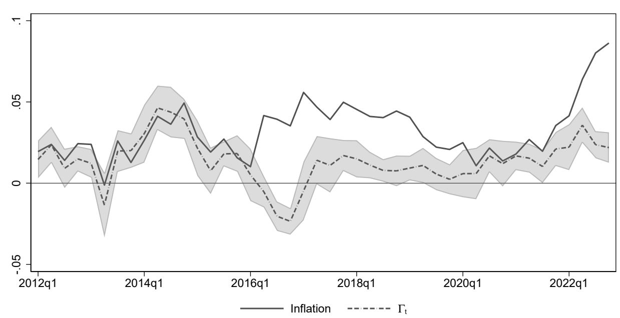
(c) CL



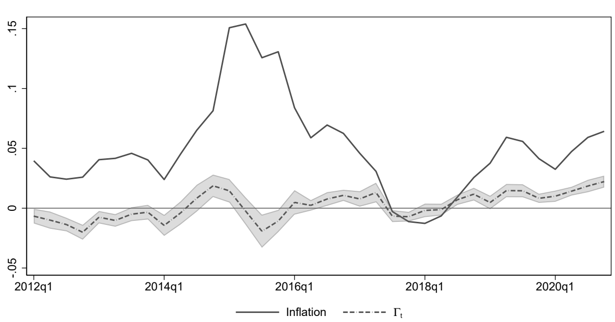
(d) CN



(e) HU



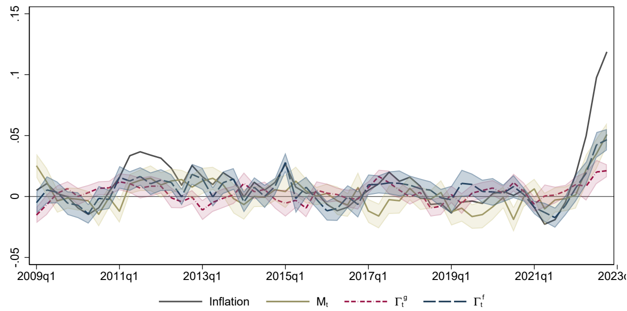
(f) MX



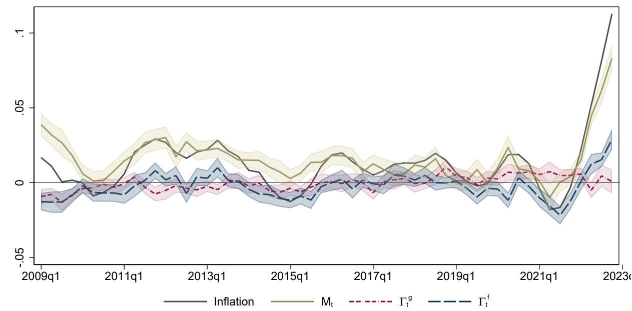
(g) RU

Notes: The figure displays the year-on-year overall inflation and the contribution of the simple granular residual until the last available period. Since data after 2020 was not available for the US, the figure for the US is only displayed in Figure 5 in the main text.

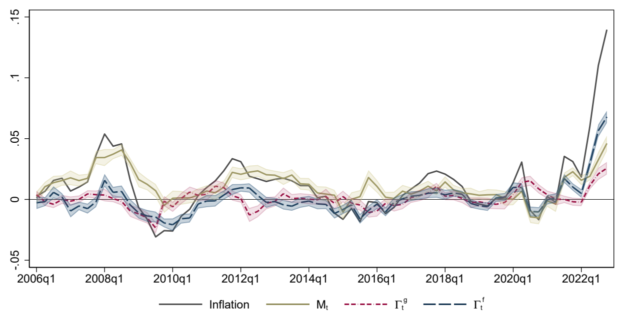
Figure A3: Aggregated retail inflation and granular components (advanced economies)



