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Consumer price rigidity in periods of low and high inflation: the case of Lithuania*

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ABSTRACT

I provide new monthly statistics on consumer price rigidity in Lithuania. The statistics are derived from CPI price records, covering an average of 90% of the ECOICOP4 weights between 2019 and 2023. Through a comparative study of two distinct periods – low inflation from January 2019 to December 2020, and high inflation from January 2021 to March 2023 – a significant shift in the frequency of price changes is observed in the latter period. This shift is mainly due to a significant rise in the frequency of price increases, while the average size of these increases has remained relatively constant over the years. Furthermore, I show that structural aggregate demand and energy shocks induced shifts in the frequency of price changes during the high-inflation period, suggesting that state-dependent sticky price models may be more suitable than time-dependent ones for explaining inflation fluctuations in Lithuania.

Keywords: consumer price rigidity, price-setting, high inflation, frequency of price changes.

JEL codes: D40, E31, E50

1 Introduction

In recent decades, granular consumer price data have shed new light on the transmission mechanism of monetary policy. Statistics on the frequency and size of price changes by individual firms have proved valuable in disciplining micro-founded, sticky-price macroeconomic models (e.g. Golosov and Lucas (2007)). The time-dependent (TD) models assume a constant and exogenous frequency of price adjustments over time (Calvo, 1983), while the state-dependent (SD) models allow this frequency to vary (e.g. in Midrigan (2011)).

Moreover, Auclert et al. (2023) demonstrated that the SD and TD models have nearly identical (linearized) Phillips curves across a wide range of parameterizations using micro price statistics. This implies that the aggregate inflation response to aggregate cost shocks is quite equivalent in the two models. However, this equivalence does not hold when significant aggregate shocks hit the economy, at which point higher-order dynamics become more relevant. More specifically, these shocks affect the frequency of price changes, a mechanism that is implausible in TD models (Alvarez et al., 2016). While evidence for this phenomenon based on granular consumer data is limited, it has been highlighted in the Mexican, Hungarian, and Argentine cases of high inflation and large aggregate shock episodes (respectively, Gagnon (2009); Karadi and Reiff (2019); Alvarez et al. (2019)). In contrast, the frequency remains constant in a near-zero inflation environment, as shown in studies such as Klenow and Kryvtsov (2008); Nakamura and Steinsson (2008) for the United States, Gautier et al. (2022) for the euro area, and Jouvanceau (2022) for Lithuania.[1] In this context, variations in the size of price changes, caused by shifts in the share of price increases, are the main drivers of inflation.

I contribute to the literature by comparing consumer price rigidity in Lithuania in low- and high-inflation periods using price records underlying consumer price indices (CPIs). To do so, I compile statistics on the frequency and size of price changes separately for these two periods and highlight which of these margins drove Lithuanian inflation in both periods. To the best of my knowledge, this is the first such comparison for an EA country.

The micro-price data, shared by Statistics Lithuania (the statistical national office), includes prices for individual "target" products, such as a 500-gram package of pasta sold in a particular store in a particular area, and covers an average of 90% of the HICP consumer weight expenditures in this period. The granularity of the data allows the calculation of consumer

[1]Other country-specific studies include Álvarez et al. (2010) for Spain, Benkovskis et al. (2012) for Latvia, Blanas et al. (2020) for Belgium, and Berardi et al. (2015) for France.

price rigidity statistics at the lowest public consumer price classification, ECOICOP4 (as in Gautier et al. (2022) for the EA from 2010 to 2019).[2] These statistics result from decomposing inflation rates at the micro level into their average size and frequency of price change margins, as in Klenow and Kryvtsov (2008). Then, HICP weights are employed to aggregate the statistics. This enables me to provide economy-wide statistics and category-specific statistics, such as for the energy and services price categories, to highlight differences in price rigidity across consumer price categories. Moreover, I can share the statistics at the ECOICOP4 level upon request, thus helping macroeconomists to calibrate models for analyzing the monetary policy transmission in Lithuania.

During the low-inflation period, I find that the aggregate average frequency of price changes is 23.5%, indicating an average gap of four months between successive price adjustments.[3] In contrast, I document that the average frequency increased to 26.3% in the high-inflation period. This change is attributed to a notable increase of 4.8 percentage points (pp) in the average frequency of price increases. In contrast, the average frequency of price decreases only declines by about 2 pp. This resulted in a significant change of 9.9 pp in the average share of price increases between the two periods.[4]

Furthermore, I find that the average size of price changes is 1.8% in the low-inflation period and jumps to 4.6% in the high-inflation period. Correspondingly, the average size of price increases and decreases changes only modestly between the two periods, by -0.6 pp and 0.3 pp, respectively. I address this puzzle using fixed effects regressions. The findings indicate that shifts in the average size are mainly due to changes in the share of price increases in both periods (as in Gautier et al. (2022) for the EA low-inflation period). Importantly, the regressions also reveal that changes in the frequency, not just the share of price increases, also play a role in driving inflation during the high-inflation period. In other words, these findings imply that during the low-inflation period, the frequency of both price increases and price decreases changed by roughly equal but opposite amounts, affecting only the average size and not the frequency of price changes. In contrast, during the high-inflation period, prices

[2]For more details on ECOICOP classification, please refer to Eurostat metadata classifications at URL: `https://ec.europa.eu/eurostat/web/metadata/classifications`.

[3]This percentage is greater than the EA average of 13.6% documented between 2010 and 2019 (Gautier et al., 2022) and the 18.1% in Lithuania from 2010 to 2018 (Jouvanceau, 2022). Nevertheless, these studies did not take into account energy-related prices, which contributed significantly to the frequency found in my analysis.

[4]A phenomenon that was observed in all the special aggregate categories, energy, non-energy industrial goods (NEIG), processed and unprocessed food, and services.

increased more frequently than they decreased, leading to an increase in both the frequency and average size of price changes. In summary, the evidence is consistent with SD models, but at odds with TD models that assume a constant frequency over time (Alvarez et al., 2016).

Delving deeper, I examine the influence of aggregate shocks on the frequency and size margins of inflation. I first estimate a Bayesian vector autoregression (BVAR) model using macroeconomic data from January 2000 to March 2023 to identify structural aggregate demand and energy (price) shocks. Then, I use local linear projections at the ECOICOP4 level as in Gautier et al. (2022) to assess their average impact on the frequency and size margins over time. I perform this exercise separately for the low- and high-inflation periods and find that the aggregate shocks contributed significantly to the variation in the frequency margin in the latter period, which is further consistent with the SD models.

The structure of the paper is as follows: in the first section, the micro-price dataset is described and the statistics are defined. In the second section, the cross-sectional statistics are presented. In the third section, the patterns in the time series are analyzed. Lastly, concluding remarks are provided.

2 Data and definitions

Statistics Lithuania provides the monthly consumer price data used in this study. The records, which total about 3 million, cover the period from January 2019 to March 2023. On average, they represent 90% of the HICP consumer weight expenditures over the period, ECOICOP4 being the 4th level or 5-digit classification of consumer prices.[5] Each entry corresponds to a specific product or service, such as a dental procedure or a kilogram of rice, and provides details about its quantity and unit, as well as the location and type of point of sale.[6] Additionally, the dataset includes "flags" that explain certain price changes, mainly promotions (sales), product replacements, and price imputations. I utilize these flags to build a "regular" set of price changes, replacing the flagged price changes with a price change as if the sales or product replacements did not occur. To exemplify, assume a product sells for 10 euros in month $m-1$. Then in month m, the price drops by 2 euros and is flagged as a discount. Afterward, in

[5] I do not observe 73 out of 303 ECOICOP4 categories. The unobserved categories with the highest weights (more than 1%) are 04510 "Electricity", 07112 "Second-hand motor cars", 08302 "Wireless telephone services" and, 09602 "Package international holidays". Most of these missing categories have 0 weights over the period.

[6] There are six geographical locations: 5 main cities (Vilnius, Kaunas, Klaipėda, Šiauliai, Panevėžys) and "another territory".

month $m+1$, the price increases by 2 euros (a so-called V-shaped price path). In that scenario, the "regular" price changes in $m+1$ will be set at 0 $\left(\frac{(p_{m+1}-p_{m-1})}{p_{m-1}}\right)$. If, in month $m+1$, the post-discount price increased by 3 instead of 2 euros, then the "regular" price change would be 10% $\left(\frac{(11-10)}{10}\right)$. Table A.1 displays the distribution of these flags in the dataset.[7]

The methodology described by Klenow and Kryvtsov (2008) is used to calculate the statistics below. This method involves decomposing inflation rates into their frequency and size margins at the micro level – ECOICOP4, in this case – and then aggregating them using the HICP ECOICOP4 weights. Before this, the *unit* prices (p_{njt}) were converted into their natural logarithm. I will define an inflation rate at the ECOICOP4 level j for each month t, as follows

$$\begin{aligned}\tilde{\pi}_{jt} &= \frac{1}{N_{jt}}\sum_{n}^{N_{jt}}(p_{njt}-p_{njt-1}) \\ &= \underbrace{\left(\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I_{njt}\right)}_{f_{jt}} \times \underbrace{\left(\frac{\frac{1}{N_{jt}}\sum_{n}^{N_{jt}}(p_{njt}-p_{njt-1})}{\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I_{njt}}\right)}_{\Delta p_{jt}}. \end{aligned} \tag{1}$$

for N price observations and J ECOICOP4s. $I_{njt}=1$ if $p_{njt}\neq p_{njt-1}$, and 0 otherwise. f_{jt} will denote the (overall) frequency of price changes, while Δp_{jt} will refer to the average size of (non-zero) price changes. The frequency of price changes can further be decomposed into

$$f_{jt}=\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I_{njt}=\underbrace{\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I^{+}_{njt}}_{f^{+}_{jt}}+\underbrace{\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I^{-}_{njt}}_{f^{-}_{jt}}. \tag{2}$$

where $I^{+}_{njt}=1$ if $p_{njt}>p_{njt-1}$, and 0 otherwise. $I^{-}_{njt}=1$ if $p_{njt}<p_{njt-1}$, and 0 otherwise. f^{+}_{jt} will denote the frequency of price increases, and f^{-}_{jt} the frequency of price decreases. The average size of price changes can also be broken down into the average size of price increases and decreases

[7] To reduce noise in the data, two steps are taken. Firstly, all seasonal price changes are removed. Secondly, price changes that fall outside the 99th percentile of the distribution of absolute price growth and all changes less than one cent are dropped. Additionally, about 6% of all price records have prices observed twice a month, mainly for fruits, vegetables, and fuels. These prices are averaged to generate monthly frequency observations.

$$
\begin{aligned}
\Delta p_{jt} &= \frac{\frac{1}{N_{jt}}\sum_n^{N_{jt}}(p_{njt}-p_{njt-1})}{\frac{1}{N_{jt}}\sum_n^{N_{jt}} I_{njt}} \\
&= \frac{f_{jt}^{+}}{f_{jt}} \times \underbrace{\frac{\frac{1}{N_{jt}}\sum_n^{N_{jt}^{+}}(p_{njt}-p_{njt-1})^{+}}{f_{jt}^{+}}}_{\Delta p_{jt}^{+}} + \frac{f_{jt}^{-}}{f_{jt}} \times \underbrace{\frac{\frac{1}{N_{jt}}\sum_n^{N_{jt}^{-}}(p_{njt}-p_{njt-1})^{-}}{f_{jt}^{-}}}_{\Delta p_{jt}^{-}}.
\end{aligned} \tag{3}
$$

where Δp_{jt}^{+} and Δp_{jt}^{-} will refer to the average size of upward and downward price changes, respectively. It is important to note that changes in the share of price increases/decreases $\left(\frac{f_{jt}^{+}}{f_{jt}}, \frac{f_{jt}^{-}}{f_{jt}}\right)$ can affect the average size of price changes, even if the average size of price increases and decreases remains constant. This will be important in understanding inflation fluctuations below. Consequently, the ECOICOP4 inflation rate also admits the following decomposition

$$
\tilde{\pi}_{jt} = f_{jt}^{+} \times \Delta p_{jt}^{+} + f_{jt}^{-} \times \Delta p_{jt}^{-}. \tag{4}
$$

Finally, the aggregate inflation rate is approximated by

$$
\pi_t = \sum_j^J \omega_{j\tau}\tilde{\pi}_{jt}. \tag{5}
$$

where $\omega_{j\tau}$ are yearly HICP weights at ECOICOP4 level.[8] Aggregate frequency and size statistics are also calculated using weighted averages.[9]

The difference in aggregate inflation rates between my study and the official HICP is illustrated in Figure 1. This can be attributed to two main factors. Firstly, ECOICOP4 price categories, such as electricity and holiday packages, are included in the official index but not in my sample. Secondly, alternative methods are utilized to determine aggregate price changes in both my research and the statistical office. Notably, the official index uses more advanced weighting methods and does not employ logarithmic price transformation.[10]

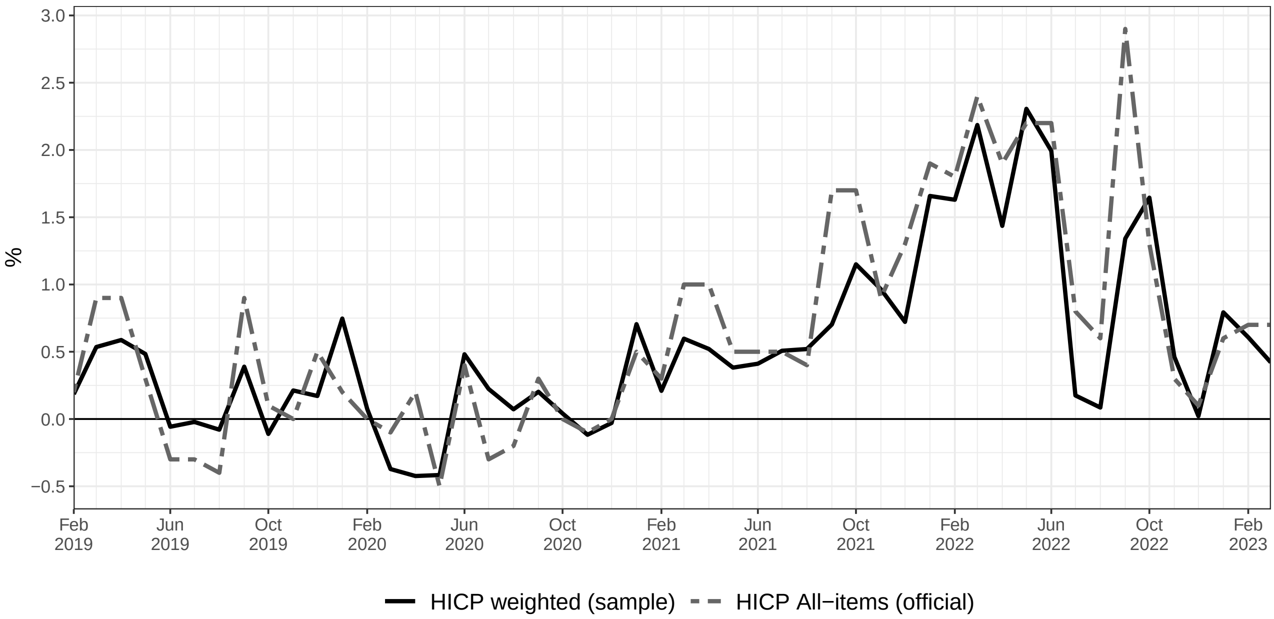
More importantly, the figure depicts two different patterns of inflation over the period. From

[8] Weights are annual only. I address the absence of certain ECOICOP4 categories by a normalization.

