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LUDMILA FADEJEVA
VALENTIN JOUVANCEAU
ALARI PAULUS

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Latvijas Banka
K. Valdemāra iela 2A, Riga, LV-1050
Tel.: +371 67022300 info@bank.lv
http://www.bank.lv https://www.macroeconomics.lv

Consumer price rigidity in the Baltic states during periods of low and high inflation*

Ludmila Fadejeva† Valentin Jouvanceau‡ Alari Paulus§

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Abstract

The Baltic states experienced the most substantial consumer price inflation of any of the EU countries shortly after the COVID-19 pandemic. The year-on-year all-items inflation rate averaged 11% from January 2021 to September 2023, peaking at around 22% in late 2022. This study examines how consumer price rigidity in the region during this period of high inflation differed from the preceding period of low inflation in 2019-2020. We use the detailed price records that underlie the official consumer price indexes to assess the frequency and the size margins of price changes. The average frequency of price changes increased by about four percentage points when inflation was high, as an increase of five percentage points in the frequency of price increases combined with a fall of one percentage point in the frequency of price cuts. The average size of price changes increased by 2.8 percentage points, mainly because the share of price increases changed. We further show that structural shocks in energy prices and aggregate demand contributed significantly to fluctuations in the inflation rate through the frequency of price changes during the period of high inflation. All this points to pricing being state-dependent in the Baltic states.

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

JEL Classification: D40, E31.

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†Latvijas Banka, ludmila.fadejeva@bank.lv

‡Lietuvos Bankas, vjouvanceau@lb.lt

§Eesti Pank, alari.paulus@eestipank.ee

1 Introduction

In a standard macroeconomic model, a firm that has fixed costs for changing prices is more likely to adjust them as inflation rises because it would rather bear the adjustment costs than maintain prices that are too far from their optimal levels (Caplin and Spulber, 1987). However, if a firm changes its prices at fixed time intervals and faces no related costs for doing so, then the timing of the price change will not depend on the level of inflation (Taylor, 1980). This illustrates how periods of high inflation can provide valuable insights into the theoretical contrast between time-dependent models (TD; Calvo, 1983) and state-dependent models (SD; e.g., Golosov and Lucas, 2007; Midrigan, 2011).

The TD and SD models are close substitutes when inflation is low, since both predict that the frequency of price changes should be insensitive to fluctuations in aggregate inflation (Auclert et al., 2023). This is supported by earlier research using the detailed price information that underlies the consumer price indexes for the United States (Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008) and the euro area (Gautier et al., 2024), in which changes in the average size of price movements were found to be the main drivers of inflation, or to be more precise, changes in the average size of price movements caused by shifts in the share of price increases.

In contrast, studies using data from Mexico (Gagnon, 2009), Hungary (Karadi and Reiff, 2019) and Argentina (Alvarez et al., 2019) have found that the frequency of price changes is strongly correlated with the inflation rate when it is high. More recently, Henkel et al. (2023) identified a notable surge in the frequency of price rises and price falls in Italy during the initial phase of the COVID-19 pandemic in 2020. They also observed an increase of 40 percentage points in the average frequency of price changes in Germany in July 2020 after VAT rates were cut, with prices primarily moving downwards. This suggests that, in addition to the impact of the level of inflation, large aggregate shocks can also contribute to fluctuations in the frequency of price changes.

The most recent bout of high inflation was experienced by many countries in Europe and elsewhere in 2021-2023. The sudden upsurge was relatively short lived and caused by a combination of the supply-side factor of a large energy price shock and the demand-side factors of the recovery from the pandemic and fiscal stimuli. The intensity and magnitude of the inflation shock reached levels that were last seen in advanced countries during the 1980s and so this episode is an important new case study, and one on which not much research has yet been done. Among the few studies that have been produced so far are Jouvanceau (2023) and Gutiérrez Chacón and Roldan-Blanco (2024), which show that the inflationary spike between 2021 and 2023 in Lithuania and Spain was accompanied by a significant increase in the frequency of price rises, while the average size of the rises and falls in prices remained largely unchanged. Additionally, Gutiérrez Chacón and Roldan-Blanco (2024) provides evidence of asymmetries in price adjustments by outlets, demonstrating that more outlets tend to adjust prices upward to align with an optimal price rather than downward. This trend has been particularly accentuated during periods of high inflation.

Our paper examines how consumer price rigidity was different in 2021-2023 to what it was during the preceding period when inflation was low in 2019-2020, and it focuses on the Baltic region. The inflation rate in the Baltic states has historically been more responsive to aggregate shocks than that in other euro area (EA) countries has, because the Baltic economies are very open and their levels of wage and price rigidity are lower (Fadejeva et al., 2017; Burriel and Galesi, 2018; Benecka et al., 2020). This was also the case in 2021-2023 when the inflation shock was not as pronounced anywhere else in the EA as it was in our sample countries, and this offers rich data for studying how the level of inflation and large aggregate shocks affect price setting. The year-on-year all-items inflation rate averaged 11% from January 2021 to September 2023 across the three countries, and it peaked at around 22% in late 2022.

The study contributes to a better understanding of price setting and dynamics in the EA, and it extends previous research that used detailed consumer price information to study price setting in Latvia (Benkovskis et al., 2012) and Lithuania (Jouvanceau, 2022). It is one of the first analyses of how the period of high inflation after the COVID-19 pandemic affected consumer price rigidity in the EA countries, adding valuable insights to the findings on the price-setting mechanism in the EA during the period before the pandemic when inflation was low (Gautier et al., 2023).

Our analysis uses the monthly price records that are used by the national statistical offices in Estonia, Latvia, and Lithuania to construct the Consumer Price Index (CPI). The whole dataset contains approximately 5 million price quotes for representative goods and services from January 2019 to June 2023, though the Lithuanian sample is slightly shorter and ends in March 2023. We form a three-country sample with common categories at the five-digit ECOICOP level 4, called ECOICOP4 for short here, which is the lowest aggregation level of the harmonised index of consumer prices (HICP). The sample covers around 65% of all the ECOICOP4 categories, and these account for about 90% of the Baltic HICP weights over this period.

Following Klenow and Kryvtsov (2008), we decompose the inflation rates into the average size and frequency of price changes at the ECOICOP4 level, and then provide statistics for several aggregate categories, doing so separately for the periods when inflation was low or high. We find that when it was low, the average frequency of price changes in the Baltic region was 21.2%. The average frequency of non-energy price changes was 16.2%, which is notably higher than the 12.4% earlier in the EA (Gautier et al., 2024). The gap is explained by the average frequency of price changes for processed and unprocessed food being higher in the Baltic states by about 7 and 9 percentage points (p.p.).[1] However, after discounts are controlled for, the frequencies are more similar. The average frequency of price changes in the Baltics when inflation was high increased by some 4 p.p. from 21.2% to 25.1%. This came mainly from a rise of 5 p.p. in the average frequency of price increases from 10.8% to 15.7%, while the average frequency of price cuts declined by 1 p.p. from 10.3% to 9.3%. However, the average amount by which prices rose or fell, and the frequency of price changes that came from discounts remained largely unchanged. These findings are consistent with the evidence observed for Spain in Gutiérrez Chacón and Roldan-Blanco (2024).

We also shed light on how the size and frequency margins of price changes explain the inflation that follow aggregate shocks by estimating linear local projections as in Gautier et al. (2024). We first use Bayesian Vector Autoregression (BVAR) models to identify both energy price and aggregate demand shocks for each Baltic country. Different shocks are then used in regression models for the counterfactual inflation rates that are constructed by keeping the average size or frequency of price changes constant. The results show that the effects of each type of shock on inflation come primarily through the size margin in both periods, and more precisely through changes in the average size that result from shifts in the share of price increases. The frequency margin responds significantly to both energy price shocks and aggregate demand shocks in the period of high inflation but the response is mostly muted in the period of low inflation. In addition, the impact on inflation accumulates gradually over time with inflation low, while the response is steeper when it is high. The response of the frequency margin to shocks during the period of high inflation is inconsistent with TD models, but the steep and short-lived response

[1] See Gautier et al. (2024, Table A6) for the results covering the sample period of 2011-2017.

of inflation and frequency shifts to shocks is consistent with what has been identified for SD models (Auclert et al., 2023). This suggests that SD models are more appropriate than TD models for explaining price setting in the Baltic states.

The paper is structured as follows. The next section describes the country-specific micro-price datasets and how the common sample was constructed. Section 3 explains inflation decompositions and presents the cross-sectional statistics. The fourth section analyses the patterns in the time series. The fifth section provides the identification of the aggregate shocks and the results of the local projection exercise. Lastly, concluding remarks are given.

2 Data

We use the monthly prices of individual goods and services that the national statistical offices in Estonia, Latvia and Lithuania collect to construct their consumer price indexes. The sample period starts in January 2019, which is the earliest data available for all three countries. The latest data available at the time of writing were from June 2023 for Estonia and Latvia, and March 2023 for Lithuania. See Table A1 in the Appendix for an overview of the datasets.