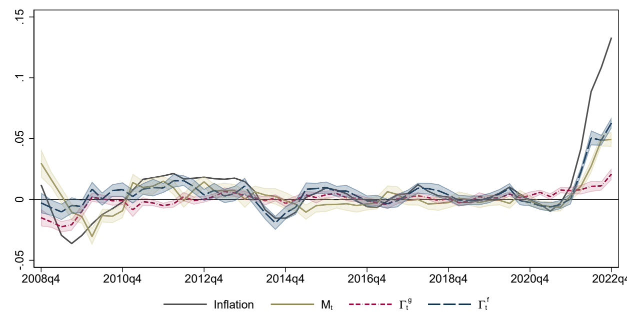
(a) AT



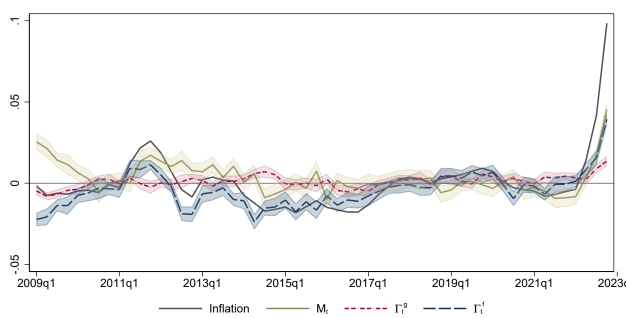
(b) BE



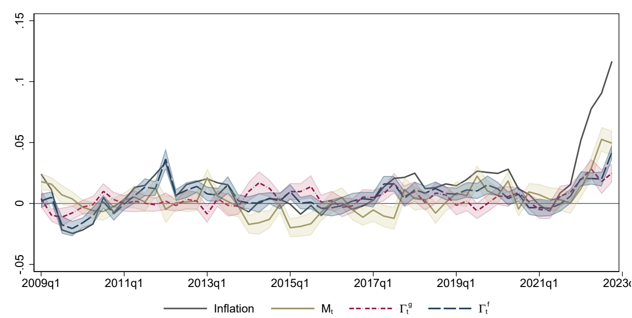
(c) DE



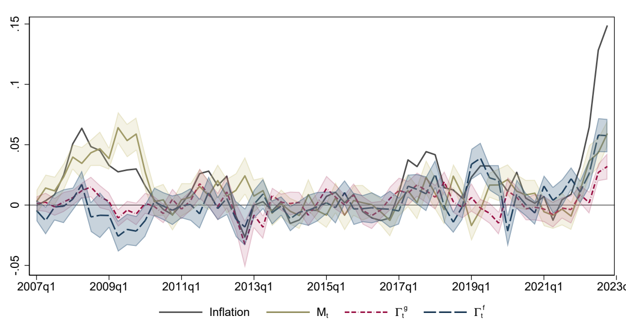
(d) ES



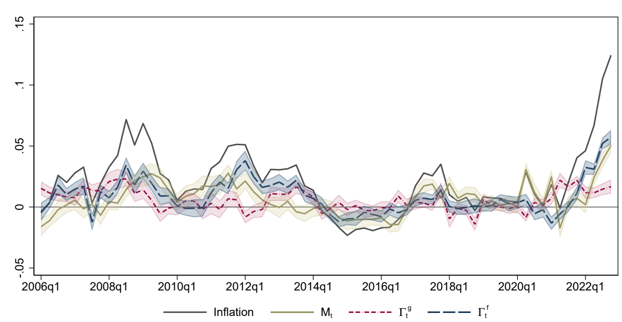
(e) FR



(f) NL

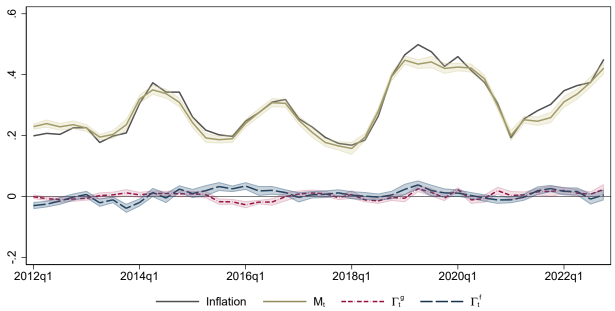


(g) SE

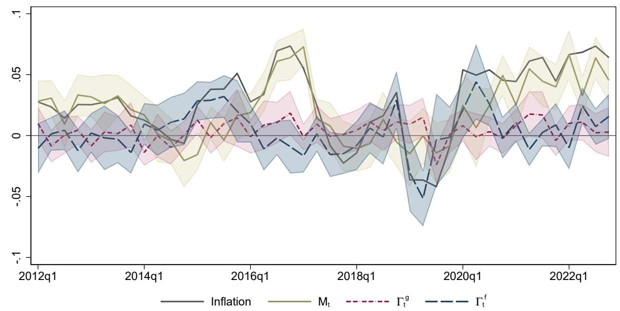


(h) UK

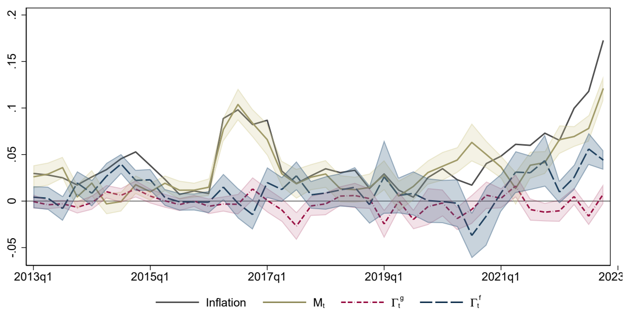
Figure A3: Aggregated retail inflation and granular components cont. (emerging markets)