[9] This means that the aggregate frequency and aggregate average size in Table 1 are averages of $\bar{f}_t = \sum_j^J \omega_{j\tau} f_{jt}$ and $\Delta\bar{p}_t = \sum_j^J \omega_{j\tau}\Delta p_{jt}$, respectively. Note however that, $\pi_t \neq \bar{f}_t \times \Delta\bar{p}_t$. Also, $\pi_t \neq \bar{f}_t^{+} \times \Delta\bar{p}_t^{+} + \bar{f}_t^{-} \times \Delta\bar{p}_t^{-}$.

[10] The goal of my study is to evaluate consumer price rigidity, rather than replicate the official inflation index. The approximations made during aggregation do not have a significant impact on the results. Specifically, only the statistics on the size of price changes are affected.

Figure 1: Aggregate HICP inflation rates: sample and official



Note: My data set covers about 90% of the ECOICOP4 HICP weights on average over the period. The official HICP inflation monthly rates are available in Eurostat.

2019M2 to 2020M12, inflation remained steady with minor fluctuations and an average value near zero. However, from 2021M1 to 2023M3, the period exhibited a markedly positive average inflation rate with greater variability. These developments have affected consumer price rigidity, which will be analyzed in the next section.

3 Cross-sectional statistics

Table 1 presents weighted aggregate statistics for the low-inflation period (2019M2-2020M12) and the high-inflation period (2021M1-2023M3) separately.[11]

During the high-inflation period, the frequency of price changes was higher, averaging 26.3% across all items, in comparison to 23.5% during the low-inflation period (first column $\bar{f}$). This increase in frequency can be attributed to a higher average frequency of price increases, rising from 12.4% to 17.2% (second column $\bar{f}^+$). In contrast, the average frequency of price decreases

[11]In the low-inflation period, one month of price observations is lost because the statistics are calculated based on month-to-month price changes. The aggregate statistics of the low-inflation period can be compared with those of Jouvanceau (2022), who analyzes a sample from January 2010 to December 2018. Note, however, that my study covers 90% of the HICP weights at the ECOICOP4 level, in contrast to Jouvanceau (2022)'s analysis, which examines only 73% and does not have access to many of the energy-related prices that contribute significantly to the statistics in my sample.

Table 1: Aggregate weighted statistics: low against high-inflation periods

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	*dur.*	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	*%inc.*	$\bar{\omega}$	*%Adj.*	*obs.*
Low inflation	%	%	%	*m.*	%	%	%	%	%	%	
All items	23.5	12.4	11.1	3.7	1.8	16.2	-17.8	58.6	100.0	10.4	1393932
Energy	80.9	38.7	42.2	0.6	-0.4	5	-5.2	47.9	11.7	1.3	11274
NEIG	16.9	8.7	8.2	5.4	0.1	20.1	-21.5	52.0	32.1	12.3	595385
Proc. food	19.3	10.9	8.3	4.7	0.9	17.9	-20	58.3	24.8	11.3	531897
Services	6.5	4.6	2.0	14.9	6.9	13.8	-15.4	76.7	26.2	0.7	136389
Unproc. food	41.6	22.4	19.1	1.9	0.6	16.7	-17.7	54.3	5.3	8.8	118987
High inflation	%	%	%	*m.*	%	%	%	%	%	%	
All items	26.3	17.2	9.1	3.3	4.6	15.6	-18.1	68.5	100.0	9.6	1673980
Energy	85.4	53.3	32.1	0.5	2.1	6.2	-6.4	63.4	11.3	1.1	14809
NEIG	18.9	11.6	7.3	4.8	3.0	18.4	-21.3	61.8	33.6	11.9	706919
Proc. food	24.3	17.0	7.3	3.6	4.0	16.1	-19.5	68.6	25.6	9.8	641206
Services	8.6	7.1	1.5	11.1	10.0	14.4	-14.7	84.9	24.1	0.6	168814
Unproc. food	42.8	25.8	17.0	1.8	3.0	17.1	-18.2	61.1	5.4	9.6	142232

Note: The statistics are based on price changes without any adjustments for sales and product replacements; the adjusted price statistics can be found in Table A.2 in Appendix A. The low-inflation sample covers 2019M2 to 2020M12, and the high-inflation 2021M1 to 2023M12. "*%inc.*" represents the proportion of price increases in total price changes, while "*%Adj.*" indicates the share of price (non-zero) changes modified to produce "regular" statistics. "$\bar{\omega}$" refers to the average share of HICP weights in each sample. "*dur.*" signifies the implied average duration, which can be calculated using: $dur = -1/ln(1-f)$ where f is the weighted average frequency. "*obs.*" refers to the number of observations, while "*m.*" indicates the number of months associated with the duration. Finally, "NEIG" stands for "non-energy industrial goods".

declined from 11.1% to 9.1% (third column $\bar{f}^{-}$).[12]

Statistics compiled by special aggregates show that the average frequency of energy price

[12]For comparison, the average frequency of price changes across all items was 18.1% in Lithuania between 2010M1 and 2018M12 (Jouvanceau, 2022) and 13.6% in the EA between 2010M1 and 2019M12 (see Appendix B, Table B.1 in Gautier et al. (2022)).

changes was about 80% in both periods.[13] The average frequency increased moderately for all other special aggregates during the high-inflation period. Specifically, it increased from 16.9% to 18.9% for non-energy industrial goods (NEIG), from 19.3% to 24.3% for processed food, from 6.5% to 8.6% for services, and from 41.6% to 42.8% for unprocessed food.

Table A.2 in Appendix A provides statistics on adjusted price changes that take into account the effects of sales and product replacements. About 10% of all price changes were adjusted in both periods, especially in the NEIG, processed, and unprocessed food categories. These adjustments reduce the average frequency by 7.2 pp in the low-inflation period and 7 pp in the high-inflation period relative to the benchmark statistics. Similar reductions in both periods suggest that sales or product substitution did not significantly affect the earlier-mentioned increase in frequency during the high-inflation period.

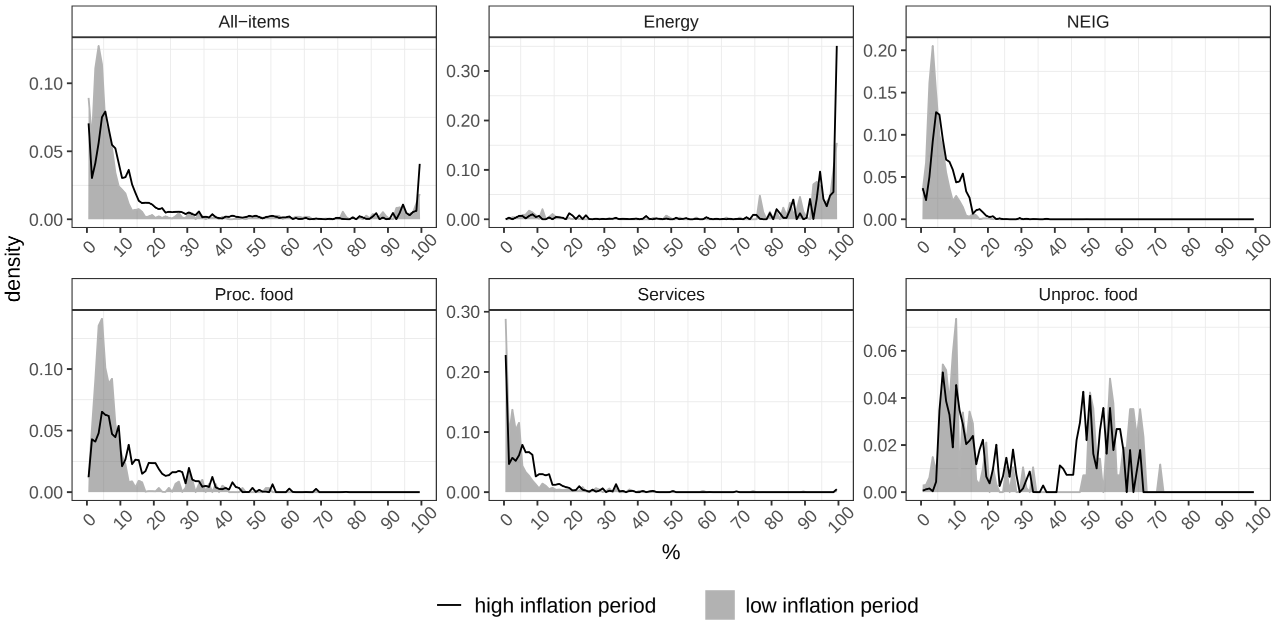
I then used the frequency statistics to calculate the average duration between two price changes. The "*dur.*" column of Table 1 shows that the average duration for all goods and services was about 4 months during the low-inflation period and 3 months during the high-inflation period. Services prices changed every 15 months during the low-inflation period and every 11 months during the high-inflation period. Processed food prices were adjusted twice a year during the low- inflation period and three times a year during the high-inflation period. Unprocessed food and energy prices were adjusted bi-monthly and monthly, respectively, regardless of the time period.

To provide a complete picture, Figure 2 displays the distribution of the frequency of price changes across ECOICOP4 categories during both low and high-inflation periods.[14] Although the distributions are similar in shape, a significant shift to the right characterizes the high-inflation period, signaling a reduction in the time interval between successive price changes (as previously indicated by the decrease in the average duration for most of the special aggregates above). The significant widening of the distribution of the processed food category between the two periods is of particular interest, highlighting that large aggregate shocks can have heterogeneous effects on the frequency of price changes for goods with comparable characteristics.

[13] This compares to 19.4% in Jouvanceau (2022). However, this comparison should be treated with caution, as the frequency statistic calculated for the sample 2010M1 to 2019M12 covers only three ECOICOP4 "energy" categories ("04522", "04530", "04549"), while for this sample there are eight ("04522", "04530", "04541", "04549", "04550", "07221", "07222", "07223"). Nevertheless, the frequency must have increased considerably, as the standard deviation of the HICP monthly growth of energy inflation rose from 1.8% to 3.2%. It should also be noted that the prices of electricity ("0451") and natural gas and town gas ("04521") are not observed in these two samples.

[14] Figure A.1 in Appendix A shows the distributions for the entire sample.

Figure 2: Aggregate distribution of the frequency of price changes across ECOICOP4: low against high-inflation periods



Note: The low-inflation sample covers 2019M2 to 2020M12, and the high inflation 2021M1 to 2023M12. The following steps for each sample compute the distributions. First, a histogram is constructed for each ECOICOP4 category, with 1% intervals between 0 and 1. Second, the final distribution is computed by averaging the relative frequencies in each interval, using the average ECOICOP4 weights in the period.

Expanding upon the decomposition of inflation rates, Table 1 provides statistics on the size of price changes. The average size of price changes for all items increased from 1.8% to 4.6% during the period of high inflation (fifth column $\Delta\bar{p}$).[15] This increase was observed across all special aggregates. Specifically, the average size of price changes rose from -0.4% to 2.1% for energy, from 0.1% to 3% for NEIG, from 0.9% to 4% for processed food, from 6.9% to 10% for services, and from 0.6% to 3% for unprocessed food. Meanwhile, the average size of price increases for all items declined from 16.2% to 15.6% (sixth column $\Delta\bar{p}^{+}$), and the average size of price decreases in absolute terms rose from 17.8% to 18.1% (seventh column $\Delta\bar{p}^{-}$) between the two periods. In summary, the average size of price changes increased significantly during the high-inflation period, while the changes in the average size of price increases and decreases were small. This phenomenon will be discussed further in the next section.

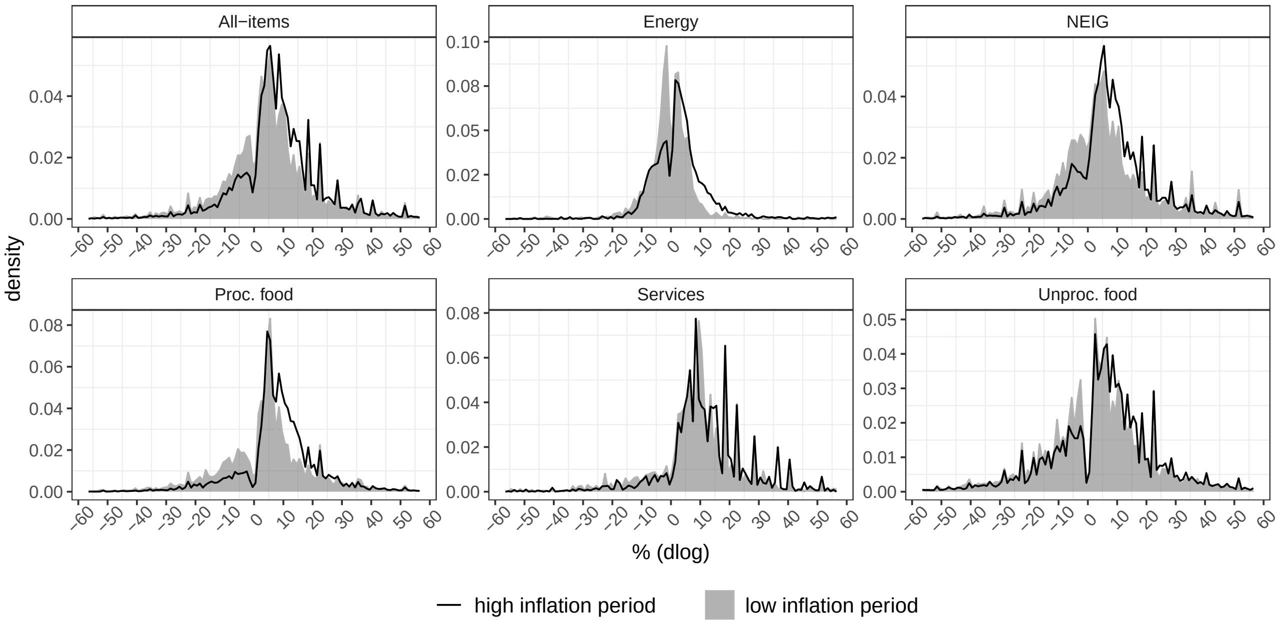
In both periods, the distributions of the size of price changes across ECOICOP4 categories have globally similar shapes, as shown in Figure 3.[16] The distributions are left-skewed, indicating a

[15]For comparison, the average size of price changes across all items was 1.7% in Lithuania between 2010M1 and 2018M12 (Jouvanceau, 2022).

[16]Figure A.2 in Appendix A displays the distributions for the entire sample, and Figure A.3 highlights what the peaks in the distributions represent in terms of percentage growth rather than log difference.

greater frequency of price increases than decreases, which is supported by the statistic in the eighth column of Table 1, which shows the average share of price increases.

Figure 3: Aggregate distribution of the size of price changes across ECOICOP4: low against high-inflation periods



Note: The low-inflation sample covers 2019M2 to 2020M12, and the high inflation 2021M1 to 2023M12. The distributions are computed by the following steps for each sample. First, a histogram is constructed for each ECOICOP4 category, with 1% intervals between 0 and 1. Second, the final distribution is computed by averaging the relative sizes in each interval, using the average ECOICOP4 weights in the period.