Our sample covers the COVID-19 pandemic, during which many countries had temporary restrictions on business operations or on people's movement. Policies that were more restrictive or that were in place for longer may have affected the regular collection of price information or the quality of the data. The Stringency Index from the Oxford Coronavirus Government Response Tracker project (Mathieu et al., 2020) shows that the Baltic countries had less restrictive policies in 2020-2021 than the EU countries did on average, and that Estonia actually applied the least stringent policies in the whole EU. In line with this, the COVID-19 restrictions seem to have had hardly any effect on data collection and coverage in the Baltics. There is no significant variation in the monthly sample sizes throughout the whole period, and the share of imputations increased only slightly from their initial low levels, from 5% to around 6% in Latvia and from 4.4% to 6.2% in Lithuania. The dataset for Estonia contains raw data without any imputations, and these data were presumably little affected as the Estonian pandemic restrictions were even milder than those in the other two countries. For comparison, the share of imputations in similar price surveys for Italy, Germany and Slovakia was around 15% in 2020 (Henkel et al., 2023).[2]

[2]While some countries temporarily reduced their VAT rates in response to the pandemic crisis and the energy price shock, there were only very few and minor changes in the VAT rates in the Baltic countries between 2020

About 20 thousand price observations are collected every month for Estonia and Latvia, while the monthly sample for Lithuania is roughly three times larger at 65 thousand observations. All three datasets include price and unit information and are similarly structured, though there are some important differences in the level of detail and in their information content, and these need to be taken into account for a consistent analysis. The data for Latvia and Lithuania track prices for target items, and are grouped by stores. The dataset for Estonia does not include an explicit pseudo-identifier for stores, but it still allows time series to be constructed for the same items from detailed brand information.

The number of the most detailed consumption categories ranges from 539 in Latvia to 949 in Lithuania.[3] The databases for Estonia and Lithuania cover about 80-90% of the ECOICOP level 4 official item weights, while the one for Latvia provides a complete coverage as it also incorporates information from additional sources. The number of ECOICOP level 4 categories that are present ranges from 189 in Estonia to 230 in Lithuania.[4] The total combined number of ECOICOP level 4 categories across all three countries is 295 out of a possible 303, indicating that there is some variation in the selection and coverage of consumption categories. Each dataset covers about 60-70% of all the available categories. Importantly, the number of ECOICOP level 4 categories remained unchanged throughout the whole period.

To better illustrate the coverage of the micro-price datasets, Figure 1 shows the aggregate dynamics of inflation for the three country samples, where the sample inflation is estimated using the database and country specific weights. The discrepancies between the official inflation rates and our sample inflation rates observed for Estonia and Lithuania arise partly from the lack of information on certain categories, such as electricity, gas, motor cars, mobile services, international flights and package holidays. More importantly, the statistical offices employ aggregation techniques that likely differ from those used in our study (see section 3), and they conduct qualitative adjustments that we are unable to implement because of the lack of information. This is demonstrated by the discrepancies seen for Latvia, despite its database covering all item weights. Furthermore, to improve the comparability of the datasets and to

and 2023. Estonia reduced the VAT rate on newspapers from 9% to 5% in August 2022. Latvia lowered the VAT rate on books and newspapers from 12% to 5% in 2022. Lithuania imposed a reduced VAT rate of 9% instead of the standard VAT rate of 21% on water supply in 2021 and catering services in 2022.

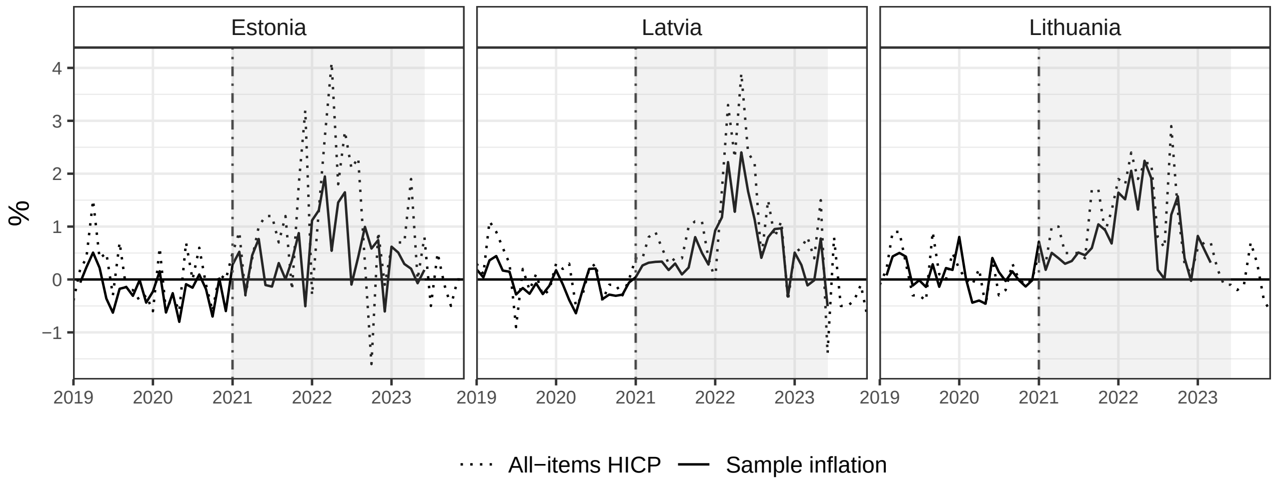
[3]First stage calculations with detailed price information were done with each national database separately by the co-author from that country because of data access restrictions. The second stage of the analysis then used semi-aggregate results pooled across the countries at the ECOICOP level 4.

[4]For more details on the ECOICOP classification, see https://ec.europa.eu/eurostat/web/metadata/classifications.

remove the effect of imputations, the final dataset used here excludes imputed prices.

This may limit the scope of our investigation in the impact of the level of inflation on aspects such as the frequency of price changes. However, the relative dynamics of inflation in our sample and the official statistics are reasonably well in line, which allows for a robust analysis of price-setting changes between the periods of low and high inflation. The period of low inflation with moderate rates that fluctuate around zero can be identified in the sample from 2019 to the end of 2020, and a period of high inflation with positive average inflation rates and greater variability from 2021 onwards, with the rates peaking a few months into 2022. We study and contrast the evolution of consumer price rigidity in these periods of low and high inflation in the subsequent analysis.

Figure 1: Sample-based aggregate rates of inflation and the official rate of inflation



Notes: The vertical bar indicates the date of separation between the samples with low and high inflation. The period of high inflation includes January 2021 and lasts until the end of June 2023, though the Lithuania sample ends with March 2023. The aggregation was done using the full sample of observations for each country and country-specific yearly weights at the ECOICOP level 4. Source: Eurostat for the official rates of inflation.

We use two types of sample in our analysis, as we have country-specific samples that include all the ECOICOP4 categories that are available, and a common sample that covers only those categories that were collected in at least two countries. This leaves 203 ECOICOP4 categories, representing on average about 90% of the HICP weights over the period; see Table 1.

Another important difference in the datasets concerns the flags. While product replacements are indicated in all the datasets, an indicator for price changes is only available for Latvia and Lithuania, and so the changes in Estonia had to be identified from a time series constructed at the item level. Indicators for discounts, or sales, were also harmonised as they were originally treated differently in each country. We consider product substitutions as breaks in the series,

Table 1: Common sample

	No. of ECOICOP4 categories (count)					Share of combined sample (%)			
	Combined sample	EE	LV	LT	Common sample	EE	LV	LT	Common sample
Total	295	189	205	230	203	64.0	69.5	78.0	68.8
Energy	10	7	8	8	8	70.0	80.0	80.0	80.0
NEIG	103	67	76	86	74	65.0	73.8	83.5	71.8
Processed food	63	55	49	60	55	87.3	77.8	95.2	87.3
Services	108	52	65	66	58	48.1	60.2	61.1	53.7
Unprocessed food	11	8	7	10	8	72.7	63.6	90.9	72.7

Notes: The combined sample presents the number of ECOICOP4 categories observed in the pooled sample of three Baltic states. The common sample of goods and services covers the ECOICOP4 categories that are collected in at least two Baltic countries. The full list of the ECOICOP4 common sample categories is given in Table A2.

and so the resulting price changes are not included in our estimates of the size and frequency of price changes.

A significant share of the price changes observed arise from short-term discounts and sales and so it is critical to distinguish these from other price changes in order to understand the more persistent price dynamics and price setting in the medium term. Temporary price reductions boost the frequency of not only price cuts, but also of price rises as the prices return to their regular level after the end of the discount.

The share of monthly *price quotes* that indicate discounts ranges from 7% in Lithuania to 12% in Estonia, which is similar to other countries; see the upper panel of Table 2. Klenow and Kryvtsov (2008) report a share of 12% for the US for example. However, discounts account for as much as half of all the *price changes* in Estonia and Latvia and about one third in Lithuania; see the middle panel of Table 2. These shares are higher than those reported for the US (Klenow and Kryvtsov, 2008) and for large European economies (Gautier et al., 2024). The share of price changes that come from discounts is largest for non-energy industrial goods (NEIG), reaching 65% in Latvia, and this is followed by the categories of processed and unprocessed food. The role of discounts is very marginal for services and energy goods, where they account for less than 5-6% of price changes.