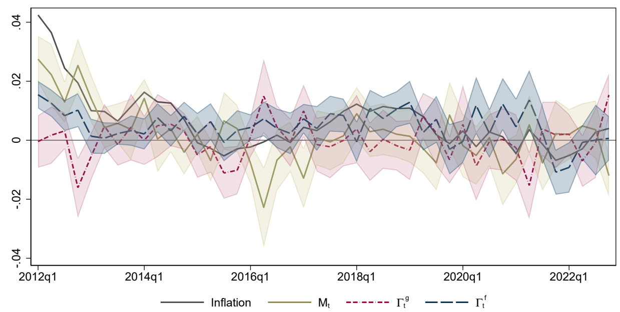
(a) AR



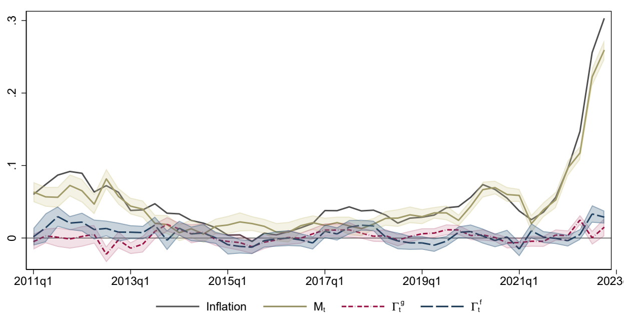
(b) BR



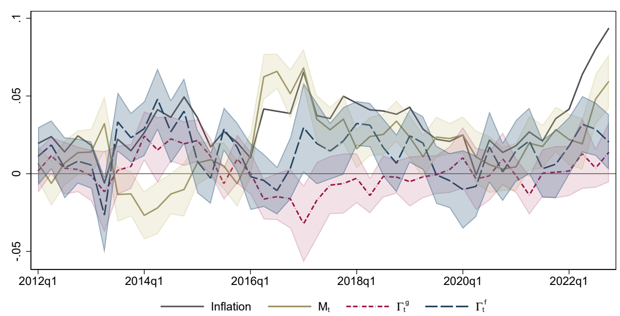
(c) CL



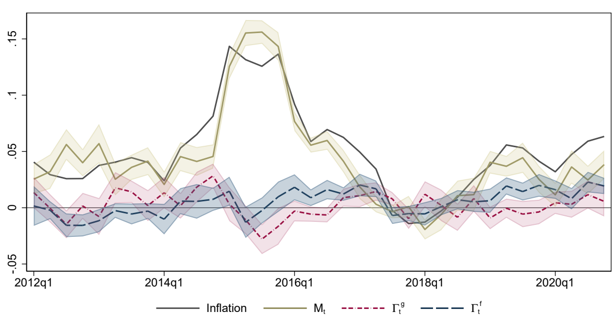
(d) CN



(e) HU



(f) MX

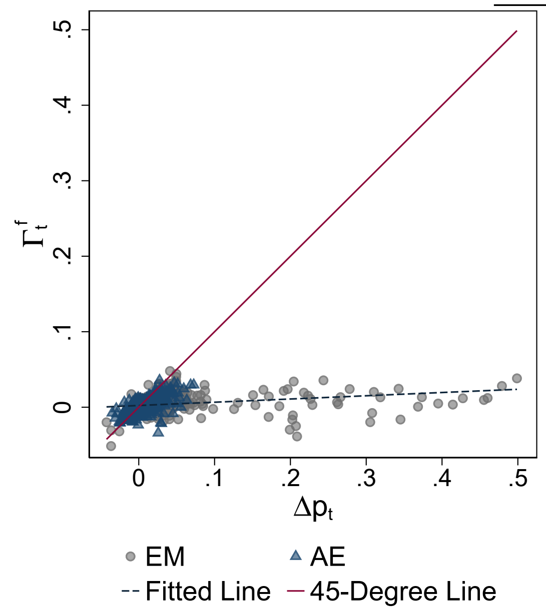


(g) RU

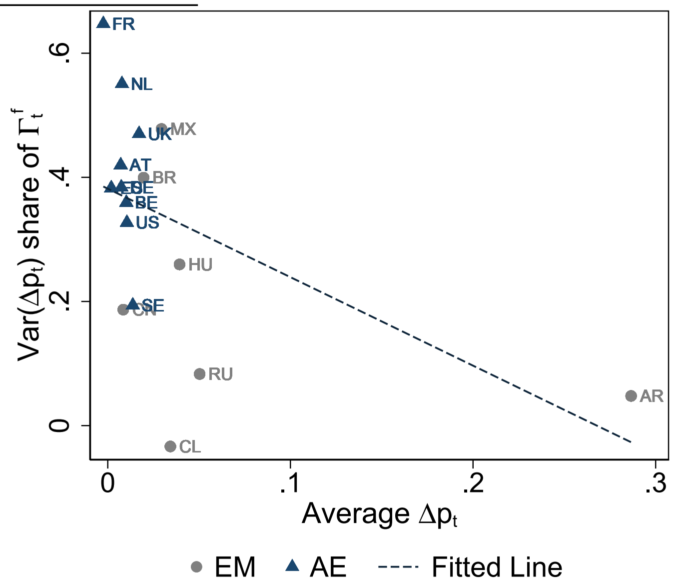
Notes: Dynamics of aggregated year-on-year sample inflation and contribution each component displayed until the last available period. Since data after 2020 was not available for the US, the figure for the US is only displayed in Figure 5 in the main text.

Figure A4: Granularity and the inflation rate, including Argentina and including Γ^{g}_{ct}

Including Argentina

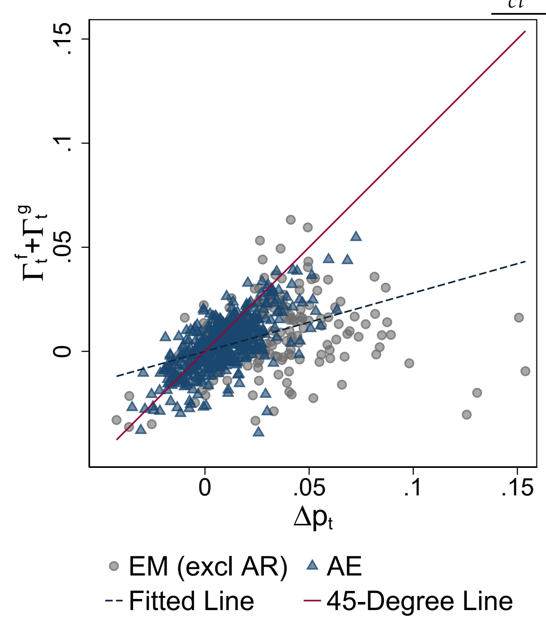


(a) Γ^{f}_{ct} vs. Δp_{ct}

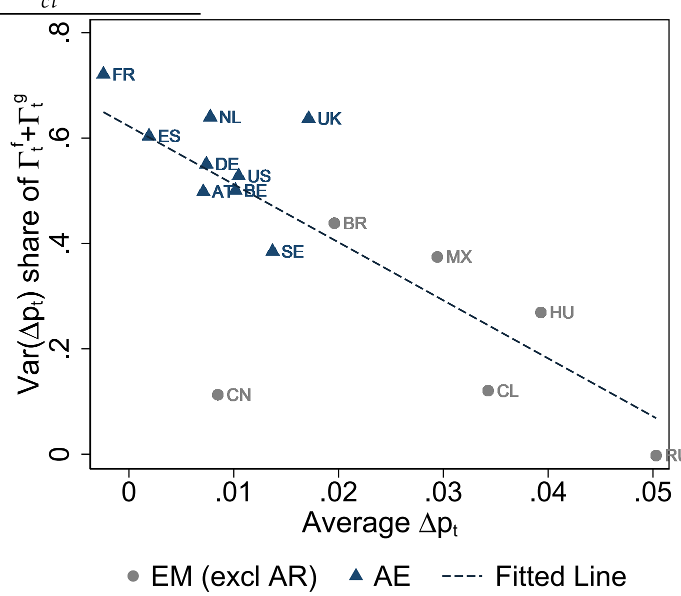


(b) Var(Δp_{ct}) share of Γ^{f}_{ct} vs. average Δp_{ct}

Γ^{f}_{ct} and Γ^{g}_{ct} combined



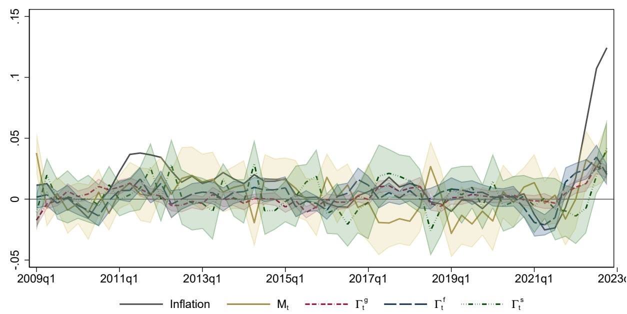
(c) $\Gamma^{f}_{ct} + \Gamma^{g}_{ct}$ vs. Δp_{ct}