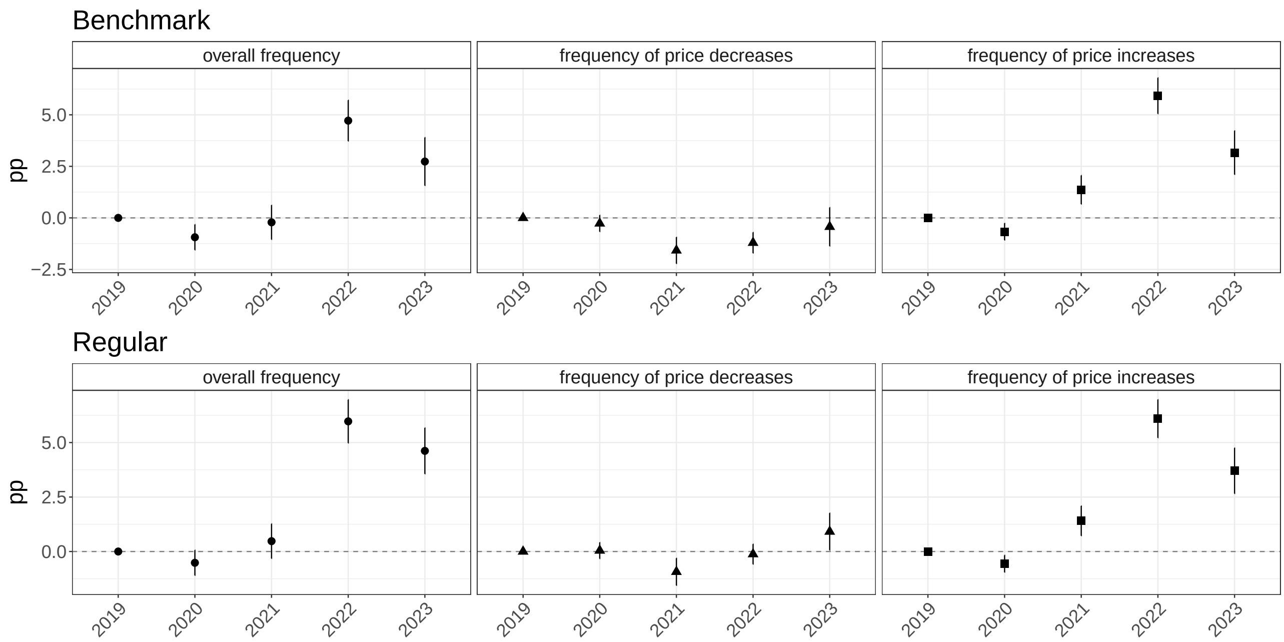
However, during the period of high inflation, there was a notable shift in the skewness of the distribution. Put simply, price changes, especially for processed food, energy, and NEIG items, experienced more frequent but moderate average price increases, with most price changes below an average size of 20% (in logarithmic difference, which is also roughly equivalent to a 20% increase in percentage terms). The importance of these frequency variations for inflation fluctuations is examined in more detail in the next section.

4 Time-series patterns

4.1 Trends in frequency and size margins

I performed fixed effects regressions at the ECOICOP4 level to identify trends in the frequency and size margins of inflation. The results depicted in Figure 4 indicate that the frequency of price changes remained constant from 2019 to 2021. The frequency of price decreases was also relatively steady over the five years, with only a slight decline in 2021 and 2022. In contrast, the frequency of price increases rose significantly, averaging 5 pp and 2.5 pp higher than in 2019, respectively.[17,18]

Figure 4: Trends in the frequency of price changes



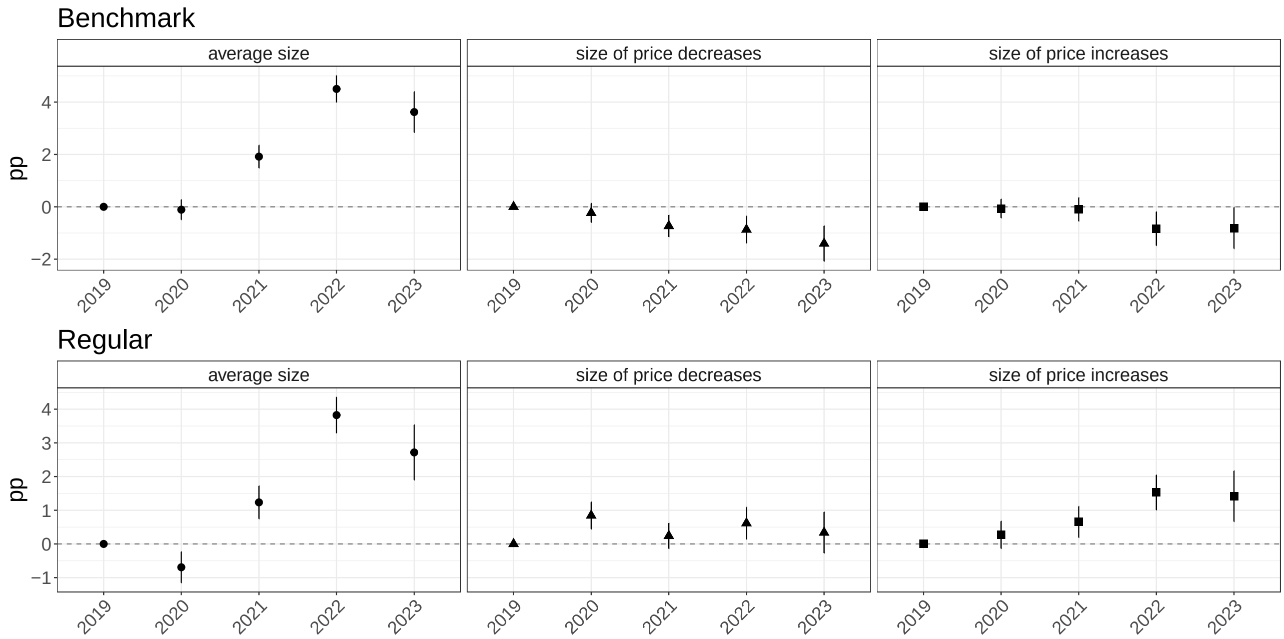
Note: Fixed-effect regressions are conducted at the ECOICOP4 level. Point estimates of the year dummies are marked by circles, triangles, and squares, while the error bars show the 95% confidence intervals corresponding to the ECOICOP4 clustered standard errors. "Benchmark" statistics are *raw* price changes, while "regular" statistics are price changes adjusted for sales and product replacements.

Relative to 2019, Figure 5 illustrates a significant increase in the average size of price changes in 2021, 2022, and 2023, with an average rise of about 2 pp, 4.5 pp, and 4 pp, respectively. Surprisingly, the average size of price increases and decreases declined by about 1 pp in the same years. Therefore, the significant increase in average size seems to be mostly due to shifts in the frequency of price changes.

[17]This pattern is also illustrated in Figure A.4 in Appendix A.

[18]Figures A.5 and A.6 in Appendix A illustrate the seasonality of the frequency and size margins. The findings indicate that in January the frequency of price increases was on average 2 to 4 pp higher than in other months, and the frequency of price decreases was on average about 1 pp lower (but similar to other months when adjusted for price changes due to sales or replacements). As a result, the frequency of price changes in January was on average around 2 to 3 pp higher than in other months. Furthermore, the average size of price changes was higher in January than in other months, on average between 2 and 3 pp (around 1.5 pp on average when adjusted for the effects of sales and product replacements). Contrarily, the average size of price increases and decreases across all months showed minimal difference (only roughly plus or minus 1 pp on average). This highlights the significant impact that frequency variation had on the average size of price changes over the period.

Figure 5: Trends in the average size of price changes



Note: Fixed-effect regressions are conducted at the ECOICOP4 level. Point estimates of the year dummies are marked by circles, triangles, and squares, while the error bars show the 95% confidence intervals corresponding to the ECOICOP4 clustered standard errors. "Benchmark" statistics are *raw* price changes, while "regular" statistics are price changes adjusted for sales and product replacements.

4.2 Margin behind the inflation

To gain a more comprehensive understanding of this phenomenon, counterfactual inflation rates were calculated to determine whether changes in size or frequency had a greater impact on inflation fluctuations (as in Gautier et al. (2022)). To assess the effect of shifts in the average size of price changes, the first step was to calculate counterfactual inflation rates assuming that the frequency of price changes remained constant over time at its average ECOICOP4 value, as follows

$$\tilde{\pi}_{jt}^{\bar{f}} \triangleq \bar{f}_j \times \Delta p_{jt}. \tag{6}$$

where a variable, such as $\bar{f}_j$, marked with an overbar means that its value is fixed at its ECOICOP4-average for the entire period under consideration. In contrast, I considered the inflation rate to be influenced only by variations in the frequency of price changes, that is

$$\tilde{\pi}_{jt}^{\Delta\bar{p}} \triangleq f_{jt} \times \Delta\bar{p}_j. \tag{7}$$

these two counterfactual inflation rates ($\tilde{\pi}_{jt}^{\bar{f}}, (6)$) and ($\tilde{\pi}_{jt}^{\Delta\bar{p}}, (7)$) have a direct relation to the inflation rate decomposed in (1) because they correspond to the varying terms of its linear approximation around the averages ($\bar{f}, \Delta\bar{p}$) as emphasized in the definition (B.1) in Appendix B.

On the other hand, changes in frequency can also affect inflation by influencing the average size of price changes, as the evidence presented above and the definition (3) show. To assess the impact of changes in average size on inflation independent of changes in frequency, I calculated the following counterfactual inflation rates, assuming that the frequency of price increases and the frequency of price decreases remained at their average ECOICOP4 levels throughout the period

$$\tilde{\pi}_{jt}^{\bar{f}^+,\bar{f}^-} \triangleq \bar{f}_j^+ \times \Delta p_{jt}^+ + \bar{f}_j^- \times \Delta p_{jt}^-. \tag{8}$$

Additionally, I considered the impact of shifts in frequency on inflation by assuming that the average size of price increases and price decreases were separately constant over time, as follows

$$\tilde{\pi}_{jt}^{\Delta\bar{p}^+,\Delta\bar{p}^-} \triangleq f_{jt}^+ \times \Delta\bar{p}_j^+ + f_{jt}^- \times \Delta\bar{p}_j^-. \tag{9}$$

These two other counterfactual inflation rates ($\tilde{\pi}_{jt}^{\bar{f}^+,\bar{f}^-}, (8)$) and ($\tilde{\pi}_{jt}^{\Delta\bar{p}^+,\Delta\bar{p}^-}, (9)$) are directly related to the inflation rate decomposed in (4) because they correspond to the varying terms of its linear approximation around the averages ($\bar{f}^+, \bar{f}^-, \Delta\bar{p}^+, \Delta\bar{p}^-$) as highlighted in the definition (B.2) in Appendix B.

Inflation rates were then regressed against each of the four counterfactual inflation rates at the ECOICOP4 level, controlling for fixed effects and month dummies. The results, presented in Table 2, indicate that fluctuations in inflation during the low-inflation period were solely influenced by changes in the average size of price changes and not by changes in the frequency of price changes. This finding is supported by the *within*-R^2 values reported in the second and third columns. Conversely, in the period of high inflation, the proportion of inflation variability accounted for by the frequency of price changes was higher, as indicated in the third column.

On the other hand, shifts in the average size of price increases and decreases taken separately had a moderate effect on inflation variability, especially during the period of high inflation, as shown in the fourth column. In contrast, shifts in the frequency of both price increases and price decreases considered separately had significant explanatory power in both periods,

Table 2: Inflation rate regressions on counterfactual inflation rates (1)

	$\tilde{\pi}_{jt}^{\bar{f}}$	$\tilde{\pi}_{jt}^{\Delta\bar{p}}$	$\tilde{\pi}_{jt}^{\bar{f}^+,\bar{f}^-}$	$\tilde{\pi}_{jt}^{\Delta\bar{p}^+,\Delta\bar{p}^-}$
Low inflation				
	1.094*** (0.0531)	1.861*** (0.273)	1.746*** (0.192)	1.306*** (0.0845)
within-R^2	0.802	0.032	0.425	0.701
obs.	5221	5221	5221	5221
High inflation				
	1.112*** (0.0392)	2.131*** (0.127)	1.337*** (0.148)	1.120*** (0.0476)
within-R^2	0.732	0.202	0.278	0.647
obs.	6109	6109	6109	6109

Note: ***, **, * denote statistical significance at 0.1%, 1% and 5% levels, respectively. Inflation (benchmark) rate regressions are conducted at the ECOICOP4 level, utilizing both month dummies and fixed effects. ECOICOP4 clustered standard errors. Definitions (6), (7), (8), and (9) provide the definitions of each counterfactual inflation presented in the first row.

as shown in the fifth column. This indicates that changes in the share of price increases were a key factor behind inflation fluctuations in both periods.[19] To help understand why, it should be emphasized that an ECOICOP4 inflation rate also allows the following decomposition:

$$\tilde{\pi}_{jt} = \alpha_{jt} \times f_{jt} \times \Delta p_{jt}^{+} + (1 - \alpha_{jt}) \times f_{jt} \times \Delta p_{jt}^{-}. \tag{10}$$

where $\alpha_{jt} = \frac{f_{jt}^{+}}{f_{jt}}$ is the share of price increases.

Importantly, Table 2 shows that the frequency did not lead to inflation during the low-inflation period. This implies that when explaining inflation, shifts in the share of price increases should have been mainly characterized by symmetric shifts in the frequency of price increases and decreases during this period. To test this, I computed the following counterfactual inflation rate

$$\tilde{\pi}_{jt}^{\bar{f},\Delta\bar{p}^+,\Delta\bar{p}^-} \triangleq \alpha_{jt} \times \bar{f}_j \times \Delta\bar{p}_j^{+} + (1 - \alpha_{jt}) \times \bar{f}_j \times \Delta\bar{p}_j^{-}. \tag{11}$$

which is an inflation rate due only to fluctuations in the share of price increases, also corre-

[19] As shown in Gautier et al. (2022) for the low-inflation period (2010-2019) in the EA.

sponding to one of three varying terms in the linear approximation of the inflation rate (10) around the averages $(\bar{\alpha}, \bar{f}, \Delta\bar{p}^{+}, \Delta\bar{p}^{-})$, as shown in the definition (B.3) in Appendix B.[20]

The *within-*R^2 in the second column of Table 3 indicates that fluctuations in the share of price increases had a significant impact on inflation during both periods. However, the role of the share of price increases decreased in importance during the high-inflation period, and the frequency of price changes became more significant, as shown in the third column.

This result is consistent with the predictions of SD models, which suggest that in a high-inflation environment, the frequency of price changes should become more important in explaining inflation fluctuations (Alvarez et al., 2019).

Table 3: Inflation rate regressions on counterfactual inflation rates (2)

	$\tilde{\pi}_{jt}^{\bar{f},\Delta\bar{p}^{+},\Delta\bar{p}^{-}}$	$\tilde{\pi}_{jt}^{\bar{\alpha},\Delta\bar{p}^{+},\Delta\bar{p}^{-}}$	$\tilde{\pi}_{jt}^{\bar{\alpha},\bar{f}}$
Low inflation			
	1.219*** (0.0619)	0.947** (0.305)	1.714*** (0.180)
within-R^2	0.542	0.007	0.408
obs.	5221	5221	5221
High inflation			
	1.180*** (0.0419)	2.072*** (0.129)	1.326*** (0.156)
within-R^2	0.487	0.169	0.263
obs.	6109	6109	6109

Note: ***, **, * denote statistical significance at 0.1%, 1% and 5% levels, respectively. Inflation (benchmark) rate regressions are conducted at the ECOICOP4 level, utilizing both month dummies and fixed effects. ECOICOP4 clustered standard errors. Definitions (11), (11*), and (11**) provide the definitions of each counterfactual inflation presented in the first row.