The majority of discounts in each country at 60-80% last for up to one month; see the bottom panel of Table 2. About 7% of discounts last longer than three months in Latvia and Lithuania, while the proportion is as high as 12% in Estonia. Virtually no discounts are longer than six months.

We use two price series in the analysis. Our benchmark series contains all the price information

Table 2: Discount prices (full sample)

	Estonia	Latvia	Lithuania
(1) Share of price quotes at discount, %	12.0	10.3	7.4
.. Unprocessed food	12.2	12.7	7.6
.. Processed food	12.9	16.7	7.3
.. Energy	2.0	1.5	1.0
.. NEIG	15.5	9.0	9.3
.. Services	0.2	0.2	0.4
(2) Share of price changes due to discounts, %	50.6	54.5	36.1
.. Unprocessed food	30.5	37.1	16.9
.. Processed food	55.9	65.0	37.6
.. Energy	1.0	5.6	1.2
.. NEIG	71.4	58.0	48.5
.. Services	4.1	3.1	2.8
(3) Distribution of discount spells by length, %			
.. 1 month	60.5	77.6	74.4
.. 2 months	18.8	8.8	13.7
.. 3 months	8.1	6.5	4.8
.. 4 months	4.2	2.5	2.3
.. 5 months	2.3	1.7	1.3
.. 6 months or more	6.2	2.8	3.4

Notes: The share of discounted prices shows the share of months when the item price was offered at a discount or sales. Only observations for which *price changes* can be determined are used, often the first month of the price series for each item, and observations with missing price information are ignored. Unweighted statistics.

including discounts, while the other series tracks only *regular* prices and excludes discounts. The benchmark series always indicates *monthly* price changes for the same items in the same locations, while the series of regular prices shows changes in regular prices only, which are relative to the last observed regular price for the same item. This means the last price observed before the start of the discount period, not the price in the previous calendar month. To reduce the influence of extreme outliers, both price series were trimmed by removing the price changes, which belonged to top 1% by their absolute log values or which did not exceed ±0.01 euros.

3 Cross-sectional statistics

To describe consumer price rigidity, the inflation rates for each country are decomposed into their frequency and size margins, following Klenow and Kryvtsov (2008). This involves deconstructing the price change (π_{cjt}) for country c at the ECOICOP level 4 category j at time t

using detailed price information as follows:

$$\pi_{cjt} = \underbrace{\left(\frac{1}{N_{cjt}}\sum_n I_{n,cjt}\right)}_{f_{cjt}} \times \underbrace{\left(\frac{\frac{1}{N_{cjt}}\sum_n (p_{n,cjt} - p_{n,cjt-1})}{\frac{1}{N_{cjt}}\sum_n I_{n,cjt}}\right)}_{\Delta p_{cjt}} \tag{1}$$

where N denotes the number of items in the ECOICOP4 category, p_n denotes the natural logarithm of the price of item n, and $I_{n,cjt}$ is an indicator of a price change that equals 1 if $p_{n,cjt} \neq p_{n,cjt-1}$ and 0 otherwise. The overall frequency of price changes is denoted by the variable f_{cjt}, indicating the degree of price rigidity, and Δp_{cjt} denotes the average size of price changes for observations with $I_{n,cjt} = 1$. Another decomposition can be applied to distinguish how price rises and price cuts drive the dynamics of aggregate inflation rates, as follows

$$\pi_{cjt} = \underbrace{\left(\frac{1}{N_{cjt}}\sum_n I^+_{n,cjt}\right)}_{f^+_{cjt}} \times \underbrace{\left(\frac{\bar{dp}^+_{cjt}}{\frac{1}{N_{cjt}}\sum_n I^+_{n,cjt}}\right)}_{\Delta p^+_{cjt}} + \underbrace{\left(\frac{1}{N_{cjt}}\sum_n I^-_{n,cjt}\right)}_{f^-_{cjt}} \times \underbrace{\left(\frac{\bar{dp}^-_{cjt}}{\frac{1}{N_{cjt}}\sum_n I^-_{n,cjt}}\right)}_{\Delta p^-_{cjt}} \tag{2}$$

where f^+_{cjt} and f^-_{cjt} denote the frequency of price rises and price cuts, while $I^+_{n,cjt}$ and $I^-_{n,cjt}$ are indicators of them. [5] The variables Δp^+_{cjt} and Δp^-_{cjt} refer to the average size of the price rises and cuts. Combining and rearranging equations (1) and (2) gives the following expression, which is useful for showing how the effect of shifts in the share of price rises $\frac{f^+_{cjt}}{f_{cjt}}$ can explain fluctuations in the average size of the price changes.

$$\Delta p_{cjt} = \frac{f^+_{cjt}}{f_{cjt}} \times \Delta p^+_{cjt} + \frac{f^-_{cjt}}{f_{cjt}} \times \Delta p^-_{cjt} \tag{3}$$

Using these decompositions, we provide statistics on the frequency and average size of price changes during the periods of low and high inflation in 2019-20 and 2021-23 in the three Baltic countries.[6] The average frequency of price changes in the period of high inflation for the sample of common categories increased by nearly 4 p.p. from 21.2% to 25.1%; see Table 3 and Figure A1. This change was driven by a rise of 5 p.p. from 10.8% to 15.7% in the average frequency of price increases combined with a fall of 1 p.p. from 10.3% to 9.3% in the average frequency of price cuts. The average share of price increases rose from 58.8% to 68.2%. These frequency changes led the average time between two consecutive price changes to shorten by about one

[5] Note that $\bar{dp}^+_{cjt} = \frac{1}{N_{cjt}}\sum_n (p_{n,cjt} - p_{n,cjt-1})I^+_{n,cjt}$, and $\bar{dp}^-_{cjt} = \frac{1}{N_{cjt}}\sum_n (p_{n,cjt} - p_{n,cjt-1})I^-_{n,cjt}$.

[6] Table A3 presents the statistics for price changes excluding discounts. Country-specific results for the full sample of observations during the periods of low and high inflation are presented in Tables A4-A9 in the Appendix, both with and without price changes from discounts.

month. Gutiérrez Chacón and Roldan-Blanco (2024) shows similar changes in the frequency of price changes in Spain, where the average frequency of price increases rose by 4 p.p. and the average frequency of price cuts fell by 1 p.p between October 2021 and April 2023.

Remarkably, there was no significant change in the average size of the positive and negative changes in price; see Table 3 and Figure A2. This meant the increase of 2.8 p.p. in the average size of price changes was mainly due to the change in the share of price increases. This finding is supported by the evidence from Spain that shows that price changes were also driven mainly by the frequency of price increases being higher when inflation was high rather than by the changes being larger in size (Gutiérrez Chacón and Roldan-Blanco, 2024).

Our sample also includes the two years of the COVID-19 pandemic. Henkel et al. (2023) showed that Italy and Germany experienced a notable surge in the frequency of price changes in 2020, which happened in Italy because of a strong pandemic effect and in Germany because of a reduction in VAT rates. The same study showed that the frequency of price changes in Latvia remained unchanged in 2020 and only increased slightly in the second half of 2021. We observe a weak response from the frequency of price changes to the initial phase of the COVID-19 pandemic in all three Baltic states, which allows us to distinguish between the two periods of 2019-2020 when the inflation rate was low, and 2021-2023 when it was significantly higher.

Even though the period of low inflation in our sample lasts only two years, it represents well the longer period of low inflation that preceded it. Gautier et al. (2024) showed that the frequency of price changes mostly remained stable in 2011-2019. Their estimates for the frequency and average size of price changes in Latvia in 2017-2019 and in Lithuania in 2010-2018 are very similar in magnitude and distribution by percentiles to our estimates for the period of 2019 to 2020.