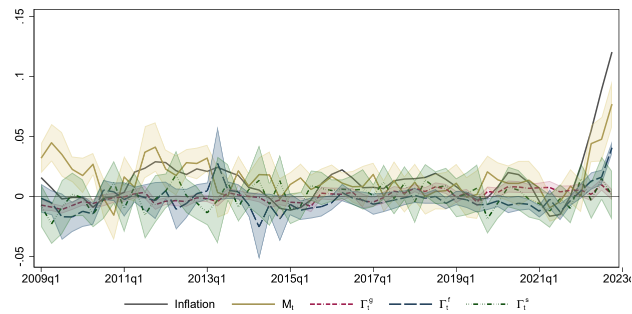
(d) Var(Δp_{ct}) share of $\Gamma^{f}_{ct} + \Gamma^{g}_{ct}$ vs. average Δp_{ct}

cNotes: The left panel displays a scatterplot of Γ^{f}_{ct} or $\Gamma^{f}_{ct} + \Gamma^{g}_{ct}$ against Δp_{ct}, pooling countries and years. The solid red line is the 45-degree line, the dashed line is the linear fit. The right panel displays a scatterplot of the Var(Δp_{ct}) share of Γ^{f}_{ct} or $\Gamma^{f}_{ct} + \Gamma^{g}_{ct}$ for country c against the average inflation of country c.

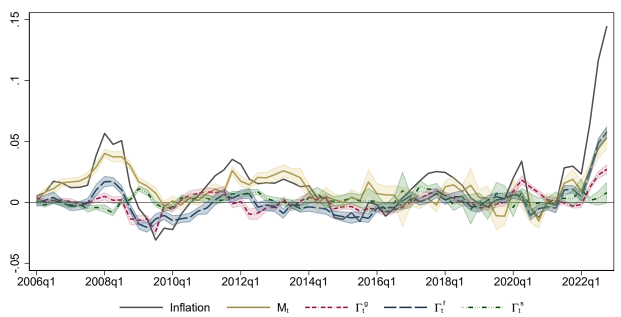
Figure A5: Aggregated retail inflation and granular components, with the retailer dimension (advanced economies)