[20]The other two terms lead to two final counterfactual rates, one for which only variations in the frequency explain inflation ($\tilde{\pi}_{jt}^{\bar{\alpha},\Delta\bar{p}^{+},\Delta\bar{p}^{-}} \triangleq \bar{\alpha}_j \times f_{jt} \times \Delta\bar{p}_j^{+} + (1-\bar{\alpha}_j) \times f_{jt} \times \Delta\bar{p}_j^{-}$. (11*)), and the other, for which only variations in the size of price increases and decreases are relevant ($\tilde{\pi}_{jt}^{\bar{\alpha},\bar{f}} \triangleq \bar{\alpha}_j \times \bar{f}_j \times \Delta p_{jt}^{+} + (1-\bar{\alpha}_j) \times \bar{f}_j \times \Delta p_{jt}^{-}$. (11**)) .

4.3 Aggregate shocks and frequency response

Another prediction of SD models is that large aggregate shocks should induce substantial changes in the frequency of price changes (Karadi and Reiff, 2019; Cavallo et al., 2023). I test whether the frequency margin of inflation gained importance during the high-inflation period due to aggregate shocks using local linear projections à la Jordà (2005). Specifically, I evaluate the impact of aggregate shocks on the counterfactual inflation rates defined above as in Gautier et al. (2022). Projections are estimated separately for the low- and high-inflation samples and are specified as follows

$$\tilde{\pi}_{jt-1,t+h} = \alpha_j + \beta_h \, Shock_t + \varepsilon_{j,t+h}. \tag{12}$$

where $\tilde{\pi}_{jt-1,t+h}$ is one of the counterfactual inflation rates described in definitions (6) to (9), cumulated to month h and α_j represents ECOICOP4 fixed-effects.[21] The variable $Shock_t$ is either the median series of aggregate demand shocks or the median series of energy (price) shocks.

These shocks are identified in a BVAR using monthly macroeconomic data from January 2000 to March 2023. The dataset includes real industrial production (excluding VAT and excise duties), the core consumer price index, and the energy-specific consumer price index, collected from Statistics Lithuania's database. All variables underwent a natural logarithm transformation. The 13-lag reduced form of the model is as follows

$$y'_t = c + \sum_{j=1}^{13} y'_{t-j} B_j + \varepsilon'_t. \tag{13}$$

where y_t is a vector of endogenous variables, c is a vector of constants, B_j is a matrix of parameters, and ε_t is a vector of exogenous innovations, $\varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)$.[22]

I identify aggregate demand and energy shocks because they are arguably the main candidates for explaining the drivers of core inflation in recent years in the EA, as highlighted in Neri et al. (2023). The identification method consists of sign restrictions on the contemporaneous impulse responses of the model, as shown in Table 4. Specifically, I assume that a positive aggregate

[21]Due to sample size, month dummies cannot be included to control for seasonality.

[22]I assume Minnesota-type priors to ensure shrinkage and model stability. I set the autoregressive coefficients to 1 for the first lag of each variable to handle the log-level data, following Litterman (1986). The rest of the hyperparameters are based on standard values as in Canova (2007).

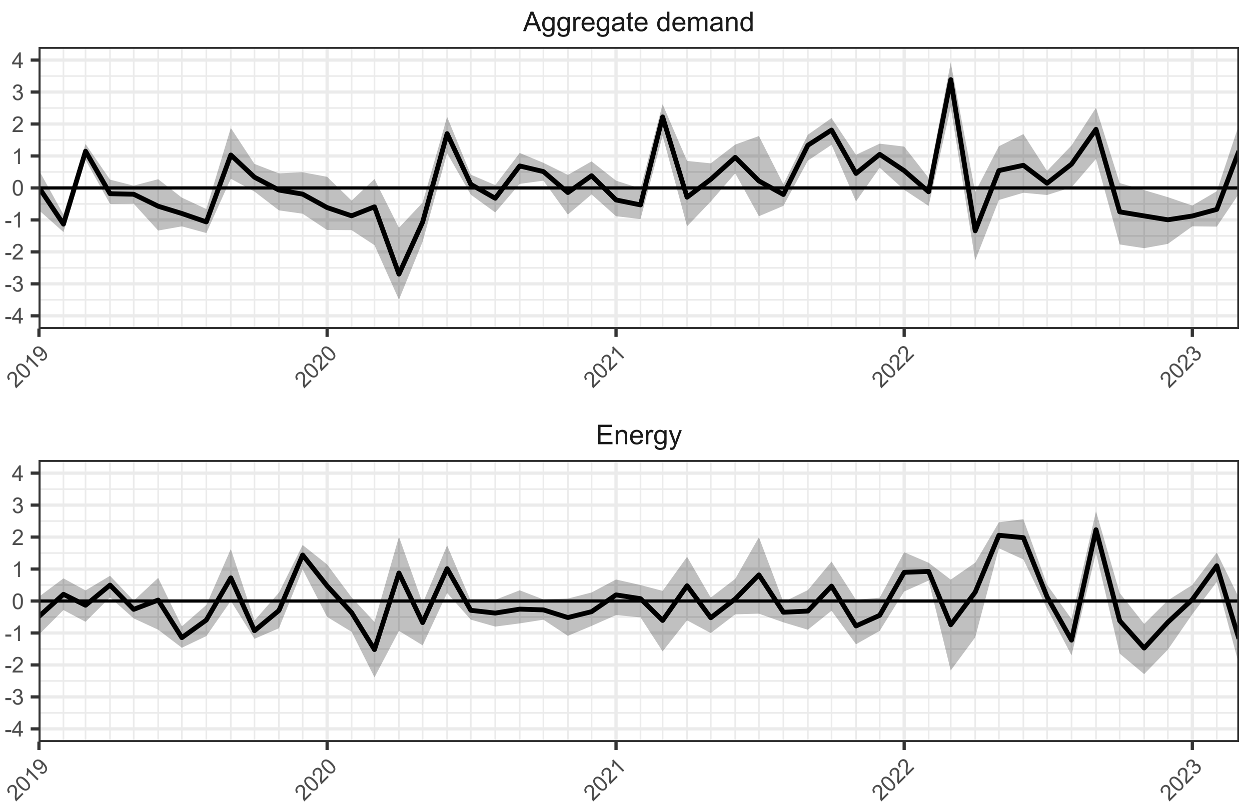
demand shock raises prices and industrial production. In addition, I suppose that a negative energy shock raises prices while reducing production.

Table 4: Sign restrictions in the BVAR

	Aggregate demand (+)	Energy (price) (-)
Real industrial production	+	-
Core CPI	+	+
CPI energy	+	+

Note: Endogenous variables in the rows, structural shocks in the columns. The signs in parentheses in the headings indicate the nature of each shock. Sign restrictions are imposed on contemporaneous relationships between variables, i.e. in the impact matrix of the impulse response. A blank in the body of the table indicates that no sign restrictions are imposed. The last shock of the model is left unidentified.

Figure 6: BVAR structural shocks 2019-2023



Note: The solid black lines represent the median of each type of structural shock based on 10,000 draws. The shaded areas show the 68% probability density intervals. The BVAR is estimated using data from January 2000 through March 2023.

Figure 6 shows the median of 10,000 draws of aggregate demand and energy shocks from 2019 to 2023, represented by black solid lines.[23] In 2020, Lithuania experienced negative aggregate demand shocks due to the effects of the initial COVID-19 quarantine. These shocks had a negative impact on core inflation, as shown in the historical decomposition in Figure A.7 in Appendix A. The rise in core inflation from 2021 to its peak in late 2022 was initially driven by negative energy shocks following Russia's invasion of Ukraine, after which positive aggregate demand shocks gained importance.

Figures 7 and 8 show the projection results, i.e. the average impact coefficients of a negative energy shock and a positive aggregate demand shock on the counterfactual inflation rates ((6)-(9)) in the low- and high-inflation periods separately.[24] Both shocks were rescaled to have an average cumulative effect of 1 pp on *plain* inflation after nine months (see the first column (β_h^{π}) of the figures).[25] This rescaling was done to contrast the qualitative difference in price-setting behavior between periods of low and high inflation.

The results show that for both types of shocks, the response of the counterfactual inflation rate with constant frequency in the second column ($\beta_h^{\bar{f}}$) closely matches the *plain* inflation response in the first column (β_h^{π}). In contrast, the response of the counterfactual rate with constant average size in the third column ($\beta_h^{\Delta\bar{p}}$) does not respond to either type of shock in the low-inflation period. This indicates that fluctuations in the average size of price changes, rather than shifts in the frequency, accounted for most of the inflation conditional on the shocks.

On the other hand, the response of the counterfactual rate with constant frequency of price increases and decreases in the fourth column ($\beta_h^{\bar{f}^+,\bar{f}^-}$) is mostly unresponsive. In contrast, the response of the counterfactual with constant average size of price increases and decreases in the fifth column ($\beta_h^{\Delta\bar{p}^+,\Delta\bar{p}^-}$) is consistent with the response of *plain* inflation (β_h^{π}). This suggests that the share of price increases responded significantly to these shocks, as illustrated in the second column ($\beta_h^{\bar{f}^+,\Delta\bar{p}^+,\Delta\bar{p}^-}$) of Figures A.8 and A.9 in Appendix A.

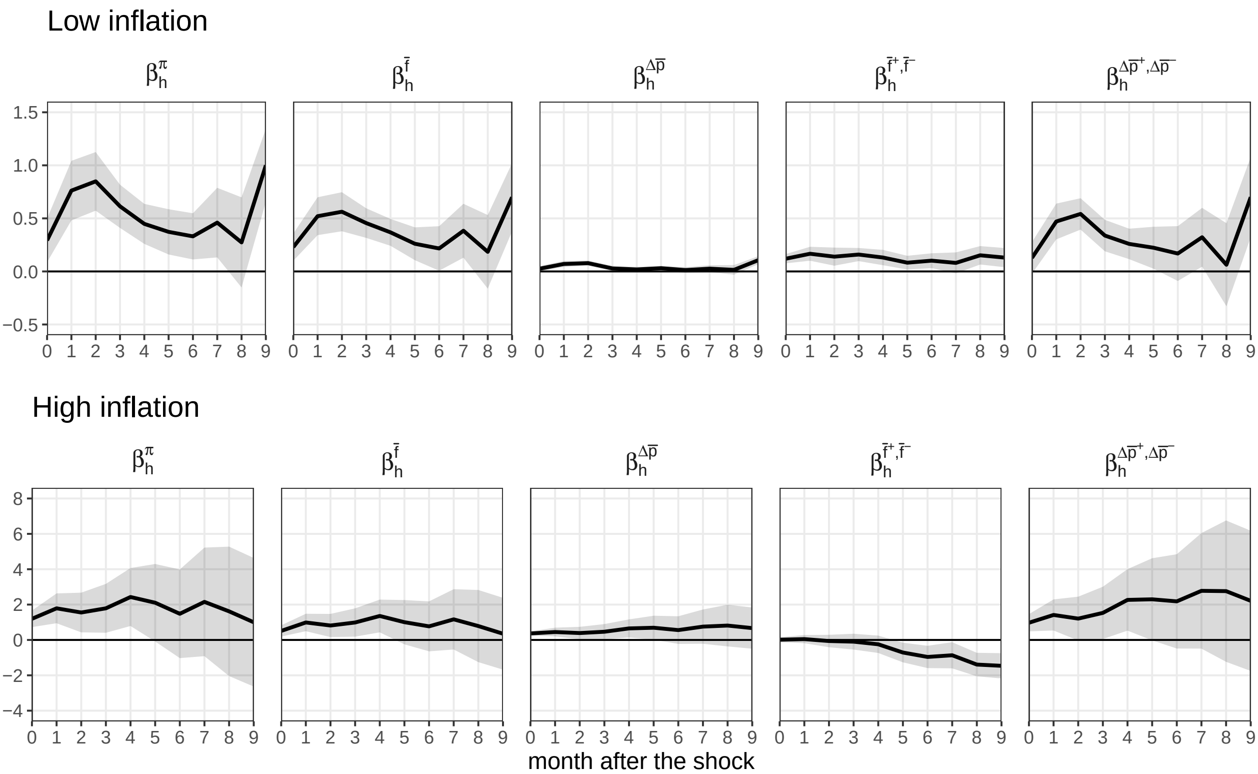
Finally, during the high-inflation period, the counterfactual rate with constant average size of price changes shows a significant response to both shocks (see the third column ($\beta_h^{\bar{f}}$)). This indicates that the shocks affected the frequency of price changes. This outcome is consistent with the predictions of SD models as described in Alvarez et al. (2016); Karadi and Reiff (2019).

[23]Note that the sign restrictions identify negative energy shocks in the data. Thus, a positive occurrence of the shocks in Figure 6 indicates a negative disturbance of that particular shock type.

[24]Projections based on the counterfactual inflation rates defined in (11), (11*) and (11**) can be found in Figures A.8 and A.9 in Appendix A.

[25]Due to the limited sample size in terms of time series length, the projections lose significant validity after nine months.

Figure 7: Responses of counterfactual inflation rates ((6)-(9)) to a negative energy shock



Note: The equation (12) describes the local linear regressions. The responses indicated by β_h^{π} relate to the reaction of plain inflation (panel 1), $\beta_h^{\bar{f}}$ of the counterfactual inflation with constant frequency (panel 2), $\beta_h^{\Delta\bar{p}}$ of the counterfactual inflation with constant average size (panel 3), $\beta_h^{\bar{f}^+,\bar{f}^-}$ of the counterfactual inflation with constant frequency of price increases and decreases (panel 4), $\beta_h^{\Delta\bar{p}^+,\Delta\bar{p}^-}$ of the counterfactual inflation with constant average size of price increases and decreases (panel 5). The shaded areas represent one standard error based on calendar (month-year) clusters.