Furthermore, there is a significant degree of heterogeneity across consumption categories in the average frequency of price changes in the two periods; see Table 3 and Figure A3. The prices of energy items vary very frequently, with 60% of items changing their prices every month, which is driven by fuels and lubricants. Unprocessed food comes next, with more than 40% of goods changing their price every month, or 27% after discounts are excluded, see Table A3. About a quarter of processed food items change price every month, or 9% without discounts. The lowest frequency of price changes is observed for NEIG at about 14%, or 5% without discounts, and services at 8% with or without discounts. The low average frequency of price adjustments for services is accompanied by a larger average share of positive price adjustments, with price

Table 3: Weighted aggregate price statistics for the Baltics in the periods of low and high inflation (common sample, including discounts)

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	21.2	10.8	10.3	4.2	1.4	15.0	-16.5	58.8	100.0	7.3
All (non-energy)	16.2	8.6	7.6	5.7	1.7	16.3	-17.9	60.1	88.6	7.6
Energy	59.9	28.2	31.7	1.1	-0.8	4.9	-5.4	48.7	11.4	0.9
NEIG	14.4	6.9	7.5	6.4	-2.5	19.4	-22.0	47.8	28.4	7.6
Processed food	22.6	12.3	10.3	3.9	0.7	16.8	-18.3	57.1	25.8	14.7
Services	7.9	4.8	3.1	12.1	6.9	12.7	-13.2	76.1	29.2	0.2
Unprocessed food	40.2	20.8	19.4	1.9	0.1	17.6	-18.7	52.5	5.3	11.8
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	25.1	15.7	9.3	3.5	4.2	15.0	-17.0	68.2	100.0	6.7
All (non-energy)	19.7	12.4	7.3	4.6	4.4	16.0	-18.5	68.8	87.8	6.9
Energy	63.6	39.8	23.9	1.0	2.6	7.5	-6.4	63.7	12.2	0.6
NEIG	17.2	9.9	7.3	5.3	1.1	18.2	-21.7	58.5	28.6	7.0
Processed food	27.4	17.7	9.6	3.1	3.8	15.8	-18.7	67.3	27.4	13.3
Services	9.4	6.8	2.6	10.2	9.1	13.4	-14.7	83.6	26.0	0.2
Unprocessed food	41.9	24.4	17.5	1.8	2.8	17.6	-18.8	59.9	5.7	11.4

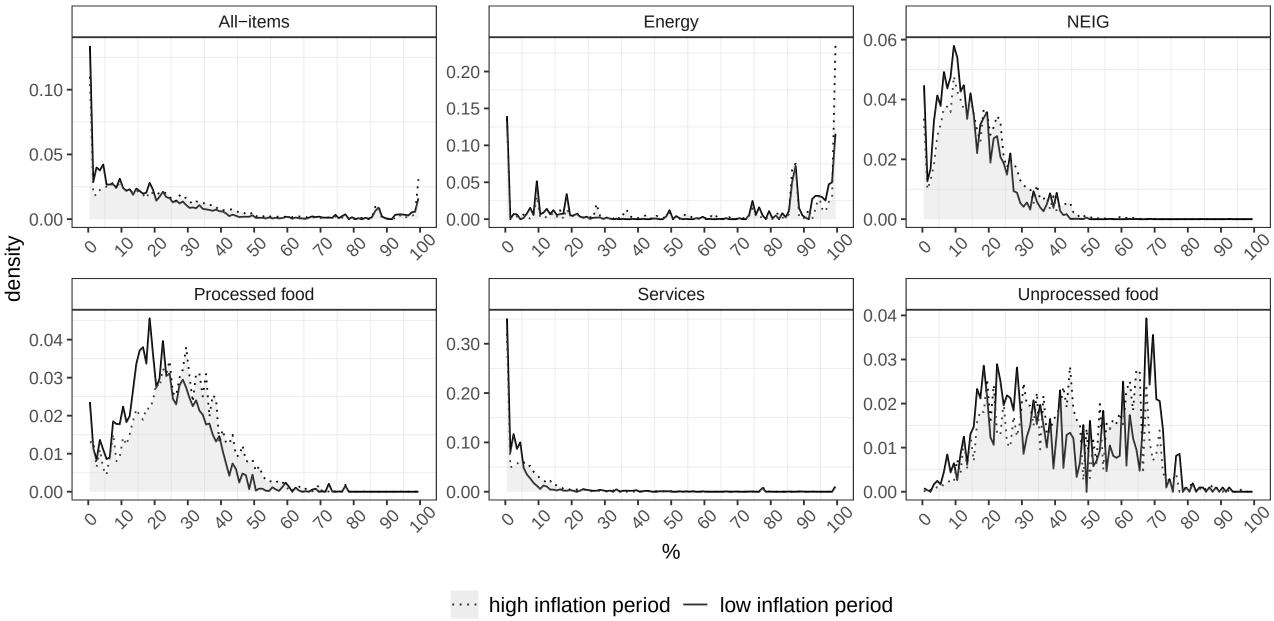
Notes: The statistics are calculated from price changes without product replacements. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The common sample of goods and services is defined as the list of ECOICOP level 4 categories covered in at least two Baltic countries. The results are estimated using the common sample and the average values of yearly weights in the corresponding period and across countries.
The columns from left to right are: the special aggregate category, the average frequency of price changes, the average frequency of price rises, the average frequency of price cuts, the average time in months between two consecutive price changes, the average size of price changes overall, the average size of price rises, the average size of price cuts, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the average frequency of price changes due to discounts. Duration is calculated as $dur = -1/ln(1-\bar{f})$.

rises accounting for more than 75% of price changes.

Prices in all categories changed more frequently during the period of high inflation. Price rises in particular became more frequent, and their average frequency increased more for energy goods, where it gained 11 p.p., processed food, up 5 p.p., and unprocessed food and NEIG, both up 3 p.p. In contrast, the average frequency of price cuts remained relatively stable across the two periods, with the exception of unprocessed food, where it fell by 2 p.p. and energy, where it lost 8 p.p. This is similar to what happened in Spain, where the frequency of price increases for processed and unprocessed food items were affected the most, each rising by roughly 5 p.p., while the frequency of negative price changes was affected little, with a slight decline observed only for food categories (Gutiérrez Chacón and Roldan-Blanco, 2024).

Figure 2 provides additional insights into price rigidity by showing the frequency distributions

Figure 2: Weighted distribution of the frequency of price changes in the Baltics (common sample, including discounts)

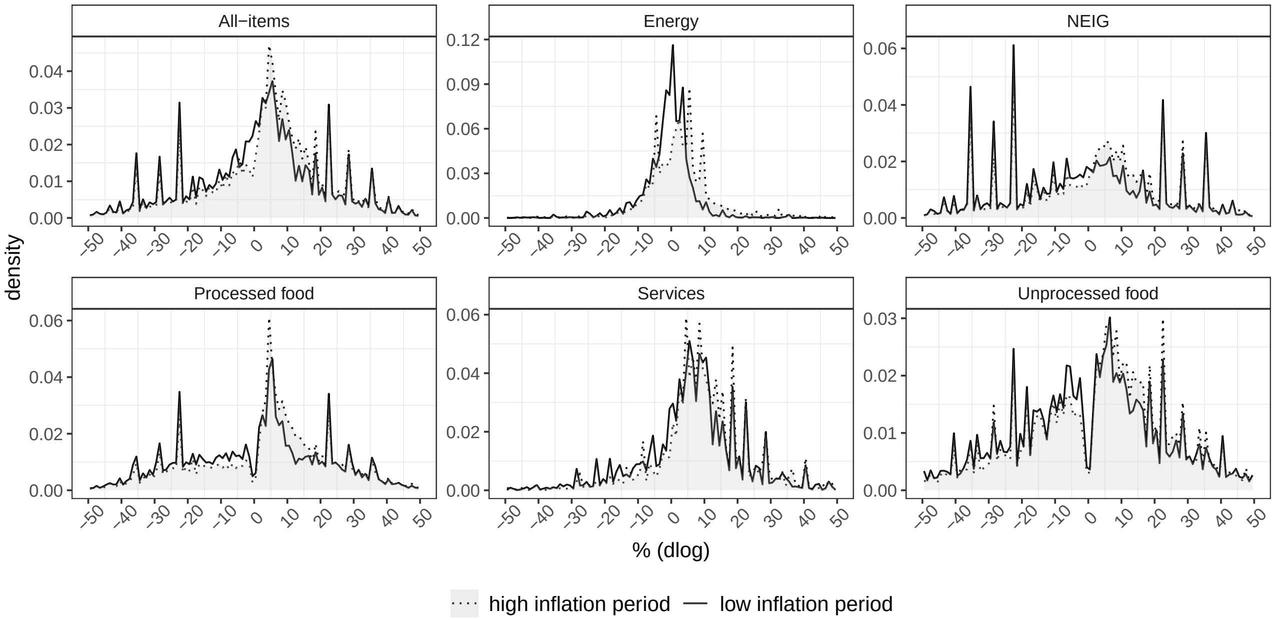


Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the common sample of goods, we first estimate for each country the frequency of price changes in each month at the detailed item level (see Table A1), and then calculate average frequencies at the ECOICOP level 4. Next, using the mean values of the weights of the corresponding country in each of the two periods, we aggregate distributions to the country and specific product group level. The weighted distribution for the Baltics is estimated by averaging the distributions obtained for each country.

by consumption category. The distributions generally have long and thin right-side tails, with monthly frequencies mainly below 20% in the sample excluding discounts; see Figure A5. Across all the categories, services have the largest share of items whose prices rarely change as around 35% of prices had no monthly changes, and 45% of items change prices with a frequency of less than once in every 24 months. The prices of goods in the category of processed food changed more frequently as about 50% of the prices change more often than once every six months, giving a frequency above 20%. The frequency distribution for the NEIG category has a similar shape to that of processed food but has a higher proportion of infrequent price changes. The highest frequency of price changes is observed for energy goods, with 12% of items changing price every month during the period of low inflation and 23% doing so during the period of high inflation. In the category of unprocessed foods, 75% of items experienced price changes at between two and six months. However, the average time between two consecutive price changes varies considerably among individual items because of the perishable and seasonal nature of items, like fruits, fish and meat.