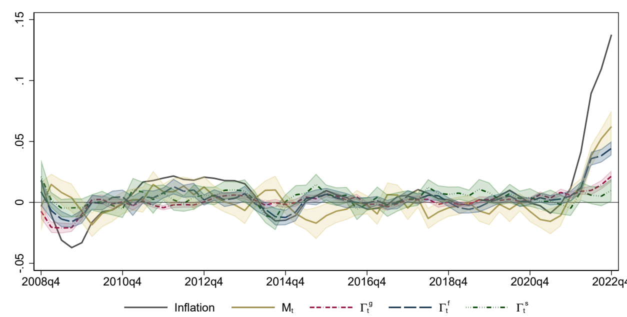
(a) AT



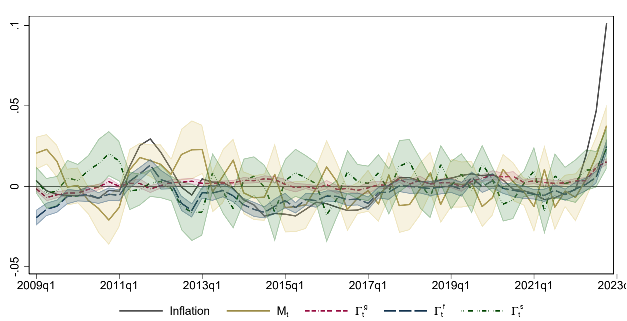
(b) BE



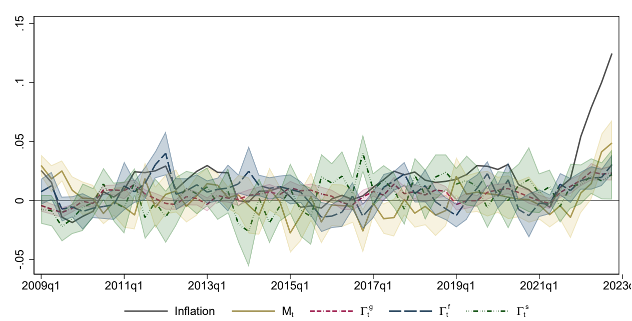
(c) DE



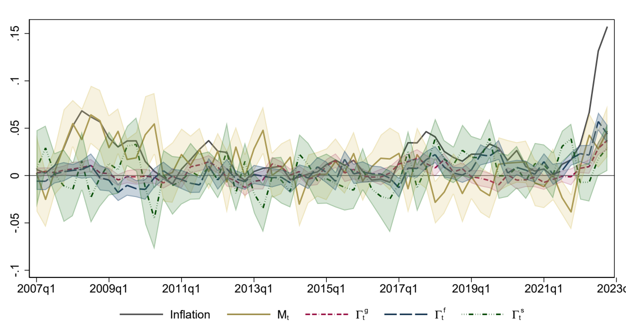
(d) ES



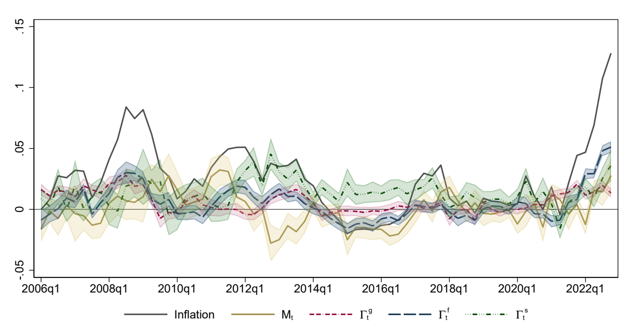
(e) FR



(f) NL

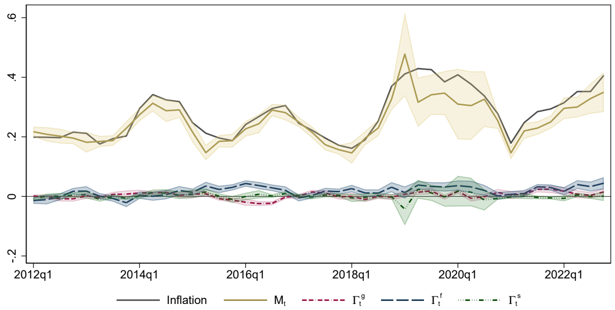


(g) SE

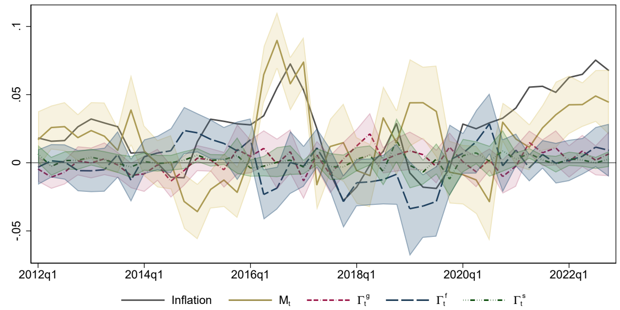


(h) UK

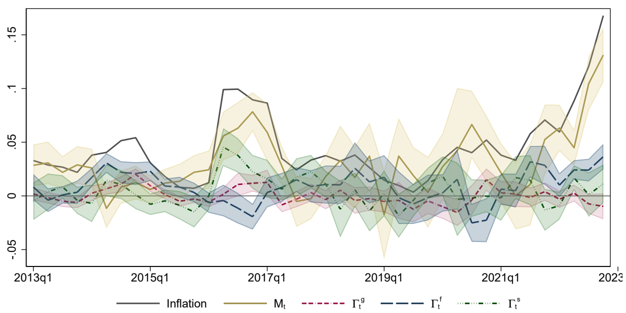
Figure A5: Aggregated retail inflation and granular components, with the retailer dimension cont. (emerging markets)



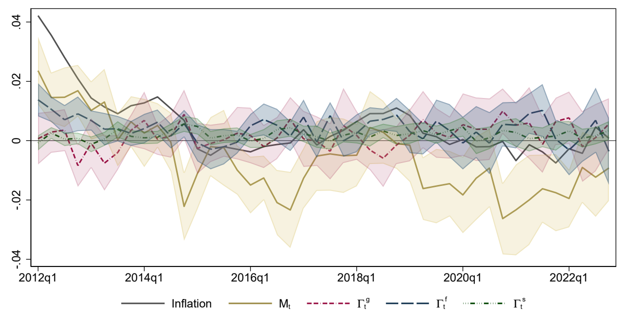
(a) AR



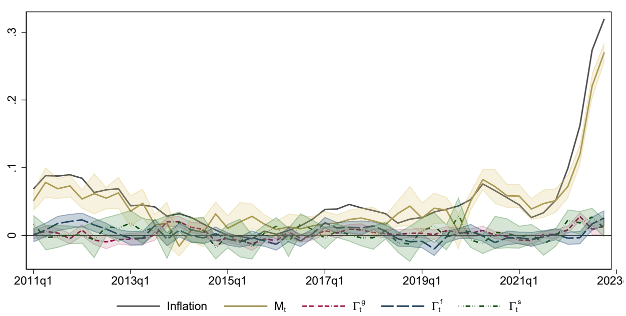
(b) BR



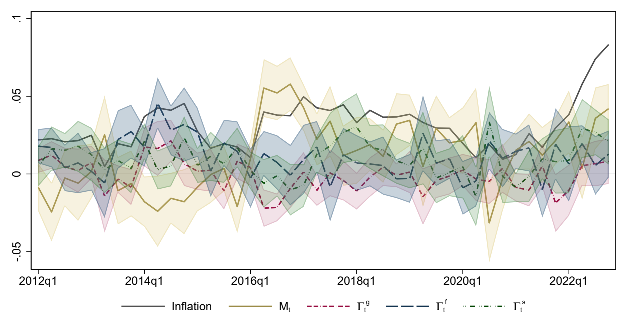
(c) CL



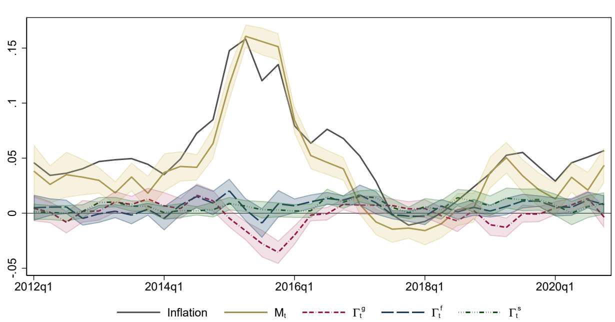
(d) CN



(e) HU



(f) MX



(g) RU

Notes: Dynamics of aggregated year-on-year sample inflation and contribution each component displayed until the last available period. Since data after 2020 was not available for the US, the figure for the US is only displayed in Figure 5 in the main text.