Furthermore, I shed light on the dynamic responses of the counterfactual inflation rates between the periods of low and high inflation by running an additional set of projections. This was done by estimating the following regressions on the full sample

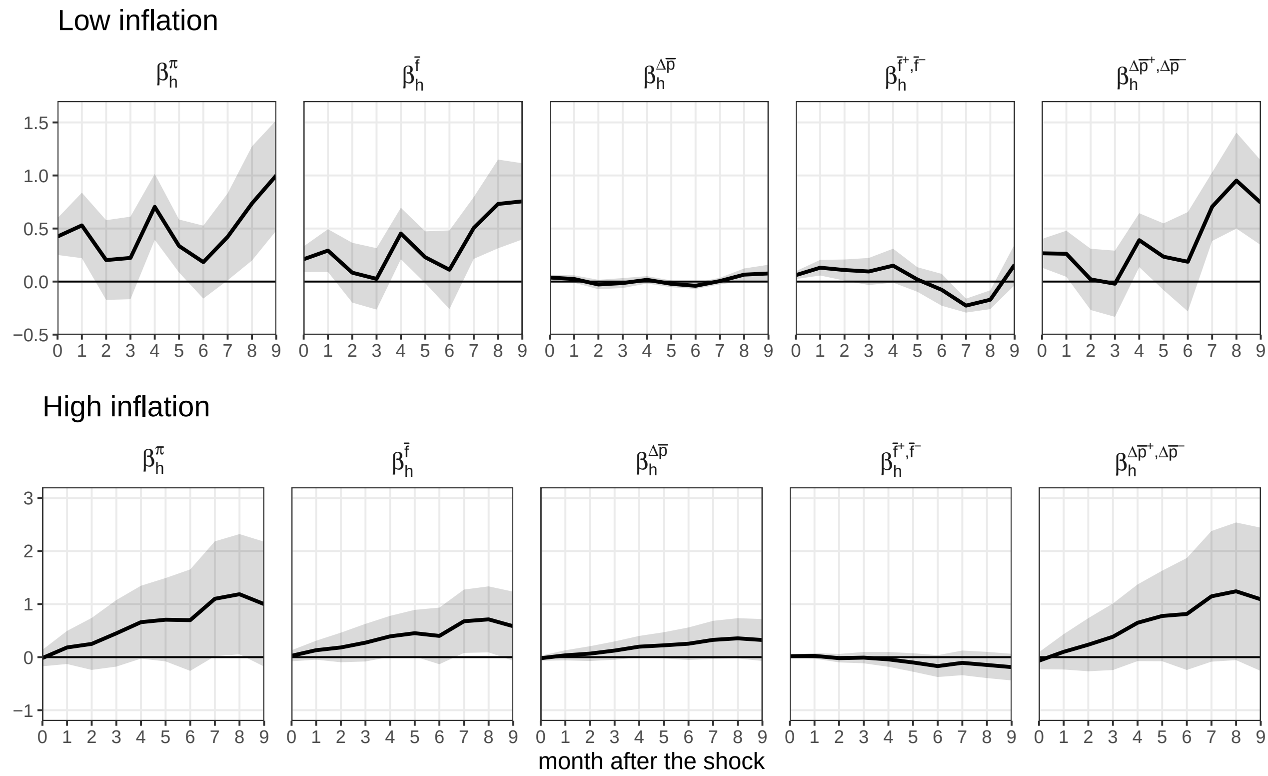
$$\tilde{\pi}_{jt-1,t+h} = \alpha_{mj} + \delta_h I_{\pi_{high}} + \chi_h \, Shock_t + \gamma_h \, Shock_t \times I_{\pi_{high}} + \epsilon_{j,t+h}. \tag{14}$$

where $I_{\pi_{high}}$ is a dummy that takes the value 1 in the high-inflation period, and α_{mj} are month-ECOICOP4 fixed effects.[26]

Figure 9 shows the responses of the counterfactual inflation rates given by the γ_h coefficients of the interaction term $Shock_t \times I_{\pi_{high}}$. In other words, it illustrates how these inflation rates respond to a one-standard-deviation shock in the high-inflation period relative to the low-

[26]Unlike the projections detailed in (12), where the margins in the counterfactual inflation rates are fixed at the sample averages for either low or high inflation, these projections compute the left-hand-side rates by fixing the margins at their sample-wide averages from 2019 to 2023.

Figure 8: Responses of counterfactual inflation rates ((6)-(9)) to a positive aggregate demand shock



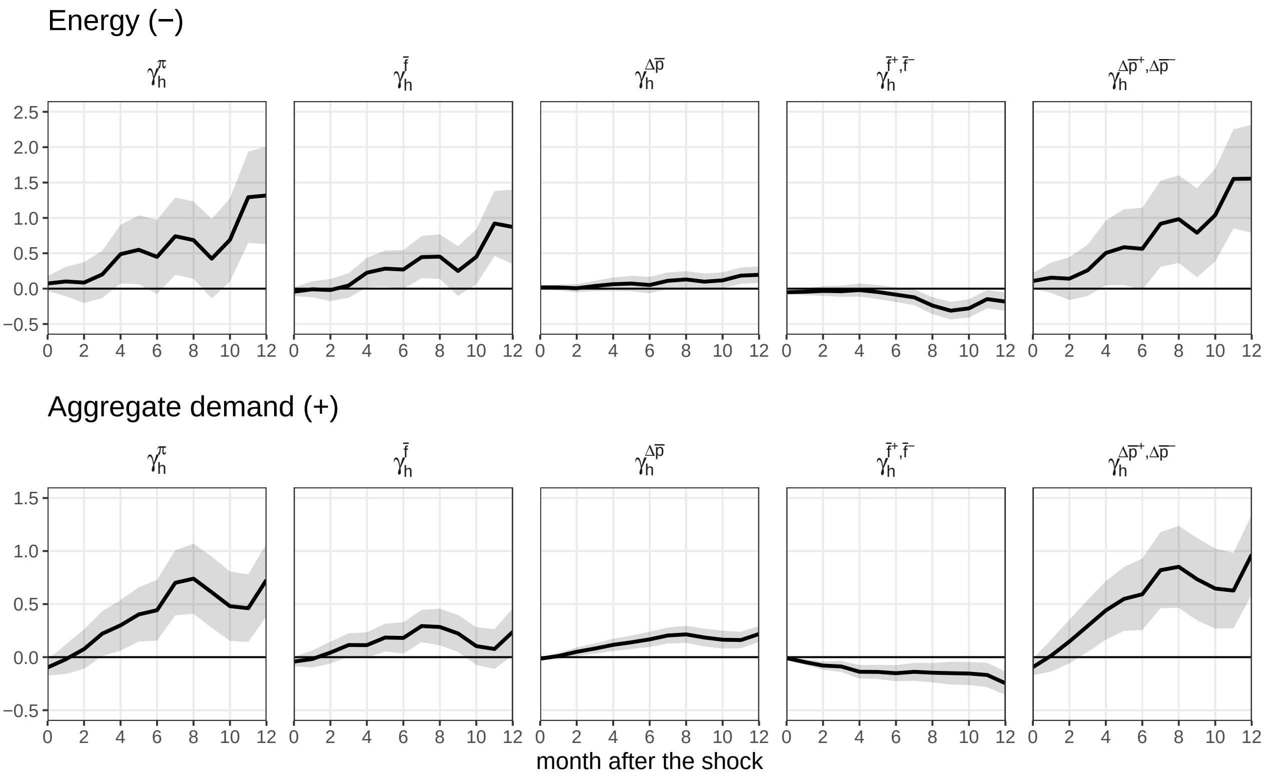
Note: The equation (12) describes the local linear regressions. The responses indicated by β_h^{π} relate to the reaction of plain inflation (panel 1), $\beta_h^{\bar{f}}$ of the counterfactual inflation with constant frequency (panel 2), $\beta_h^{\Delta\bar{p}}$ of the counterfactual inflation with constant average size (panel 3), $\beta_h^{\bar{f}^+,\bar{f}^-}$ of the counterfactual inflation with constant frequency of price increases and decreases (panel 4), $\beta_h^{\Delta\bar{p}^+,\Delta\bar{p}^-}$ of the counterfactual inflation with constant average size of price increases and decreases (panel 5). The shaded areas represent one standard error based on calendar (month-year) clusters.

inflation period.

On impact, *plain* inflation reacts similarly in both periods (see column 1, γ_h^{π}). However, differences accumulate over time and become substantial after one year. This finding emphasizes that aggregate shocks have a larger pass-through to consumer prices in a high-inflation environment in Lithuania, as predicted by SD models. Additionally, the pass-through is faster, as demonstrated by the response of the counterfactual inflation rate, which is solely influenced by changes in the frequency of price changes (see column 3, $\gamma_h^{\Delta\bar{p}}$).

It is important to note that the accelerated pass-through occurs approximately three months after the shocks. Large shocks should, in theory, have a quicker impact because they substantially increase the probability of price adjustments (Cavallo et al., 2023). This is because prices deviate quickly and considerably from their optimal level. Arguably, inflation rates and shock sizes in Lithuania have been too small to cause such rapid and substantial changes in all prices.

Figure 9: Responses of counterfactual inflation rates to aggregate shocks in the high-inflation period relative to the low-inflation period



Note: The equation (14) describes the local linear regressions. The responses indicated by γ_h^{π} relate to the reaction of plain inflation (panel 1), $\gamma_h^{\bar{f}}$ of the counterfactual inflation with constant frequency (panel 2), $\gamma_h^{\Delta\bar{p}}$ of the counterfactual inflation with constant average size (panel 3), $\gamma_h^{\bar{f}^+,\bar{f}^-}$ of the counterfactual inflation with constant frequency of price increases and decreases (panel 4), $\gamma_h^{\Delta\bar{p}^+,\Delta\bar{p}^-}$ of the counterfactual inflation with constant average size of price increases and decreases (panel 5). The shaded areas represent one standard error based on calendar (month-year) clusters.

Therefore, it is unlikely that these projections would reveal such a phenomenon.[27]

5 Conclusion

The underlying price records of the CPI provided by Statistics Lithuania, the official statistical office of Lithuania, were analyzed in this study. The dataset covers about 90% of the HICP weights at the ECOICOP4 level. The study aimed to examine the differences in consumer price rigidity in Lithuania during a period of low-inflation, from January 2019 to December 2020, and during a period of high inflation, from January 2021 to March 2023.

[27]To highlight this phenomenon, one could refine the identification of shocks. For instance, assuming stochastic volatility in the BVAR model could result in capturing more substantial shocks. Then, the projections should rather focus on specific price categories, such as food and energy, where prices are more flexible. These considerations are beyond the scope of this paper and are left for further research.

The analysis based on the decomposition of inflation rates at the ECOICOP4 level showed that the average frequency of price changes was 23.5% in the low-inflation period and grew by 2.8 pp in the high-inflation period. This increase was mainly due to a significant rise of 4.8 pp in the average frequency of price increases, while the average frequency of price decreases fell by 2 pp. As a result, the average share of price increases increased by 9.9 pp.

Furthermore, the average size of price changes was 1.8% during the low-inflation period and increased by 2.8 pp during the high-inflation period. Interestingly, this increase was not primarily due to significant shifts in the average size of price increases and decreases, which changed by -0.6 and 0.3 pp, respectively. The change in the average size was mainly due to a sharp rise in the frequency of price increases, resulting in a significant increase in both the share of price increases and the frequency of price changes. The latter changed because the frequency of price decreases did not decline to a similar extent as the frequency of price increases.

Moreover, my findings show that during the high-inflation period, inflationary aggregate shocks - such as energy (price) and aggregate demand shocks - caused significant shifts in the frequency of price changes, while they did not do so during the low-inflation period. SD models predict that such a phenomenon should occur when large aggregate shocks hit and inflation is high, as demonstrated in Alvarez et al. (2019); Auclert et al. (2023).

Arguably, these findings hold importance for macroeconomists who aim to construct and calibrate models analyzing the transmission of monetary policy in Lithuania. Additionally, detailed ECOICOP4 statistics can be shared upon request.

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Appendix A

Table A.1: Price change flags

Flag	Definition	Regular		Observation	Share (%)
		sale	product replacement		
1	Product prices start to be recorded			79	∼ 0
AKC	Promotion	x		121060	3.9
HK	A product of the same quality at the same price has appeared		x	24165	0.8
HK(1-8)	Repeat of last month's price			136213	4.4
HK9	Repeat of last month's price (COVID imputation)			56139	1.8
ISP	Collection sale	x		1286	∼ 0
KIE	Quantity discount	x		10	∼ 0
KK	New price component			4	∼ 0
KP	Change in quality (within the ranges -70% to -30% and +30% to +70%)		x	51	∼ 0
KTK	Other replacement product		x	37430	1.2
KTN	Other discount	x		1043	∼ 0
KTP	Another reason			469	∼ 0
MEN	Monthly discount	x		13274	0.4
MOK	Changes in tax rates			53	∼ 0
NEZ	Slight change in quality (within the range -29% to +29%)		x	3001	0.1
NK	New collection		x	3316	∼ 0
NS	Price of a seasonal product in the new season		x	25	∼ 0
PK	New product component		x	3	∼ 0
PSS	Weekend discount	x		227	∼ 0
RGL	Change in regulated price			544	∼ 0
RK	The price was incorrectly stated			833	∼ 0
RP	The price has actually changed			387696	12.6
SAV	Weekly discount	x		18901	0.6
SEZ	Seasonal discount	x		477	∼ 0
SVE	Festive/Holiday discount	x		153	∼ 0
YP	Exceptional supply or demand		x	427	∼ 0

Note: In the table, an "x" denotes that a flag has been utilized to generate a series of "regular" price changes that factor in the effects of sales promotions and product replacements. "Share (%)" denotes the percentage of flagged observations within the overall number of price observations.

Table A.2: Aggregate weighted statistics: low against high-inflation periods, adjusted price changes

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\%Adj.$	$obs.$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%	
All items	16.3	9.0	7.3	5.6	4.2	11.8	-11.0	65.9	100.0	10.4	1393932
Energy	80.4	38.5	42.0	0.6	-0.4	4.5	-4.6	47.6	11.7	1.3	11274
NEIG	5.0	3.2	1.8	19.6	4.2	12.7	-11.0	63.9	32.1	12.3	595385
Proc. food	8.7	5.9	2.8	11.0	3.6	12.3	-12.3	67.2	24.8	11.3	531897
Services	5.5	4.0	1.5	17.8	8.0	13.3	-13.6	80.4	26.2	0.7	136389
Unproc. food	32.7	18.5	14.2	2.5	2.1	13.5	-12.9	58.3	5.3	8.8	118987
High inflation	%	%	%	$m.$	%	%	%	%	%	%	
All items	19.2	13.6	5.6	4.7	6.9	12.2	-11.4	76.9	100.0	9.6	1673980
Energy	85.0	53.1	31.9	0.5	2.3	5.9	-5.1	64.1	11.3	1.1	14809
NEIG	7.5	5.8	1.7	12.8	7.0	12.7	-11.5	76.1	33.6	11.9	706919
Proc. food	14.8	12.1	2.7	6.3	6.7	12.2	-12.3	78.6	25.6	9.8	641206
Services	7.8	6.7	1.1	12.3	10.5	14.2	-13.1	86.6	24.1	0.6	168814
Unproc. food	33.2	21.1	12.1	2.5	4.2	14.2	-13.1	65.3	5.4	9.6	142232

Note: The statistics are based on price changes adjusted for sales and product replacements (see A.1 for additional information). The low-inflation sample covers 2019M2 to 2020M12, and the high inflation 2021M1 to 2023M12. "$\%inc.$" represents the proportion of price increases in total price changes, while "$\%Adj.$" indicates the share of price (non-zero) changes modified to produce "regular" statistics. "$\bar{\omega}$" refers to the average share of HICP weights in each sample. "$dur.$" signifies the implied average duration, which can be calculated using: $dur = -1/ln(1-f)$ where f is the weighted average frequency. "$obs.$" refers to the number of observations, while "$m.$" indicates the number of months associated with the duration. Finally, "NEIG" stands for "non-energy industrial goods".