During the period of high inflation, the distributions of all categories shifted to the right, indicating that a greater proportion of items experienced more frequent price changes. The most significant shifts were observed for processed food, NEIG, and services.

Figure 3: Weighted distribution of the size of price changes in the Baltics (common sample, including discounts)



Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the common sample of goods, the distribution of size changes is obtained for each country and ECOICOP level 4 category using the arithmetic mean of price changes at the detailed item level (see Table A1). Next, using the mean values of the weights of the corresponding country in each of the two periods, we aggregate ECOICOP4 distributions to the country and specific product group level. The weighted distribution for the Baltics is estimated by averaging the distributions obtained for each country.

Additionally, Figure 3 shows the distribution of the size of price changes by consumption category.[7] The distributions are quite spread out and are somewhat asymmetric, with the share of small price rises exceeding that of small price cuts, giving shapes similar to those observed earlier in the EA (Gautier et al., 2024). The most frequent size of price changes is about 5% in both the periods of low and high inflation. About 18.5% of all price changes remain between -20.5% and +20.5%. The peaks of large price changes are caused by discounting practices and are mainly visible for the NEIG and processed food categories.[8] Figure A6 shows nonetheless that large price changes are still prevalent in the size distribution of price changes for services and NEIG even after discounts are excluded.

Importantly, these distributions show that the significant change in the average size of price changes during the period of high inflation, as reported in Table 3, is caused by a right shift in the frequency of price changes that are small to moderate. This illustrates how an increase

[7] Country-specific distributions of the size of price changes are presented in Figures A8, A10 and A12 in the Appendix.

[8] The size of discount values are estimated using logarithmic differences, and so the peaks in the figure are slightly different from the regularly used discount markers of 20%, 30% and 35%.

in the frequency of price increases can result in a significant change in the average size of price changes. We explore this phenomenon further in the following sections.

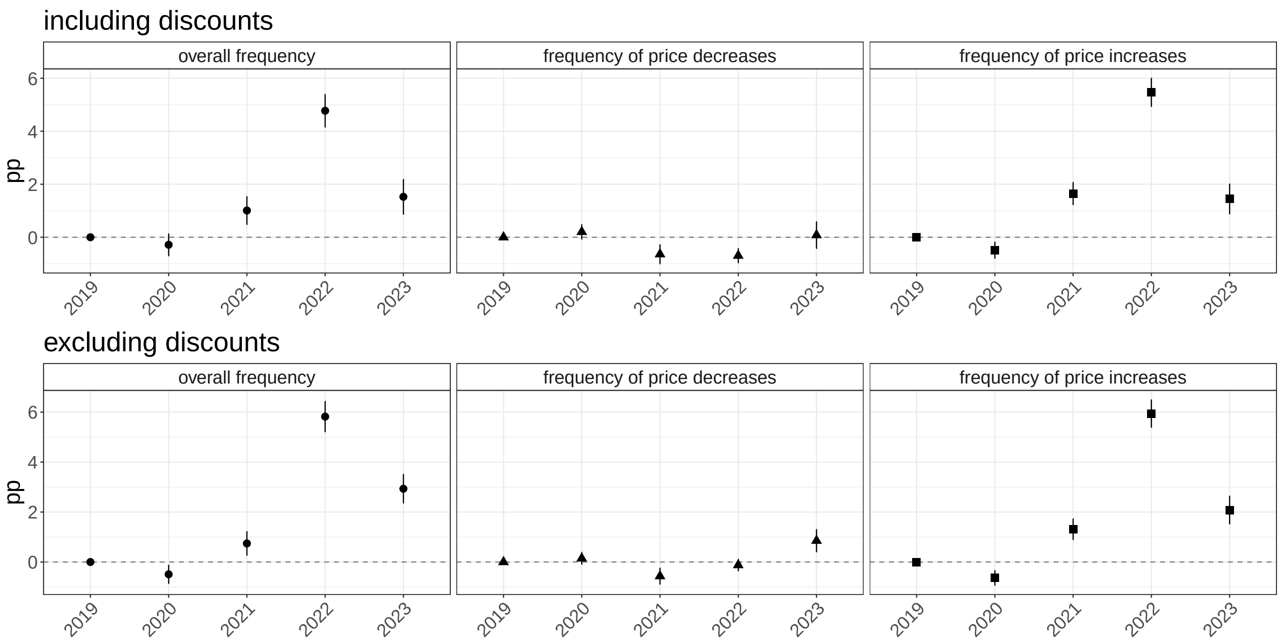
4 Time-series statistics

To identify the annual trends and seasonality in the frequency and size margins of the price changes in the Baltics, we use fixed effects regression models at the ECOICOP level 4, similarly to Gautier et al. (2024). The general specification is as follows:

$$margin_{jt} = \alpha_{cj} + \mu_\tau + \gamma_m + \varepsilon_{jt} \tag{4}$$

where α_{cj} denotes the ECOICOP4-country fixed effects, μ_τ is the vector of calendar year dummies for estimating trends, and γ_m is the vector of calendar month dummies for identifying seasonality. We analyse the seasonality and trends by estimating multiple specifications. The dependent variable $margin$ denotes the frequency of price changes, the frequency of price rises, the frequency of price cuts, the average size of price changes, the average size of price rises, and the average size of price cuts in different specifications.

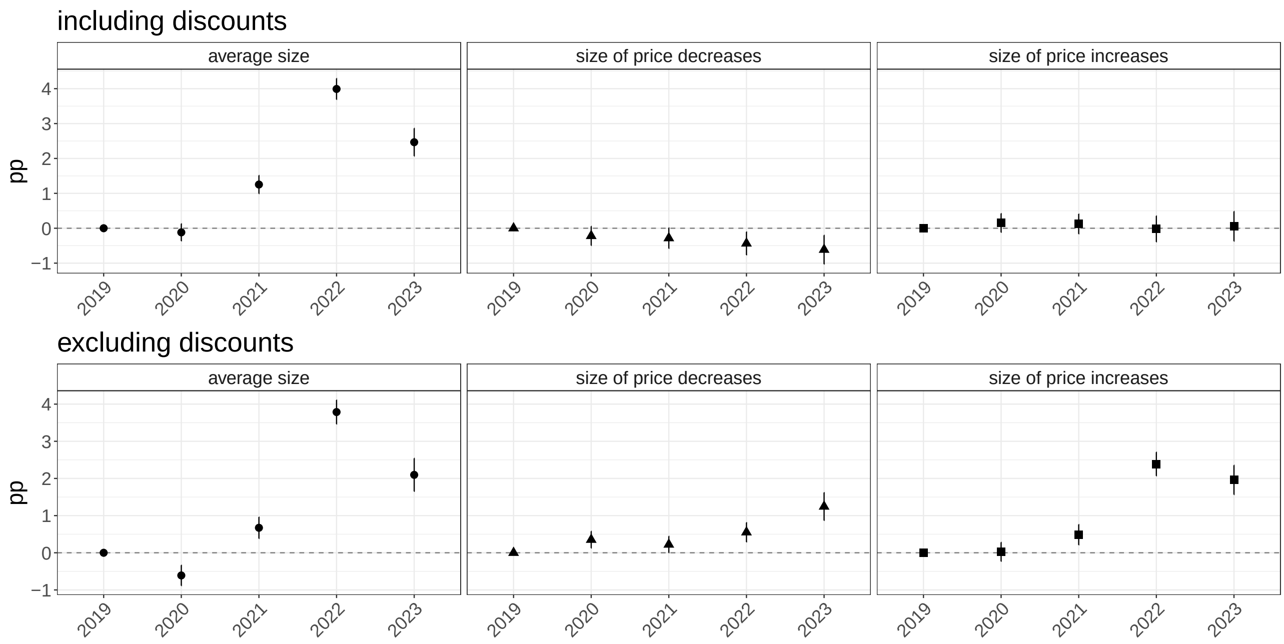
Figure 4: Annual trends in the frequency margins



Notes: ECOICOP4-country fixed effects regression results, see equation (4). Point estimates of the year dummies are marked by circles, triangles, and squares, while error bars show the 95% confidence intervals corresponding to the ECOICOP4-country clustered standard errors.

The results of the regressions show that the frequency of price changes was substantially higher every year when inflation was high, and especially in 2022 when the energy price shock was at its peak; see Figure 4. Annual trends also confirm that the jump in the frequency of price changes was caused primarily by the frequency of price rises being higher, while annual variation in the frequency of price cuts was very limited. The results are barely affected by sales as the estimated regression coefficients are very similar to those obtained from the sample that excludes discounts. The small differences between the upper and the lower parts of the figure imply that the frequency of regular price changes increased marginally more than the frequency of price changes related to sales.