Table A7: Robustness summary statistics and correlations of factor components

	a) Basic firm match				B) 2 Factors				C) 3 Factors			
	Mean	St. Dev	Corr	Var(Δp_{ct}) share	Mean	St. Dev	Corr	Var(Δp_{ct}) share	Mean	St. Dev	Corr	Var(Δp_{ct}) share
Advanced Economies (N. Obs = 457)												
Δp_{ct}	0.84	1.63	1.00	1.00	0.84	1.63	1.00	1.00	0.84	1.63	1.00	1.00
$\mathcal{M}_{ct}$	0.51	1.20	0.61	0.44	0.53	1.19	0.60	0.44	0.53	1.19	0.60	0.44
Γ^f_{ct}	0.21	0.95	0.66	0.40	0.19	0.96	0.67	0.41	0.19	0.96	0.67	0.41
$\sum_f w_{fct-4}\delta_{fct}$	0.19	0.90	0.59	0.34	0.17	0.90	0.60	0.34	0.14	0.88	0.59	0.33
$\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$	0.02	0.37	0.27	0.07	0.02	0.42	0.26	0.07	0.05	0.42	0.30	0.09
$\Gamma^{f\in top10f}_{ct}$	*0.14*	*0.64*	*0.64*	*0.25*	*0.12*	*0.63*	*0.66*	*0.26*	*0.12*	*0.63*	*0.66*	*0.26*
$\Gamma^{f\notin top10f}_{ct}$	*0.07*	*0.48*	*0.46*	*0.15*	*0.06*	*0.49*	*0.47*	*0.15*	*0.06*	*0.49*	*0.47*	*0.15*
Γ^g_{ct}	0.12	0.67	0.40	0.15	0.12	0.66	0.40	0.15	0.12	0.66	0.40	0.15
$\sum_g w_{gct-4}\delta_{gct}$	0.08	0.57	0.25	0.09	0.09	0.52	0.18	0.06	0.08	0.45	0.09	0.02
$\sum_f w_{gct-4}\lambda_{gc}\eta^G_{ct}$	0.04	0.32	0.40	0.06	0.03	0.38	0.45	0.08	0.04	0.50	0.45	0.13
Emerging Markets (N. Obs = 252)												
Δp_{ct}	6.69	10.06	1.00	1.00	6.69	10.06	1.00	1.00	6.69	10.06	1.00	1.00
$\mathcal{M}_{ct}$	6.01	9.99	0.99	0.80	6.00	9.99	0.99	0.80	6.00	9.99	0.99	0.80
Γ^f_{ct}	0.66	1.40	0.13	0.20	0.66	1.39	0.13	0.20	0.66	1.39	0.13	0.20
$\sum_f w_{fct-4}\delta_{fct}$	0.69	1.36	0.16	0.20	0.70	1.33	0.15	0.19	0.75	1.25	0.12	0.19
$\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$	-0.03	0.37	-0.10	0.01	-0.04	0.45	-0.04	0.02	-0.09	0.62	0.05	0.02
$\Gamma^{f\in top10f}_{ct}$	*0.33*	*0.89*	*0.09*	*0.10*	*0.33*	*0.89*	*0.09*	*0.10*	*0.33*	*0.89*	*0.09*	*0.10*
$\Gamma^{f\notin top10f}_{ct}$	*0.33*	*0.72*	*0.14*	*0.11*	*0.33*	*0.72*	*0.14*	*0.10*	*0.33*	*0.72*	*0.14*	*0.10*
Γ^g_{ct}	0.03	0.91	0.05	-0.00	0.03	0.92	0.05	-0.00	0.03	0.92	0.05	-0.00
$\sum_g w_{gct-4}\delta_{gct}$	0.01	0.86	0.09	-0.00	0.02	0.75	0.13	0.00	0.01	0.70	0.12	-0.00
$\sum_f w_{gct-4}\lambda_{gc}\eta^G_{ct}$	0.02	0.41	-0.07	0.00	0.01	0.59	-0.08	-0.01	0.03	0.67	-0.06	0.00

Notes: "Mean" denotes the average inflation rate, "St. Dev." the standard deviation, "Corr" the correlation between the component in the row and actual sample inflation, and "Var(Δp_{ct}) share" denotes the share of the variance of actual inflation accounted for by each component. The top panel reports the results computed pooling nine advanced economies (Austria, Belgium, Germany, Spain, France, the Netherlands, Sweden, UK, US) and the bottom panel seven emerging markets (Argentina, Brazil, Chile, China, Hungary, Mexico and Russia). Panel A) displays the results using the baseline estimation on a sample using a simpler methodology for matching firms (see Appendix A). Panels B) and C) use the baseline firm matching, but include 2 or 3 factors respectively in the EM PCA. Post-2020 period excluded.

Table A8: Summary statistics and correlations of factor components: a single common factor for g and f

	Mean	St. Dev	Corr	Var(Δp_{ct}) share
Advanced Economies (N. Obs = 457)				
Δp_{ct}	0.84	1.63	1.00	1.00
$\mathcal{M}_{ct}$	0.53	1.19	0.60	0.44
Γ^{f}_{ct}	0.19	0.96	0.67	0.41
$\sum_f w_{fct-4}\delta_{fct}$	0.18	0.92	0.60	0.35
$\sum_f w_{fct-4}\lambda_{fc}\eta_{ct}$	0.01	0.34	0.28	0.07
$\Gamma^{f\in top10f}_{ct}$	*0.12*	*0.63*	*0.66*	*0.26*
$\Gamma^{f\notin top10f}_{ct}$	*0.06*	*0.49*	*0.47*	*0.15*
Γ^{g}_{ct}	0.12	0.66	0.40	0.15
$\sum_g w_{gct-4}\delta_{gct}$	0.12	0.63	0.37	0.13
$\sum_g w_{gct-4}\lambda_{gc}\eta_{ct}$	-0.00	0.16	0.21	0.02
Emerging Economies (N. Obs = 252)				
Δp_{ct}	6.69	10.06	1.00	1.00
$\mathcal{M}_{ct}$	6.00	9.99	0.60	0.80
Γ^{f}_{ct}	0.66	1.39	0.67	0.20
$\sum_f w_{fct-4}\delta_{fct}$	0.70	1.35	0.60	0.19
$\sum_f w_{fct-4}\lambda_{fc}\eta_{ct}$	-0.04	0.38	0.28	0.01
$\Gamma^{f\in top10f}_{ct}$	*0.33*	*0.89*	*0.66*	*0.10*
$\Gamma^{f\notin top10f}_{ct}$	*0.33*	*0.72*	*0.47*	*0.10*
Γ^{g}_{ct}	0.03	0.92	0.40	-0.00
$\sum_g w_{gct-4}\delta_{gct}$	0.03	0.91	0.37	0.00
$\sum_g w_{gct-4}\lambda_{gc}\eta_{ct}$	-0.00	0.09	0.21	-0.01

Notes: "Mean" denotes the average inflation rate, "St. Dev." the standard deviation, "Corr" the correlation between the component in the row and aggregated sample inflation Δp_{ct}, and "Var(Δp_{ct}) share" denotes the share of the variance of actual inflation accounted for by each component. The top panel reports the results computed pooling nine advanced economies (Austria, Belgium, Germany, Spain, France, the Netherlands, Sweden, UK, US) and the bottom panel seven emerging markets (Argentina, Brazil, Chile, China, Hungary, Mexico and Russia). Post-2020 period excluded.