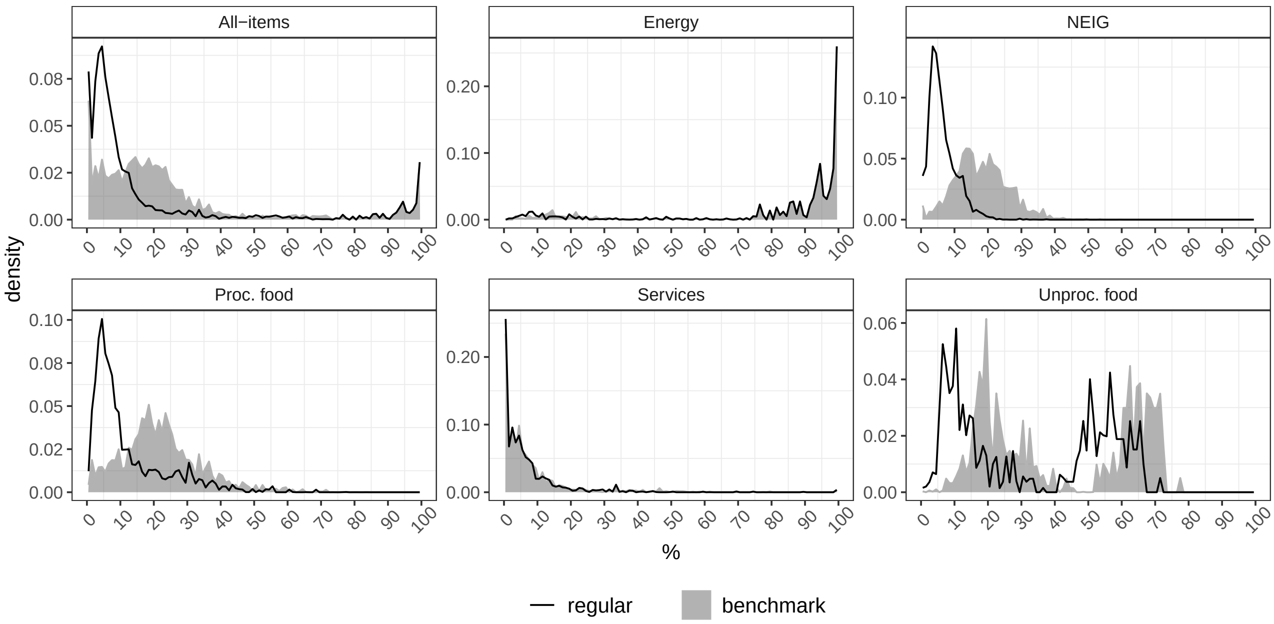
Table A.3: Aggregate weighted statistics: full-sample 2019-2023

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\%Adj.$	$obs.$
Benchmark	%	%	%	$m.$	%	%	%	%	%	%	
All items	25	15	10	3.5	3.3	15.9	-17.9	64	100.0	-	3067912
Energy	83.3	46.4	36.9	0.6	0.9	5.6	-5.8	56.1	11.5	-	26083
NEIG	18	10.3	7.7	5.0	1.7	19.2	-21.4	57.5	33	-	1302304
Proc. food	22	14.3	7.7	4.0	2.6	16.9	-19.7	64	25.3	-	1173103
Services	7.6	5.9	1.7	12.6	8.6	14.2	-15.1	81	24.9	-	305203
Unproc. food	42.2	24.3	18	1.8	1.9	16.9	-18	58	5.3	-	261219
Regular	%	%	%	$m.$	%	%	%	%	%	%	
All items	17.9	11.5	6.4	5.1	5.7	12.0	-11.2	72	100.0	10.0	3067912
Energy	82.9	46.2	36.7	0.6	1.0	5.2	-4.8	56.3	11.5	1.2	26083
NEIG	6.4	4.7	1.7	15.2	5.8	12.7	-11.3	70.7	33	12.0	1302304
Proc. food	12.0	9.3	2.7	7.8	5.3	12.3	-12.3	73.5	25.3	10.4	1173103
Services	6.7	5.4	1.3	14.4	9.4	13.8	-13.4	83.7	24.9	0.7	305203
Unproc. food	33.0	19.9	13.1	2.5	3.3	13.8	-13.0	62.1	5.3	9.2	261219

Note: "$\%inc.$" represents the proportion of price increases in total price changes, while "$\%Adj.$" indicates the share of price (non-zero) changes modified to produce "regular" statistics. "$\bar{\omega}$" refers to the average share of HICP weights in each sample. "$dur.$" signifies the implied average duration, which can be calculated using: $dur = -1/ln(1-f)$ where f is the weighted average frequency. "$obs.$" refers to the number of observations, while "$m.$" indicates the number of months associated with the duration. Finally, "NEIG" stands for "non-energy industrial goods".

Figure A.1 shows the aggregate distribution of the frequency of price changes across ECOICOP4 for the entire sample. Most frequencies (excluding 0) for NEIG, processed food, and services fall between 0 and 30%, while they are more widely distributed for unprocessed food and energy categories. Specifically, the frequencies for NEIG and processed food mainly range from 10% to 30%, indicating an average price change every 3 to 10 months. For services, the majority of the frequencies are below 10%, which means that prices are fixed for at least 10 months on average. Frequencies for unprocessed foods show a distribution with multiple peaks around 20% and 60%, indicating the perishable nature of items such as meat, fish, and fruit. The frequency distribution for energy prices displays a significant negative skew, revealing that price changes occur on average every month.

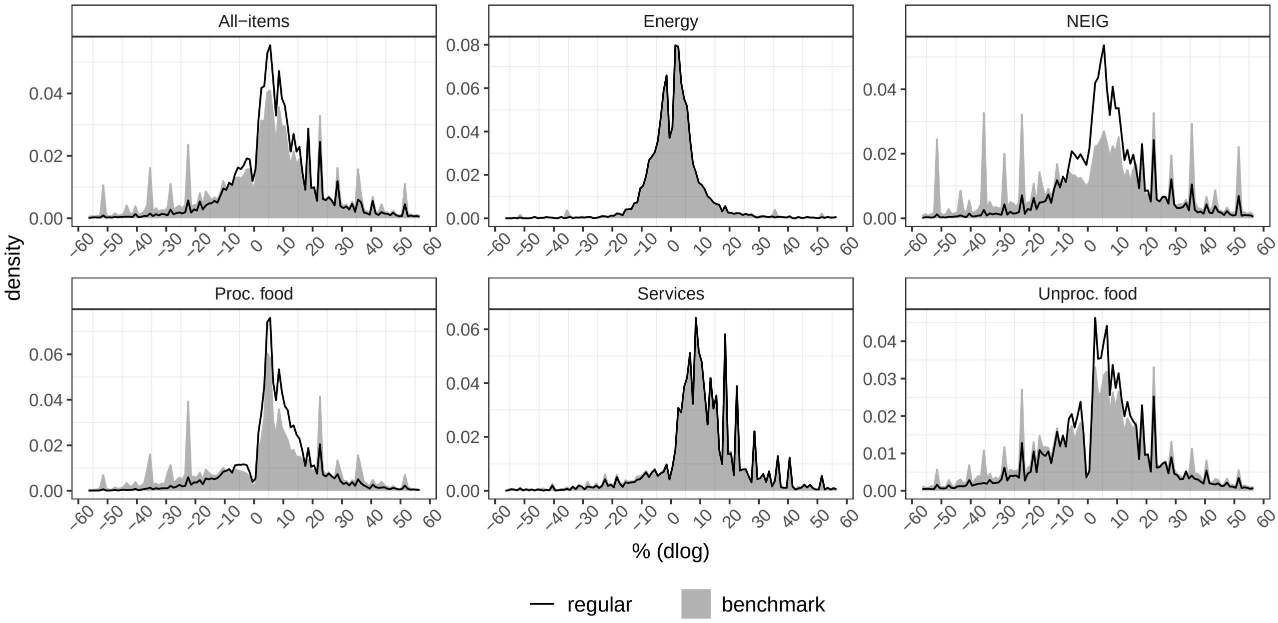
Figure A.1: Aggregate distribution of the frequency of price changes across ECOICOP4 (2019-2023)



Note: To compute the distributions, the following steps are taken. First, a histogram is constructed for each ECOICOP4 category, with 1% intervals between 0 and 1. Second, the final distribution is computed by averaging the relative frequencies in each interval, using the average ECOICOP4 weights between 2019 to 2023. "Regular" corresponds to price changes adjusted for sales and replacements (see section 2).

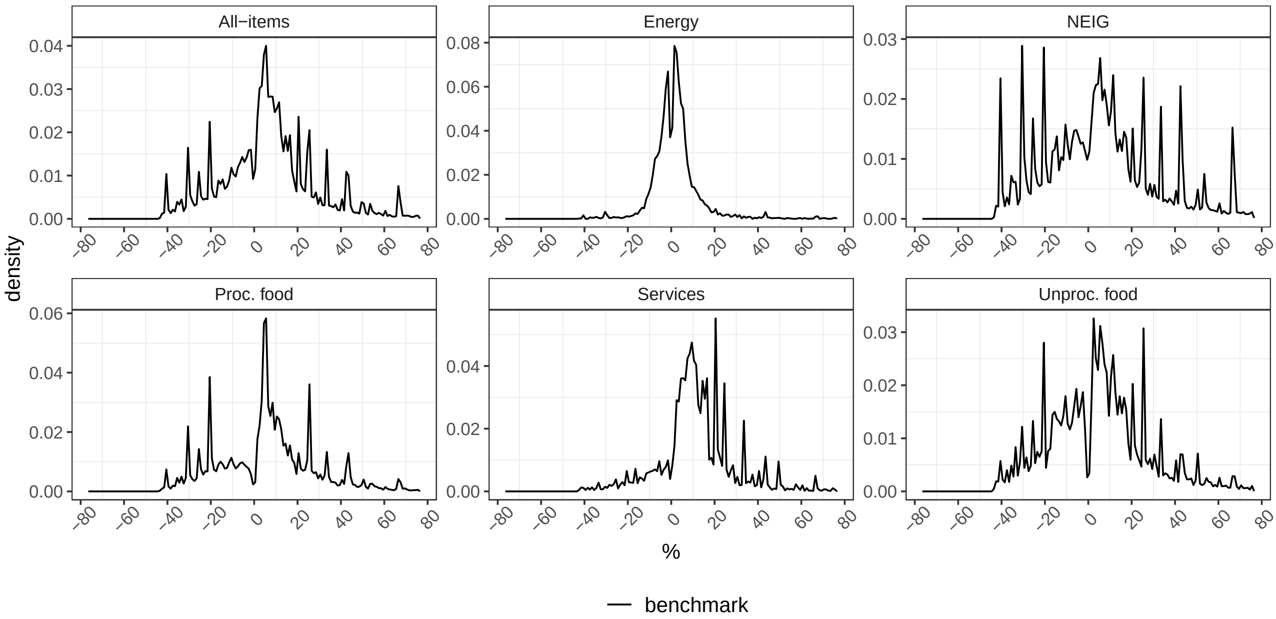
Figure A.2 indicates a globally negative skew in the aggregate distributions of the size of price changes across ECOICOP4 in the entire sample, suggesting a greater frequency of price increases compared to price decreases. Table A.3 in the main text provides additional evidence supporting this phenomenon. Additionally, the distributions display peaks at (-)5%, (-)20%, and (-)25% (see Figure A.3 in the Appendix for the size distributions in growth rates). These patterns indicate the impact of sales and product replacements.

Figure A.2: Aggregate distribution of the size of price changes across ECOICOP4 (2019-2023)



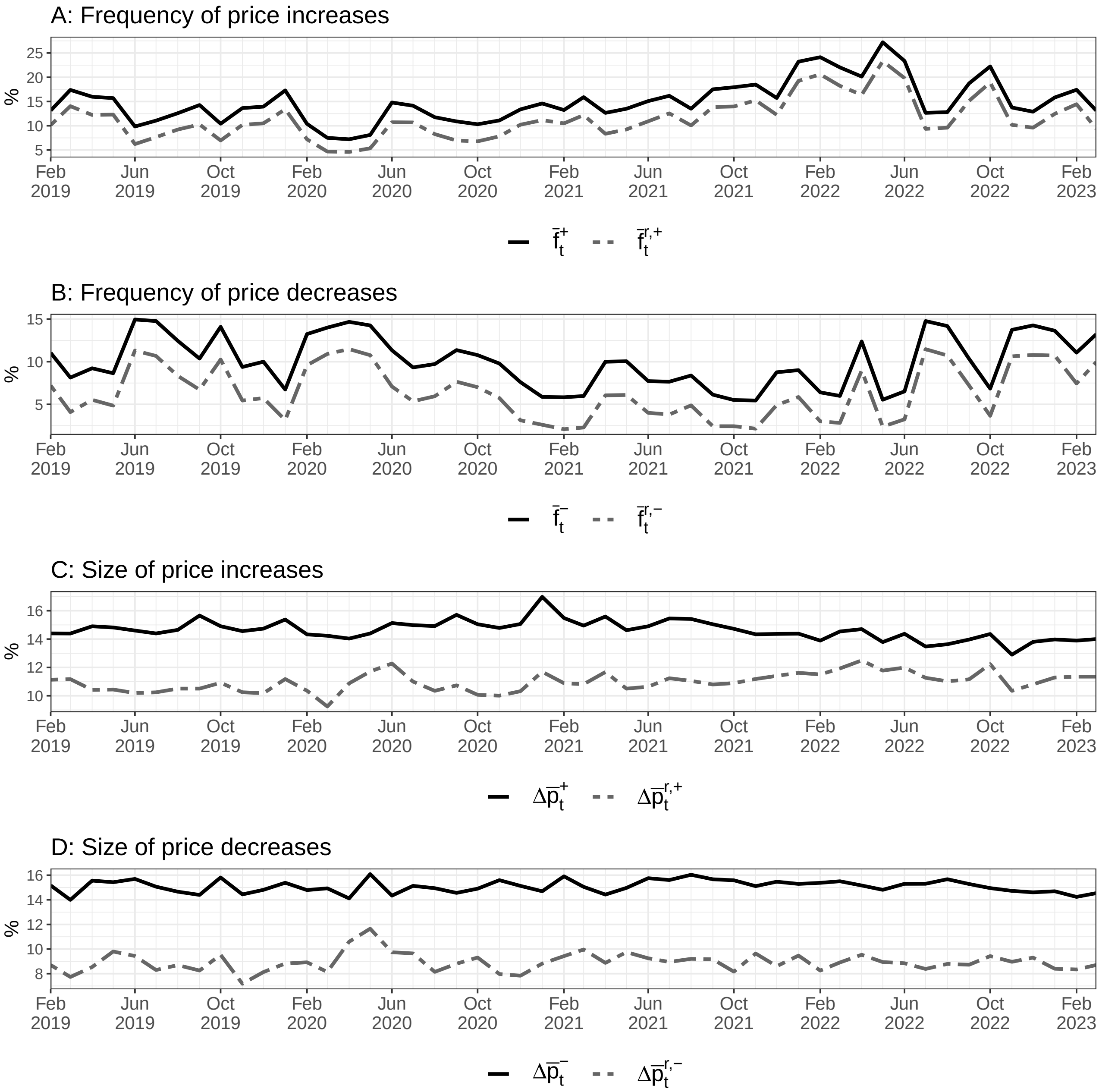
Note: To compute the distributions, the following steps are taken. First, a histogram is constructed for each ECOICOP4 category, with 1% intervals between 0 and 1. Second, the final distribution is computed by averaging the relative size in each interval, using the average ECOICOP4 weights between 2019 to 2023. "Regular" corresponds to price changes adjusted for sales and replacements (see section 2).