Figure 5: Annual trends in the average size margins

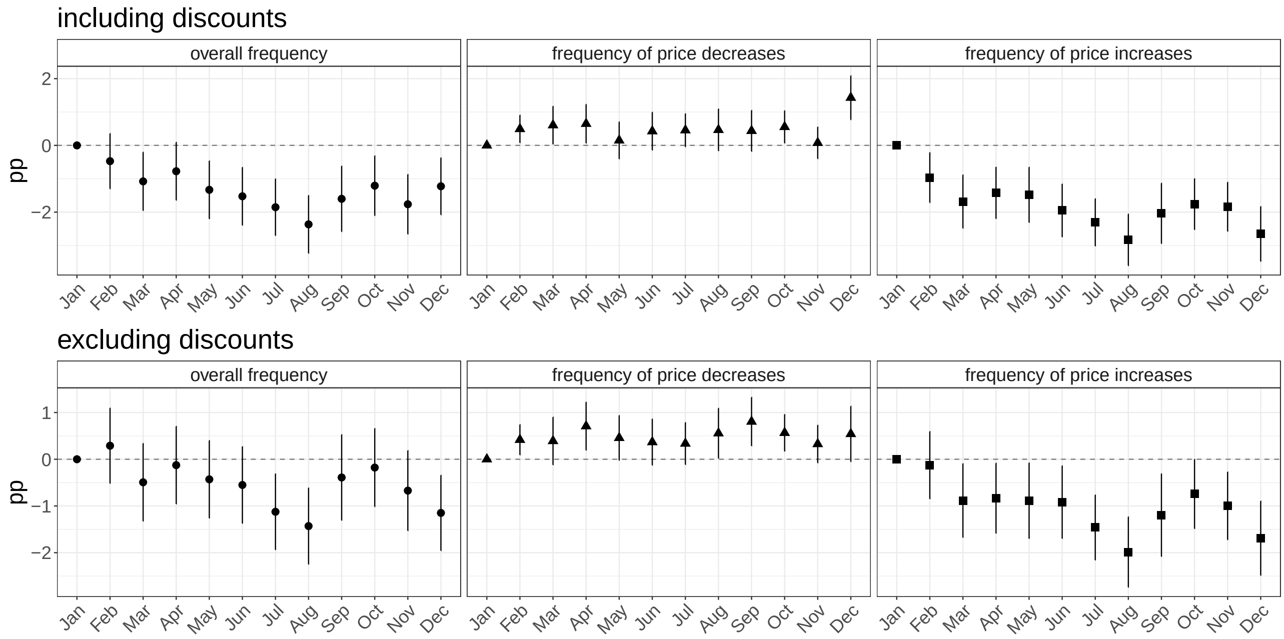


Notes: ECOICOP4-country fixed effects regression results, see equation (4). Point estimates of the year dummies are marked by circles, triangles, and squares, while error bars show the 95% confidence intervals corresponding to the ECOICOP4-country clustered standard errors.

The annual trends in the average size of the price changes plotted in Figure 5 follow the same pattern as those for the frequency of price changes. However, no substantial differences emerge between the year coefficients when the average size of the price rises and the average size of the price cuts are considered separately, implying that the average size of the price changes simply reflects the higher frequency of price rises. This clearly holds for the benchmark sample of prices including discounts, but the story is more nuanced when discounts are excluded. The lower part of the figure shows that the average size of both positive and negative changes in regular prices became larger in 2022 and 2023, and especially so for price rises.

Why this was not visible in the dynamics of the average size of price cuts and price rises together

Figure 6: Seasonality in the frequency margins

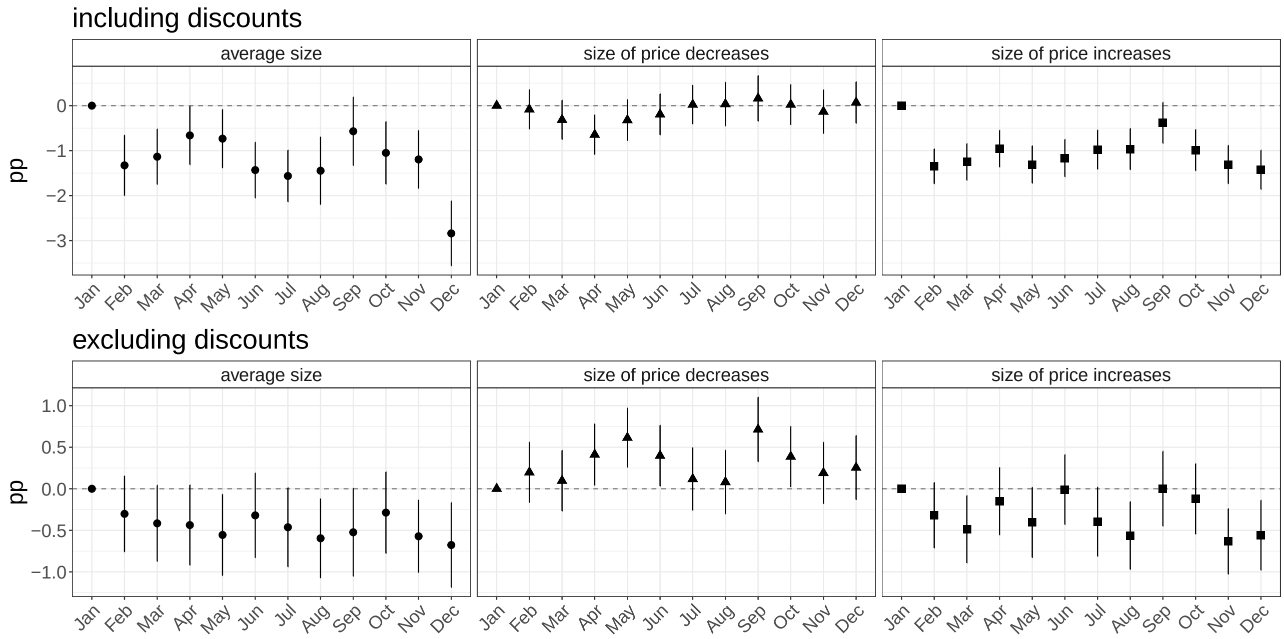


Notes: ECOICOP4-country fixed effects regression results, see equation (4). Point estimates of the month dummies are marked by circles, triangles, and squares, while error bars show the 95% confidence intervals corresponding to the ECOICOP4-country clustered standard errors.

with discounts included can be explained by the average size of price changes in sales being notably larger than the changes in regular prices. The average size of sale discounts remained relatively stable over time, but changes in regular prices became larger and were more prevalent than sales, and so there were two opposing influences acting on the average size of the price changes. The upper part of Figure 5 suggests that these effects balanced each other out. The outcome would have been different if the composition of price changes had remained the same or if the average size of the price changes had increased both for regular prices and sale prices.

There are also some seasonal patterns by calendar month, and these are different for price rises and for price cuts; see Figures 6 and 7. Price increases exhibit a January-effect, meaning that price rises tend to be more frequent and on average larger at the start of the year than in any other month. The relative frequency of price increases is lowest in the summer months and towards the end of the year. The frequency of price cuts varies much less throughout the year and tends to be lowest in January, and there is not much seasonality in the average size of price cuts including discounts. The seasonal patterns in frequencies are essentially unaffected by the exclusion of discounts, like with the annual trends. The seasonal patterns in the average size of regular price increases show that they tend to be higher in the first month of each quarter than in the other months in the same quarter. Overall, the seasonal patterns in frequencies

Figure 7: Seasonality in the average size margins



Notes: ECOICOP4-country fixed effects regression results, see equation (4). Point estimates of the month dummies are marked by circles, triangles, and squares, while error bars show the 95% confidence intervals corresponding to the ECOICOP4-country clustered standard errors.

and average sizes are, if anything, more similar when the sample is restricted to regular price changes.

5 The role of aggregate shocks

The average frequency of price changes became substantially higher when inflation was high as was shown in Table 3. This increase is not consistent with the prediction of TD models but it is inline with SD models. In these models, significant aggregate inflationary shocks can cause the frequency of price rises to vary significantly against the frequency of price cuts, raising the overall frequency of price changes (Alvarez et al., 2019; Karadi and Reiff, 2019; Auclert et al., 2023).

To test whether this phenomenon occurs during the period of high inflation, we first use a monthly BVAR model to identify structural shocks in each country. The model includes time series for the manufacturing production volume index, the core consumer price index, the energy-specific consumer price index, and the unemployment rate for residents aged 15 to 74, all collected from the Eurostat database. The sample period runs from 2002M1 to 2023M9 for each country. All the variables, except the unemployment rate are transformed into natural logarithms. We estimate the reduced form of the model with 13 lags as follows

$$y'_t = a + \sum_{j=1}^{13} y'_{t-j} B_j + \varepsilon'_t. \tag{5}$$

where y_t is the vector of endogenous variables, a is the vector of constants, B_j is the parameter matrix, and ε_t is the vector of exogenous innovations $\varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon)$.[9]

To facilitate model identification we impose sign restrictions on contemporaneous variable impulse responses to the structural shocks, as set out in Table 4 and similar to Neri et al. (2023).[10] We assume that a positive aggregate demand shock should lead to higher core consumer prices, larger manufacturing production, and a lower unemployment rate, while a positive energy price shock should cause both core and energy prices to rise, and manufacturing production to contract.