Table A9: Robustness summary statistics and correlations of factor components: retailer sample

	A) Dropping unidentified retailers				B) Regional unidentified retailer				C) Firm and category components only			
	Mean	St. Dev	Corr	Var(Δp^r_{ct}) share	Mean	St. Dev	Corr	Var(Δp^r_{ct}) share	Mean	St. Dev	Corr	Var(Δp^r_{ct}) share
Advanced Economies (N. Obs = 457)												
Δp^r_{ct}	1.07	1.76	1.00	1.00	1.05	1.72	1.00	1.00	1.05	1.72	1.00	1.00
$\mathcal{M}_{ct}$	0.39	1.52	0.31	0.29	0.41	1.48	0.35	0.32	0.66	1.17	0.63	0.45
Γ^f_{ct}	0.11	0.96	0.65	0.37	0.08	0.91	0.64	0.35	0.23	0.94	0.72	0.39
$\sum_f w_{fct-4}\delta_{fct}$	0.11	0.94	0.59	0.31	0.07	0.87	0.57	0.29	0.23	0.88	0.64	0.31
$\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$	0.01	0.31	0.23	0.06	0.00	0.32	0.24	0.06	0.00	0.35	0.31	0.08
Γ^g_{ct}	0.17	0.66	0.48	0.16	0.16	0.65	0.47	0.16	0.17	0.65	0.47	0.16
$\sum_g w_{gct-4}\delta_{gct}$	0.13	0.55	0.32	0.09	0.13	0.54	0.31	0.09	0.13	0.54	0.32	0.09
$\sum_g w_{gct-4}\lambda_{gc}\eta^G_{ct}$	0.03	0.34	0.42	0.07	0.03	0.33	0.41	0.07	0.03	0.33	0.41	0.07
Γ^s_{ct}	0.40	1.21	0.27	0.18	0.41	1.16	0.27	0.17	-	-	-	-
$\sum_s w_{sct-4}\delta_{sct}$	0.42	1.15	0.26	0.16	0.42	1.13	0.29	0.17	-	-	-	-
$\sum_f w_{sct-4}\lambda_{sc}\eta^S_{ct}$	-0.02	0.41	0.08	0.03	-0.01	0.30	-0.04	-0.00	-	-	-	-
Emerging Markets (N. Obs = 252)												
Δp^r_{ct}	6.71	10.05	1.00	1.00	6.68	10.06	1.00	1.00	6.69	10.05	1.00	1.00
$\mathcal{M}_{ct}$	5.92	9.99	0.98	0.80	5.78	10.45	0.97	0.74	6.08	10.02	0.99	0.83
Γ^f_{ct}	0.24	1.34	0.13	0.09	0.37	1.29	0.07	0.12	0.56	1.24	0.12	0.15
$\sum_f w_{fct-4}\delta_{fct}$	0.27	1.32	0.16	0.08	0.41	1.24	0.11	0.15	0.57	1.23	0.15	0.16
$\sum_f w_{fct-4}\lambda_{fc}\eta^F_{ct}$	-0.03	0.33	-0.10	0.00	-0.04	0.39	-0.09	-0.03	-0.01	0.24	-0.14	-0.01
Γ^g_{ct}	0.05	0.97	-0.05	0.01	0.03	0.95	0.02	0.01	0.05	0.92	0.00	0.01
$\sum_g w_{gct-4}\delta_{gct}$	0.06	0.90	-0.05	0.02	0.04	0.87	0.06	0.03	0.06	0.83	0.02	0.04
$\sum_g w_{gct-4}\lambda_{gc}\eta^G_{ct}$	-0.01	0.43	-0.00	-0.01	-0.01	0.34	-0.09	-0.02	-0.01	0.41	-0.04	-0.03
Γ^s_{ct}	0.49	1.33	0.11	0.11	0.50	1.72	-0.09	0.13	-	-	-	-
$\sum_s w_{sct-4}\delta_{sct}$	0.45	1.24	0.09	0.08	0.47	1.46	-0.10	0.11	-	-	-	-
$\sum_f w_{sct-4}\lambda_{sc}\eta^S_{ct}$	0.04	0.60	0.07	0.03	0.03	0.78	-0.02	0.02	-	-	-	-

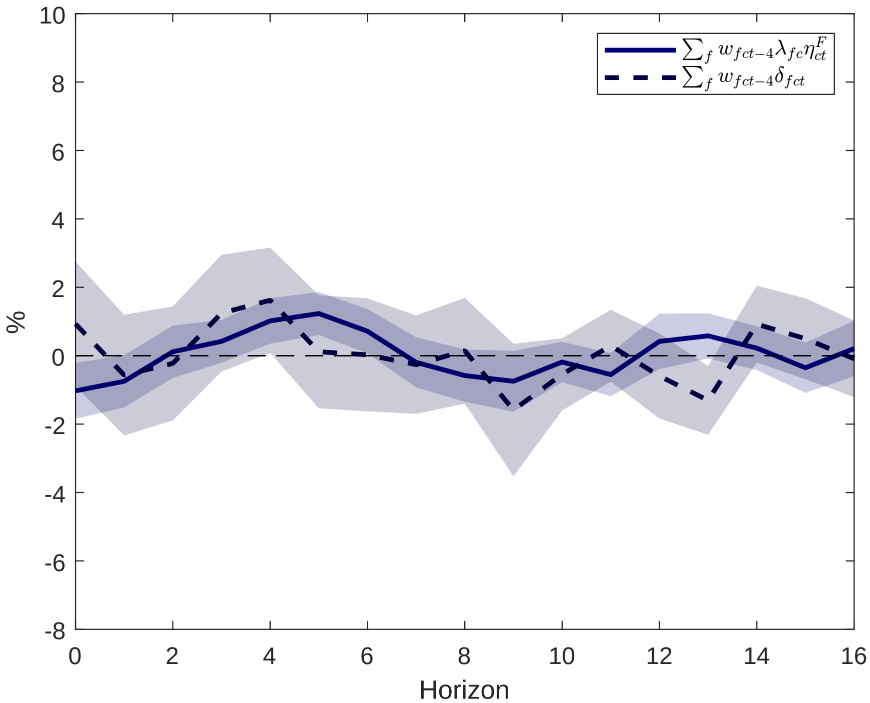
Notes: "Mean" denotes the average inflation rate, "St. Dev." the standard deviation, "Corr" the correlation between the component in the row and aggregated sample inflation Δp^r_{ct} using the product-retailer level dataset, and "Var(Δp_{ct}) share" denotes the share of the variance of actual inflation accounted for by each component. The top panel reports the results computed pooling nine advanced economies (Austria, Belgium, Germany, Spain, France, the Netherlands, Sweden, UK, US) and the bottom panel seven emerging markets (Argentina, Brazil, Chile, China, Hungary, Mexico and Russia). Panel A) keeps unidentified retailers but assigns it to an artificial regional retailer using the household region information. Panel B) only estimates Γ^f_{ct} and Γ^g_{ct} on the baseline product-retailer level sample. Δp^r_{ct} refers to aggregated inflation computed using the retailer-country-quarter level sample, which slightly differs from the aggregated inflation in the baseline sample Δp_{ct}. Post-2020 period excluded.