Figure A.3: Aggregate distribution of the size of price changes across ECOICOP4 (in %, 2019-2023)



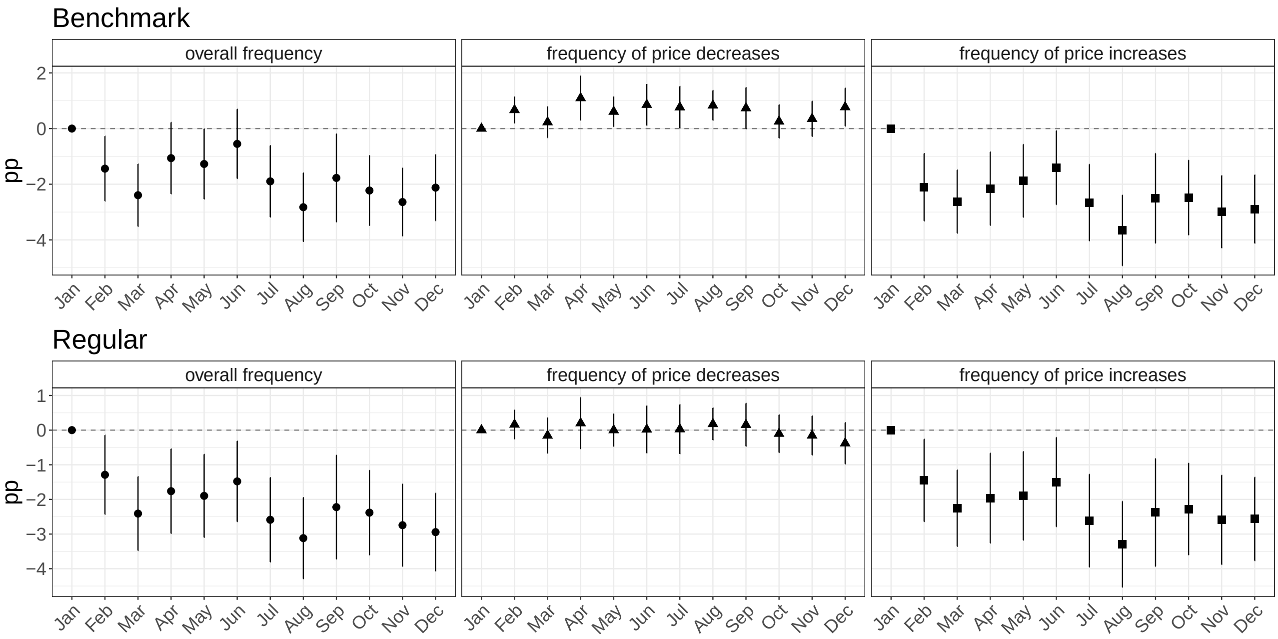
Note: To compute the distributions, the following steps are taken. First, a histogram is constructed for each ECOICOP4 category, with 1% intervals between 0 and 1. Second, the final distribution is computed by averaging the relative size in each interval, using the average ECOICOP4 weights between 2019 to 2023.

Figure A.4: Weighted average frequency and size of price changes over time



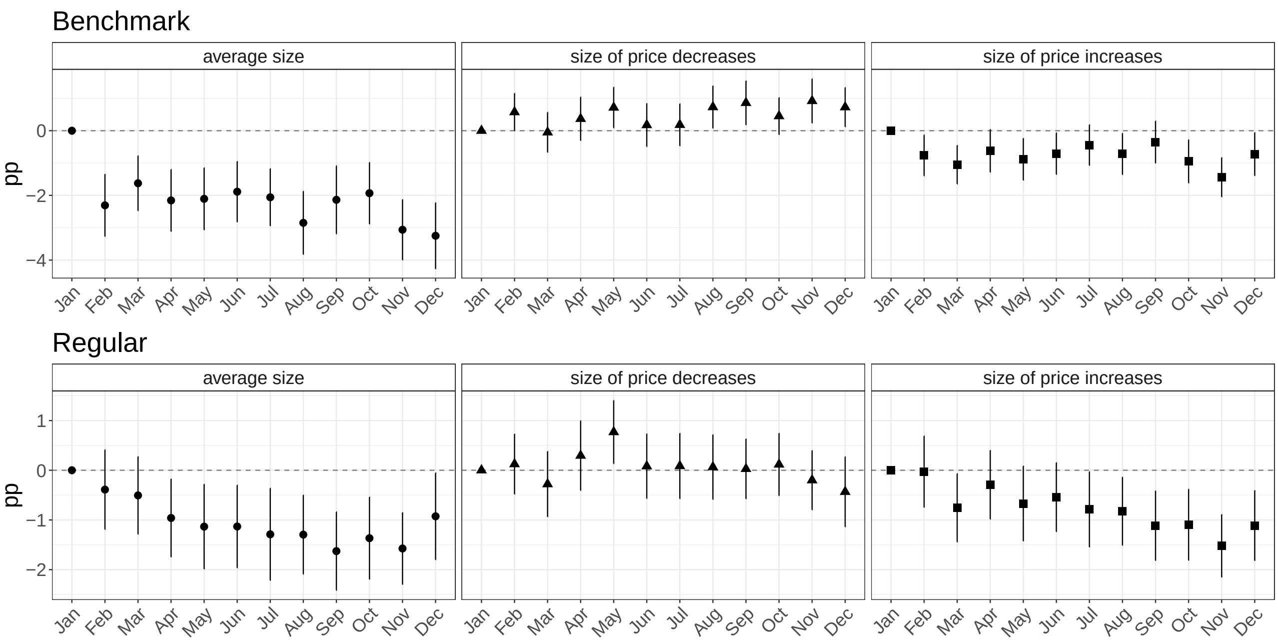
Note: "Benchmark" statistics are shown as black solid lines, and "regular" statistics as dashed lines. The superscript "r" in the legends refers to the "regular" price change series.

Figure A.5: Seasonality in the frequency of price changes



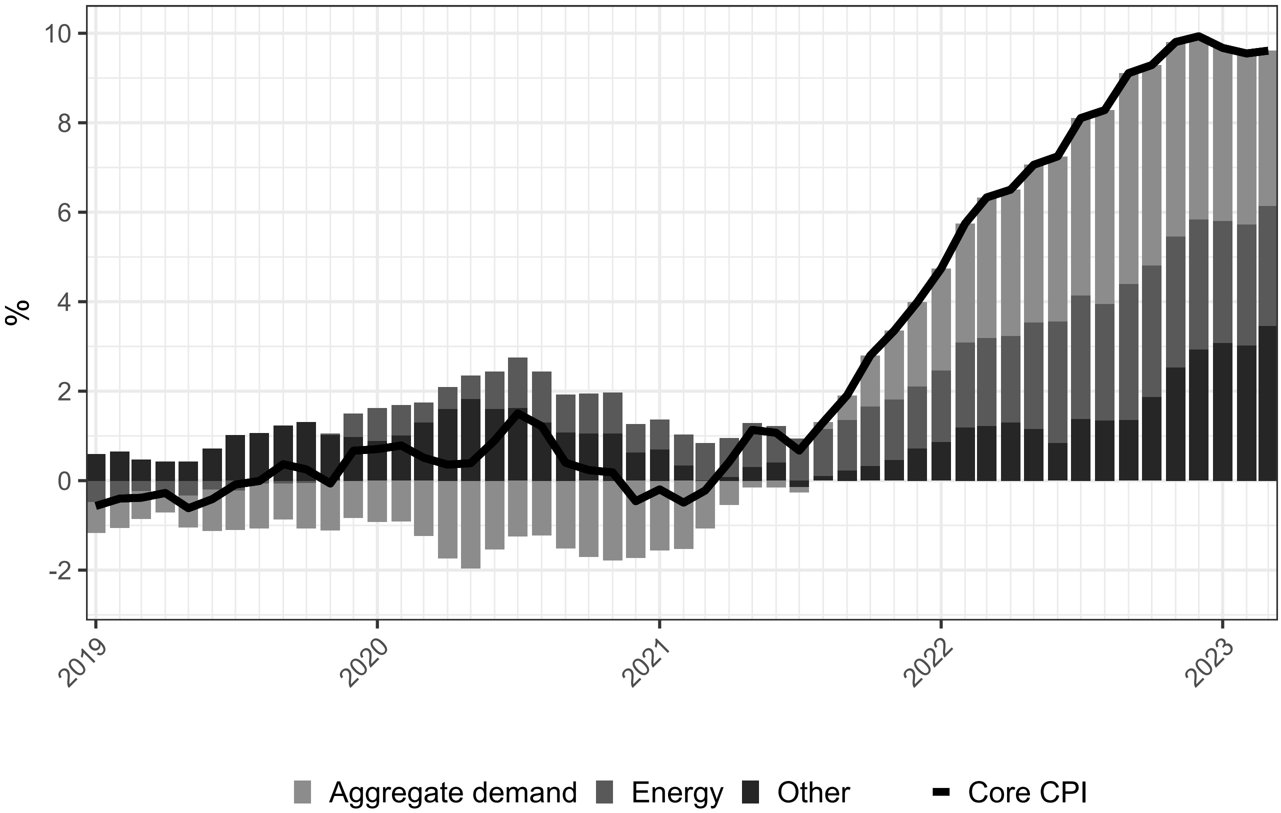
Note: Fixed-effect regressions are conducted at the ECOICOP4 level. Point estimates of the month dummies are marked by circles, triangles, and squares, while the error bars show the 95% confidence intervals corresponding to the ECOICOP4 clustered standard errors. "Benchmark" statistics are *raw* price changes, while "regular" statistics are price changes adjusted for sales and product replacements.

Figure A.6: Seasonality in the average size of price changes



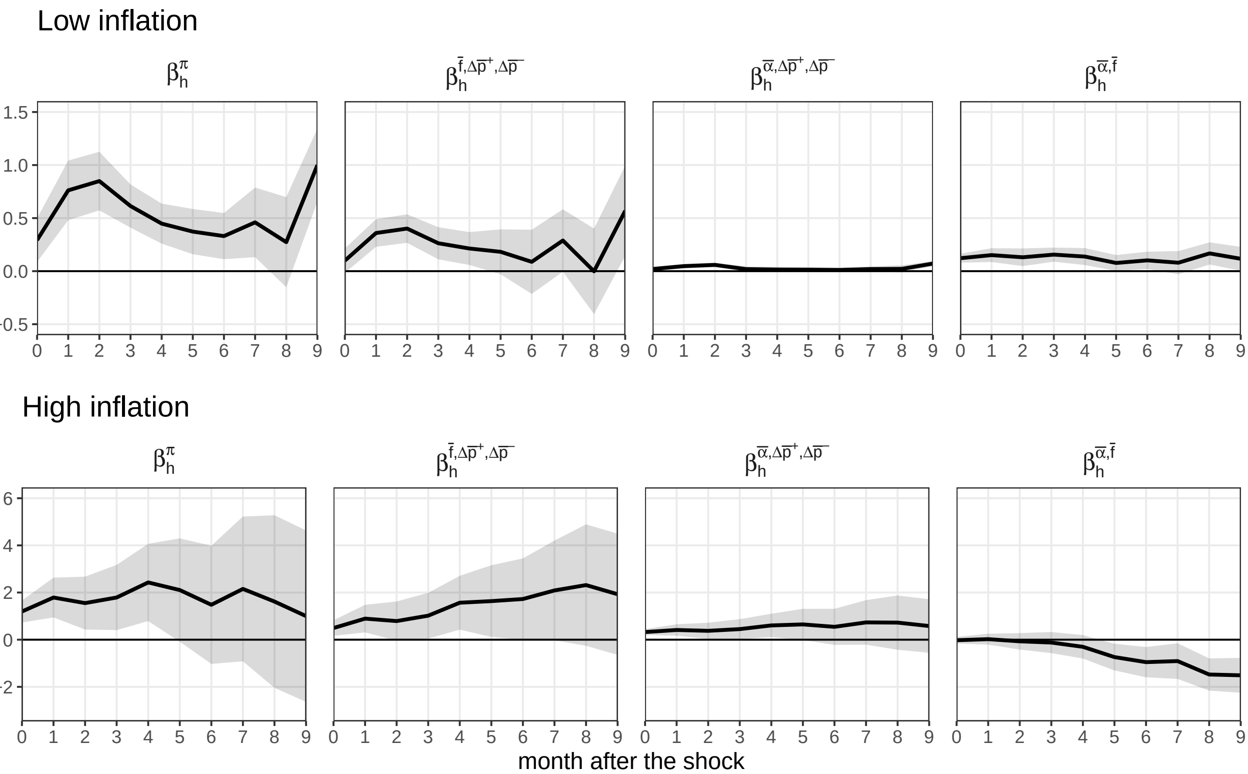
Note: Fixed-effect regressions are conducted at the ECOICOP4 level. Point estimates of the month dummies are marked by circles, triangles, and squares, while the error bars show the 95% confidence intervals corresponding to the ECOICOP4 clustered standard errors. "Benchmark" statistics are *raw* price changes, while "regular" statistics are price changes adjusted for sales and product replacements.

Figure A.7: Historical decomposition year-on-year core CPI growth, 2019-2023



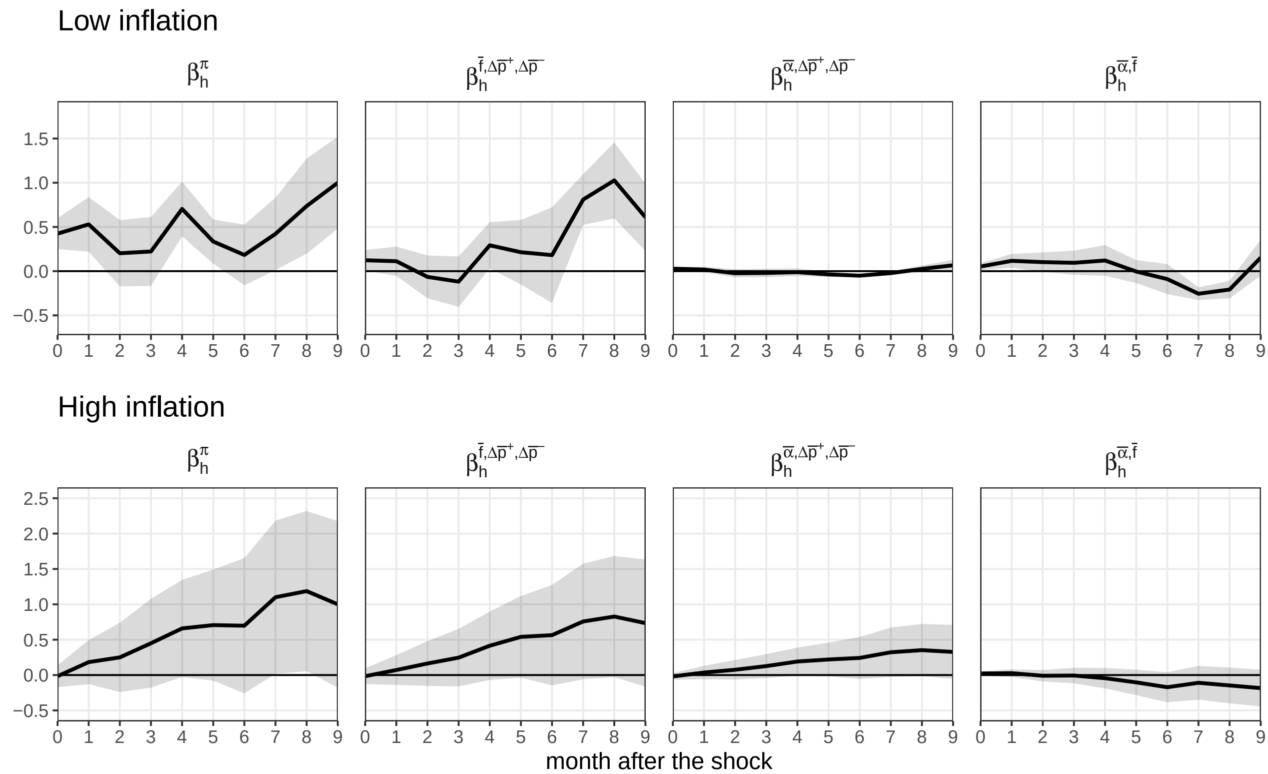
Note: The black line shows the year-over-year growth in the core CPI, expressed as its deviation from the model's unconditional forecast. The stacked bars depict the contribution of each shock to the evolution of the core CPI. This decomposition is calculated using the average from 10,000 draws that satisfied the sign restrictions.