Table 4: Sign restrictions in each BVAR

	Aggregate demand (+)	Energy price (+)
Manufacturing prod.	+	-
Core CPI	+	+
CPI energy		+
Unemployment rate	-	

Notes: Endogenous variables are listed in the rows while structural shocks are presented in the columns. The signs in parentheses in the headings signify the nature of each shock. Sign restrictions are imposed on the effect of an impulse response on impact. A blank cell within the table signifies that no sign restrictions are imposed. "Manufacturing prod." is the manufacturing production volume index.

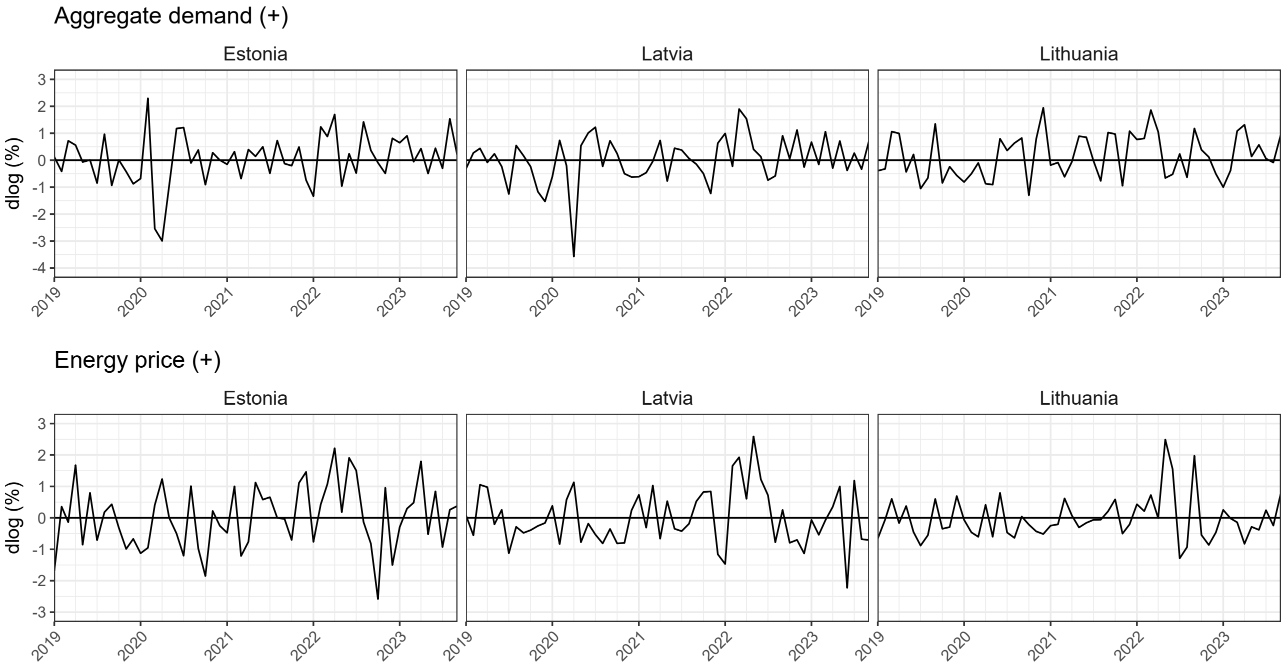
Figure 8 shows the median estimates from 10,000 draws of aggregate demand and energy shocks from 2019 to 2023. In early 2020, the Baltic states experienced a significant negative aggregate

[9] We employ Minnesota priors to guarantee model stability, as there are log-level variables present; see Litterman (1986). The hyperparameters are determined using the standard values outlined in Canova (2007).

[10] Neri et al. (2023) employ sign and narrative restrictions to identify five structural shocks: aggregate demand, aggregate supply, inflation expectations, energy, and monetary policy. Their objective was to provide an explanatory framework for the recent dynamics of EA inflation. In contrast, we adopt a simpler approach, where we assume that monetary policy and inflation expectations shocks can be considered part of aggregate demand disturbances. We also posit that energy price shocks have played the most pivotal role in influencing recent inflation dynamics in the Baltic region, beyond influences exerted by other supply-side shocks, such as technology shocks. By focusing on these two shocks, we effectively assume that sign restrictions are sufficient to let us identify aggregate demand and energy shocks, given their dissimilarity. The identification from the sign restrictions is conducted using the algorithm of Rubio-Ramirez et al. (2010).

demand shock caused by the first global wave of the COVID-19 pandemic and the subsequent states of emergency and lockdown. After that there were positive aggregate demand shocks in late 2021 and early 2022, which probably reflected the global economic recovery after the second wave of the pandemic. The three countries then faced their largest energy price shocks in the first quarter of 2022, because of global supply shortages and the Russian invasion of Ukraine.

Figure 8: BVAR structural shocks in 2019-2023



Notes: The black lines illustrate the median of every type of structural shock, based on 10,000 posterior draws. The signs in parentheses in the headings signify the nature of each shock.

We examine the effects of the estimated shocks on the frequency and size margins using the approach described in Gautier et al. (2024). This method computes counterfactual inflation rates at a granular level and evaluates their average response to our estimated shocks using local linear projections (Jordà, 2005). These counterfactual inflation rates are constructed by keeping the frequency or average size margin constant and using earlier decompositions. One type of counterfactual inflation rate is calculated for each country at the ECOICOP level 4 as follows

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

where $\bar{f}_j$ is the average frequency over the period considered, with the periods of low and high inflation taken separately. This counterfactual inflation rate assumes that only variations in the average size of the price changes had an impact on inflation over the period. We then construct another counterfactual rate that assumes that only variations in the frequency of the price changes have influenced inflation:[11]

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

where $\Delta\bar{p}_j$ is the average size of the price changes over the period considered. In addition, changes in the share of price rises can also influence inflation by affecting the average size of the price changes, as highlighted by the definition (3). To capture the effect on inflation of changes in the average size of price rises and price cuts, independently of changes in the relative frequency of them, we calculate the following counterfactual rate:

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

where $\bar{f}_j^+$ and $\bar{f}_j^-$ represent the average frequency of price rises and price cuts over the period considered. We then symmetrically assess the impact of changes in the frequency of price changes on inflation, assuming that the average size of the price rises and price cuts remains constant over time:

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

where $\Delta\bar{p}_j^+$ and $\Delta\bar{p}_j^-$ refer to the average size of the price rises and price cuts over the period considered.[12]

In the final step, we estimate the average response of the sample-based aggregate inflation rate and the counterfactual inflation rates to the aggregate shocks identified earlier with the BVAR models using local linear projections, doing so separately for the periods of low and high inflation:

$$\tilde{\pi}_{cjt-1,t+h} = \alpha_{cj} + \beta_h \, Shock_{c,t} + \varepsilon_{cjt+h} \tag{10}$$

[11] These two counterfactual inflation rates, $\tilde{\pi}_{jt}^{\bar{f}}$ in eq. (6) and $\tilde{\pi}_{jt}^{\Delta\bar{p}}$ in eq. (7), are directly related to the inflation rate decomposed in eq. (1). For each inflation rate at the ECOICOP level 4, they correspond to the two varying terms of its linear approximation around the averages $(\bar{f}_j, \Delta\bar{p}_j)$ as follows: $\pi(f_{jt}, \Delta p_{jt}) = \underbrace{-(\bar{f}_j \Delta\bar{p}_j)}_{constant} + \underbrace{\Delta\bar{p}_j f_{jt}}_{\tilde{\pi}_{jt}^{\Delta\bar{p}_j}} + \underbrace{\bar{f}_j \Delta p_{jt}}_{\tilde{\pi}_{jt}^{\bar{f}_j}}$.