Table A10: Robustness summary statistics and correlations of factor components: Post-2020 period included

	Mean	St. Dev	Corr	Var(Δp_{ct}) share
Advanced Economies (N. Obs = 521)				
Δp_{ct}	1.22	2.50	1.00	1.00
$\mathcal{M}_{ct}$	0.67	1.43	0.75	0.43
Γ^f_{ct}	0.34	1.26	0.82	0.41
$\sum_f w_{fct-4}\delta_{fct}$	0.28	1.05	0.63	0.26
$\sum_f w_{fct-4}\lambda_{fc}\eta^f_{ct}$	0.07	0.66	0.57	0.16
$\Gamma^{f\in top10f}_{ct}$	*0.24*	*0.87*	*0.83*	*0.29*
$\Gamma^{f\notin top10f}_{ct}$	*0.11*	*0.54*	*0.59*	*0.12*
Γ^g_{ct}	0.21	0.73	0.55	0.16
$\sum_g w_{gct-4}\delta_{gct}$	0.13	0.61	0.34	0.08
$\sum_g w_{gct-4}\lambda_{gc}\eta^g_{ct}$	0.07	0.38	0.51	0.08
Emerging Economies (N. Obs = 300)				
Δp_{ct}	7.31	10.44	1.00	1.00
$\mathcal{M}_{ct}$	6.48	10.21	0.75	0.86
Γ^f_{ct}	0.74	1.39	0.82	0.09
$\sum_f w_{fct-4}\delta_{fct}$	0.74	1.33	0.63	0.09
$\sum_f w_{fct-4}\lambda_{fc}\eta^f_{ct}$	-0.00	0.40	0.57	0.01
$\Gamma^{f\in top10f}_{ct}$	*0.38*	*0.91*	*0.83*	*0.05*
$\Gamma^{f\notin top10f}_{ct}$	*0.35*	*0.72*	*0.59*	*0.05*
Γ^g_{ct}	0.10	0.95	0.55	0.04
$\sum_g w_{gct-4}\delta_{gct}$	0.08	0.89	0.34	0.04
$\sum_g w_{gct-4}\lambda_{gc}\eta^g_{ct}$	-0.01	0.36	0.51	0.01

Notes: "Mean" denotes the average inflation rate, "St. Dev." the standard deviation, "Corr" the correlation between the component in the row and aggregated sample inflation Δp_{ct}, and "Var(Δp_{ct}) share" denotes the share of the variance of actual inflation accounted for by each component. The top panel reports the results computed pooling nine advanced economies (Austria, Belgium, Germany, Spain, France, the Netherlands, Sweden, UK, US) and the bottom panel seven emerging markets (Argentina, Brazil, Chile, China, Hungary, Mexico and Russia).

Figure A6: IRFs on the subcomponents of Γ^{f}_{ct}



Notes: The figure displays the results of the local projections on the component capturing the higher sensitivity of large firms to common shocks and on the component capturing the idiosyncratic shocks to large firms. Shaded areas represent 90% confidence bands based on HAC standard errors.

Previous volumes in this series

1239 January 2024	The use and disuse of fintech credit: when buy now, pay later meets credit reporting	Yanfei Dong, Jiayin Hu, Yiping Huang, Han Qiu and Yingguang Zhang
1238 December 2024	Fiscal stimulus plans and households' expectations	Fiorella De Fiore, Marco Jacopo Lombardi and Albert Pierres Tejada
1237 December 2024	The macroeconomics of green transitions	Gregor Boehl, Flora Budianto and Előd Takáts
1236 December 2024	Savings-and-credit contracts	Bernardus van Doornik, Armando Gomes, David Schoenherr and Janis Skrastins
1235 December 2024	Aggregate debt servicing and the limit on private credit	Mathias Drehmann, Mikael Juselius and Sarah Quincy
1234 December 2024	Targeted Inflation Targeting: Some Evidence and Theory	Boris Hofmann, Cristina Manea and Benoît Mojon
1233 December 2024	Fire Sales of Safe Assets	Gabor Pinter, Emil Siriwardane and Danny Walker
1232 December 2024	Bond supply, yield drifts, and liquidity provision before macroeconomic announcements	Dong Lou, Gabor Pinter, Semih Uslu and Danny Walker
1231 December 2024	Central bank communication and media coverage	Fiorella De Fiore, Alexis Maurin, Andrej Mijakovic and Damiano Sandri
1230 December 2024	Whither inflation targeting as a global monetary standard?	Claudio Borio
1229 November 2024	Through stormy seas: how fragile is liquidity across asset classes and time?	Nihad Aliyev, Matteo Aquilina, Khaladdin Rzayev and Sonya Zhu
1228 November 2024	Retail fast payment systems as a catalyst for digital finance	Giulio Cornelli, Jon Frost, Jonathan Warren, Clair Yang and Carolina Velásquez
1227 November 2024	Decentralised dealers? Examining liquidity provision in decentralised exchanges	Matteo Aquilina, Sean Foley, Leonardo Gambacorta and William Krekel
1226 November 2024	How Does Fiscal Policy affect the Transmission of Monetary Policy into Cross-border Bank Lending? Cross-country Evidence	Swapan-Kumar Pradhan, Előd Takáts and Judit Temesvary

All volumes are available on our website www.bis.org.