Figure A.8: Responses of counterfactual inflation rates ((11),(11*),(11**)) to a negative energy shock



Note: The equation (12) describes the local linear regressions. The responses indicated by β_h^{π} relate to the reaction of plain inflation (panel 1), $\beta_h^{\bar{f},\Delta\bar{p}^+,\Delta\bar{p}^-}$ of the counterfactual inflation with constant frequency and average size of price increases and decreases (panel 2), $\beta_h^{\bar{\alpha},\Delta\bar{p}^+,\Delta\bar{p}^-}$ of the counterfactual inflation with constant share of price increases and average size of price increases and decreases (panel 3), and $\beta_h^{\bar{\alpha},\bar{f}}$ of the counterfactual inflation with constant share of price increases and frequency (panel 4). The shaded areas represent one standard error based on calendar (month-year) clusters.

Figure A.9: Responses of counterfactual inflation rates ((11),(11*),(11**)) to a positive demand shock



Note: The equation (12) describes the local linear regressions. The responses indicated by β_h^{π} relate to the reaction of plain inflation (panel 1), $\beta_h^{\bar{f},\Delta\bar{p}^+,\Delta\bar{p}^-}$ of the counterfactual inflation with constant frequency and average size of price increases and decreases (panel 2), $\beta_h^{\bar{\alpha},\Delta\bar{p}^+,\Delta\bar{p}^-}$ of the counterfactual inflation with constant share of price increases and average size of price increases and decreases (panel 3), and $\beta_h^{\bar{\alpha},\bar{f}}$ of the counterfactual inflation with constant share of price increases and frequency (panel 4). The shaded areas represent one standard error based on calendar (month-year) clusters.

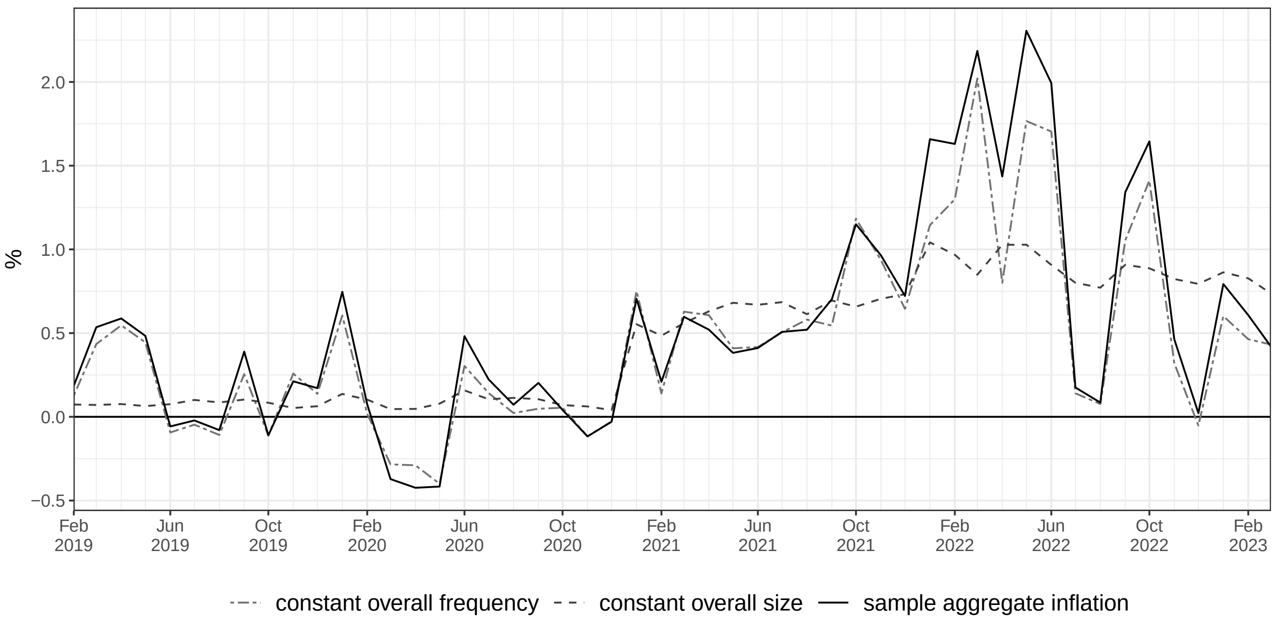
Appendix B

The relationship between the ECOICOP4 inflation rates and the counterfactual inflation rates (defined in (6), (7), (8), and (9)) can be understood by computing first-degree Taylor expansions. As per equation (1), the j inflation rates ($\tilde{\pi}_{jt}$) are comprised of two variables - f_{jt} and Δp_{jt}. Additionally, these inflation rates can be broken down into two terms and four variables, as illustrated in the (4) definition. One can compute the following first-degree Taylor expansion around the period averages ($\bar{f}$ and $\Delta\bar{p}$) of an inflation rate j composed of two variables (1) as:

$$\begin{aligned} \pi(f_t, \Delta p_t) &= \bar{f}\Delta\bar{p} + \Delta\bar{p}(f_t - \bar{f}) + \bar{f}(\Delta p_t - \Delta\bar{p}) \\ &= \underbrace{-(\bar{f}\Delta\bar{p})}_{constant} + \underbrace{\Delta\bar{p}f_t}_{\tilde{\pi}_t^{\Delta\bar{p}}} + \underbrace{\bar{f}\Delta p_t}_{\tilde{\pi}_t^{\bar{f}}}. \end{aligned} \tag{B.1}$$

Clarifying the relationship between the counterfactual rates in definitions (6) and (7) and the inflation rate as defined in (1), these two counterfactual rates are weighted and aggregated, and then compared to the weighted aggregate inflation in Figure B.1.

Figure B.1: Aggregate weighted inflation against counterfactual inflation rates (defined in (B.1))

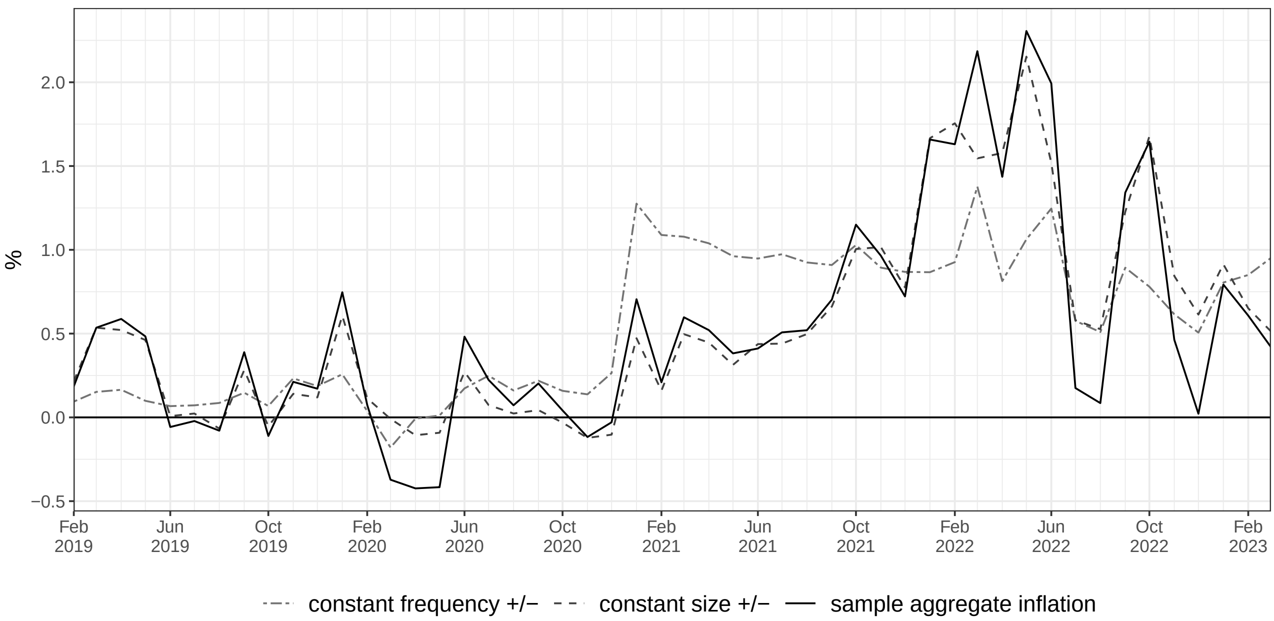


Furthermore, the first-degree Taylor expansion of an inflation rate j, consisting of two terms and four variables as defined in (4), around the period averages ($\bar{f}^+$, $\bar{f}^-$, $\Delta\bar{p}^+$, $\Delta\bar{p}^-$) is

$$\begin{aligned}
\pi(f_t^+, f_t^-, \Delta p_t^+, \Delta p_t^-) &= \bar{f}^+\Delta\bar{p}^+ + \bar{f}^-\Delta\bar{p}^- + \bar{f}^+(\Delta p_t^+ - \Delta\bar{p}^+) + \Delta\bar{p}^+(f_t^+ - \bar{f}^+) \\
&\quad + \bar{f}^-(\Delta p_t^- - \Delta\bar{p}^-) + \Delta\bar{p}^-(f_t^- - \bar{f}^-) \\
&= \underbrace{-(\bar{f}^+\Delta\bar{p}^+ + \bar{f}^-\Delta\bar{p}^-)}_{constant} \\
&\quad + \underbrace{\bar{f}^+\Delta p_t^+ + \bar{f}^-\Delta p_t^-}_{\tilde{\pi}_t^{\bar{f}^+,\bar{f}^-}} \\
&\quad + \underbrace{\Delta\bar{p}^+ f_t^+ + \Delta\bar{p}^- f_t^-}_{\tilde{\pi}_t^{\Delta\bar{p}^+,\Delta\bar{p}^-}}.
\end{aligned} \tag{B.2}$$

Clarifying the relationship between the counterfactual rates in definitions (7) and (8) and the inflation rate as defined in (4), these two counterfactual rates are weighted and aggregated, and then compared to the weighted aggregate inflation in Figure B.2.

Figure B.2: Aggregate weighted inflation against counterfactual inflation rates (defined in (B.2))



Finally, the first-degree Taylor expansion of an inflation rate j, consisting of three terms and four variables as defined in (10), around the period averages ($\bar{\alpha}$, $\bar{f}$, $\Delta\bar{p}^+$, $\Delta\bar{p}^-$) is

$$\begin{aligned}
\pi(\alpha_t, f_t, \Delta p_t^+, \Delta p_t^-) &= \bar{\alpha}\bar{f}\Delta\bar{p}^+ + \bar{f}\Delta\bar{p}^- - \bar{\alpha}\bar{f}\Delta\bar{p}^- \\
&\quad + \bar{f}(\Delta\bar{p}^+ - \Delta\bar{p}^-)(\alpha_t - \bar{\alpha}) + (\bar{\alpha}\Delta\bar{p}^+ + (1-\bar{\alpha})\Delta\bar{p}^-)(f_t - \bar{f}) \\
&\quad + \bar{\alpha}\bar{f}(\Delta p_t^+ - \Delta\bar{p}^+) + (1-\bar{\alpha})\bar{f}(\Delta p_t^- - \Delta\bar{p}^-) \\
&= \underbrace{-2(\bar{\alpha}\bar{f}\Delta\bar{p}^+ + \bar{f}\Delta\bar{p}^- - \bar{\alpha}\bar{f}\Delta\bar{p}^-)}_{constant} + \\
&\quad + \underbrace{\alpha_t\bar{f}\Delta\bar{p}^+ + (1-\alpha_t)\bar{f}\Delta\bar{p}^-}_{\tilde{\pi}_t^{\bar{f},\Delta\bar{p}^+,\Delta\bar{p}^-}} \\
&\quad + \underbrace{\bar{\alpha}\Delta\bar{p}^+ f_t + (1-\bar{\alpha})\Delta\bar{p}^- f_t}_{\tilde{\pi}_t^{\bar{\alpha},\Delta\bar{p}^+,\Delta\bar{p}^-}} \\
&\quad + \underbrace{\bar{\alpha}\bar{f}\Delta p_t^+ + (1-\bar{\alpha})\bar{f}\Delta p_t^-}_{\tilde{\pi}_t^{\bar{\alpha},\bar{f}}}.
\end{aligned} \tag{B.3}$$

Clarifying the relationship between the counterfactual rates in definitions (11), (11*), and (11**) and the inflation rate as defined in (10), these three counterfactual rates are weighted and aggregated, and then compared to the weighted aggregate inflation in Figure B.3.

Figure B.3: Aggregate weighted inflation against counterfactual inflation rates (defined in (B.3))

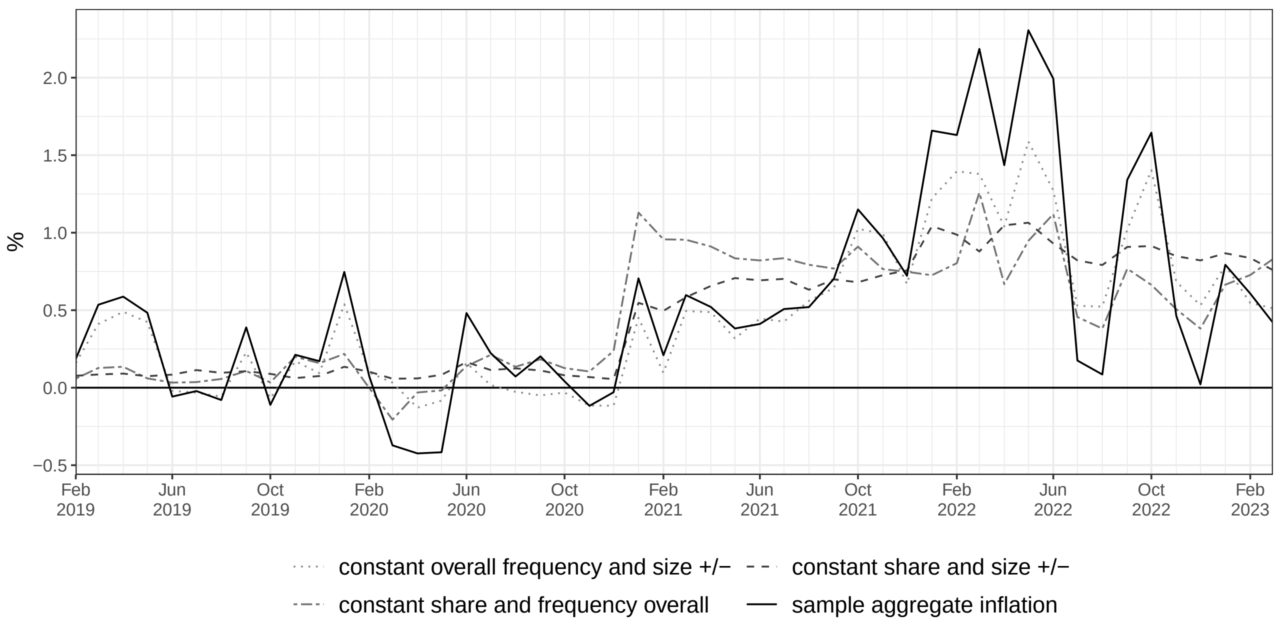


Figure B.4 highlights that all three aggregated linear inflation rate approximations defined in (B.1), (B.2), and (B.3) lead to close matches with aggregated weighted inflation.

Figure B.4: Aggregate weighted inflation against approximated inflation rates