[12] These two counterfactual inflation rates, $\tilde{\pi}_{jt}^{\bar{f}^+,\bar{f}^-}$ in eq. (8) and $\tilde{\pi}_{jt}^{\Delta\bar{p}^+,\Delta\bar{p}^-}$ in eq. (9), are directly related to the inflation rate decomposed in eq. (2). For each inflation rate at the ECOICOP level 4, they correspond to the two varying terms of its linear approximation around the averages $(\bar{f}_j^+, \bar{f}_j^-, \Delta\bar{p}_j^+, \Delta\bar{p}_j^-)$ as follows: $\pi(f_{jt}^+, f_{jt}^-, \Delta p_{jt}^+, \Delta p_{jt}^-) = \underbrace{-(\bar{f}_j^+ \Delta\bar{p}_j^+ + \bar{f}_j^- \Delta\bar{p}_j^-)}_{constant} + \underbrace{\bar{f}_j^+ \Delta p_{jt}^+ + \bar{f}_j^- \Delta p_{jt}^-}_{\tilde{\pi}_{jt}^{\bar{f}_j^+,\bar{f}_j^-}} + \underbrace{\Delta\bar{p}_j^+ f_{jt}^+ + \Delta\bar{p}_j^- f_{jt}^-}_{\tilde{\pi}_{jt}^{\Delta\bar{p}_j^+,\Delta\bar{p}_j^-}}$.

where α_{cj} denotes the ECOICOP4-country fixed effects, c indicates a country and j is an ECOICOP level 4 category. The dependent variable $\tilde{\pi}_{cjt-1,t+h}$ means that each counterfactual inflation rate is cumulated over nine months, so horizon $h \in \{0, \ldots, 9\}$.[13] $Shock_{c,t}$ corresponds to the aggregate demand or energy price shocks in each country. All the regressions are weighted by yearly country-specific ECOICOP4 HICP weights.[14]

Figure 9 depicts the cumulative impact on inflation rates of positive shocks to energy prices and aggregate demand. The plots in column 1 indicate the response of the aggregate sample-based inflation rate (β^{π}) and the plots in columns 2-5 show the responses of the counterfactual inflation rates, distinguishing between the periods of low and high inflation.[15] The standard deviation of energy price shocks in the three countries was 1% during the period of high inflation, but lower in the low inflation period at 0.66%. This difference in the magnitude of the shocks is thus the main cause of the gap in the response of the inflation rate shown in the upper left plot. More importantly, the shapes of the responses are different in the periods of low and high inflation. Inflation increases immediately when it is initially low, but then remains relatively stable for a few months before showing a delayed bounce. This illustrates the impact of nominal rigidities on the transmission of a typical aggregate cost shock. When inflation is high in contrast, the initial reaction is followed by a further increase, which eventually declines after a few months. The faster and less persistent response of prices during the period of high inflation is consistent with SD models (Cavallo et al., 2023).

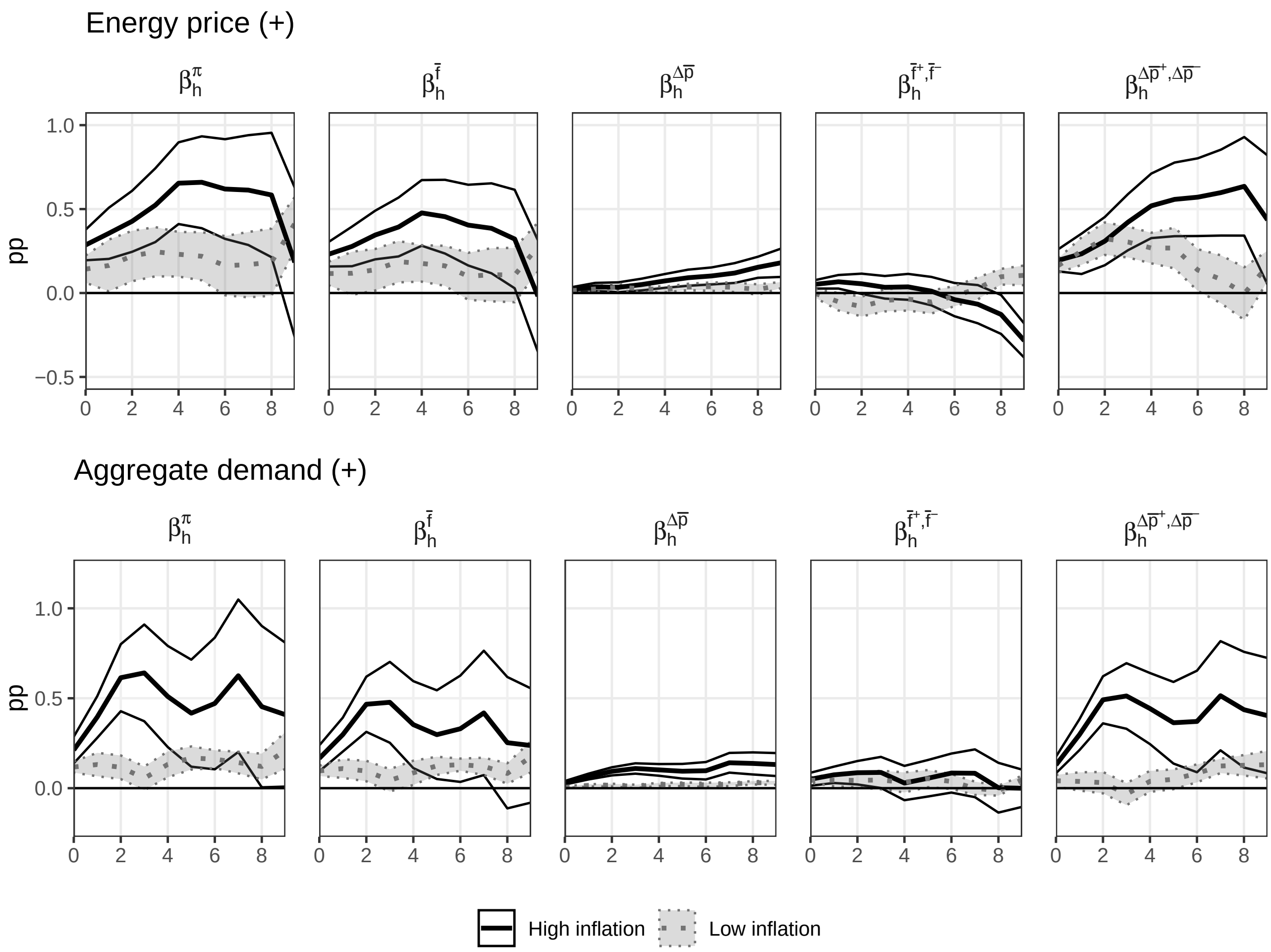
Furthermore, the second and third plots in the upper row show that shifts in the average size margin are the main drivers of the response of inflation to a positive energy price shock in both periods. However, the fourth plot reveals that the average size of price rises and price cuts barely responds to the shock over the horizons, when the two types of change are considered separately. The changes in the average size can therefore be attributed to shifts in the relative frequency of the price changes and this is demonstrated by the response of the counterfactual rate in the last plot in the upper row. The same mechanism is found in Gautier et al. (2024),

[13]In addition to the variables described earlier, two lags of the log real manufacturing production for each country are included in the regressions with aggregate demand shocks. This is done to mitigate the impact on the estimate and potential endogeneity issues induced by the large swings in macroeconomic conditions in the Baltic region during this period.

[14]The projections could be made more robust by including month dummies; however, the length of the time series in the two periods does not allow for such robustness.

[15]Country-specific projections are shown in Figures A13 and A14 in the Appendix. The mechanisms remain equivalent, albeit with quantitative differences that are mostly due to the size of the shocks, which differ from country to country. In this design, the effects of the shocks are symmetric. The limited sample size means that we cannot estimate the responses by separating the shocks into their negative and positive occurrences.

Figure 9: Cumulative responses of inflation rates to structural shocks in the Baltics



Notes: The plots in column 1 (β_h^{π}) indicate the response of the sample-based inflation rate, those in column 2 ($\beta_h^{\bar{f}}$) are that of counterfactual inflation with a constant frequency, those in column 3 ($\beta_h^{\Delta\bar{p}}$) that of counterfactual inflation with a constant average size, those in column 4 ($\beta_h^{\bar{f}^+,\bar{f}^-}$) that of counterfactual inflation with a constant frequency of price rises and cuts, and the plots in column 5 ($\tilde{\pi}_{jt}^{\Delta\bar{p}^+,\Delta\bar{p}^-}$) that of counterfactual inflation with a constant average size of price rises and cuts. The shaded areas represent a standard error based on calendar clusters (month-year).

who analyse the responses of frequency and size to aggregate shocks in the EA countries during the period of low inflation from 2010 to 2019.

The response of the counterfactual inflation rate, assuming only changes in the frequency margin, is mostly muted for all time horizons during the period of low inflation (see the middle plot in the upper row), but it exhibits a statistically significant reaction during the period of high inflation. This is inconsistent with TD models but is again an important characteristic of SD models (Alvarez et al., 2019).

With the aggregate demand shocks, we find that their standard deviation was higher at 1% in the period of low inflation than in the period of high inflation, when it was 0.73%, mainly because of the impact of the COVID-19 pandemic. However, a positive demand shock, though smaller in magnitude, had a larger inflationary impact in the period of high inflation, as shown in the left plot in the lower row. Another difference is that the inflationary effect accumulated gradually over time when inflation was low, while the response was steeper when it was high.

Like with the energy price shock, the primary factor driving the response of inflation to an aggregate demand shock in both periods was the average size margin (see the second plot). Furthermore, the last plot in the lower row indicates that these changes in size were caused by variations in the share of price rises. More importantly, the response of the counterfactual inflation rate that varies only with the frequency margin is significant only in the period of high inflation (see the middle plot). This reinforces the finding that SD models would be more appropriate for describing the price-setting mechanisms in the Baltics.

To gain further insights and better assess how the counterfactual inflation rates in the Baltics reacted to the structural shocks in the period of high inflation relative to how they reacted in the period of low inflation, we perform additional regressions on the full sample as in Jouvanceau (2023).

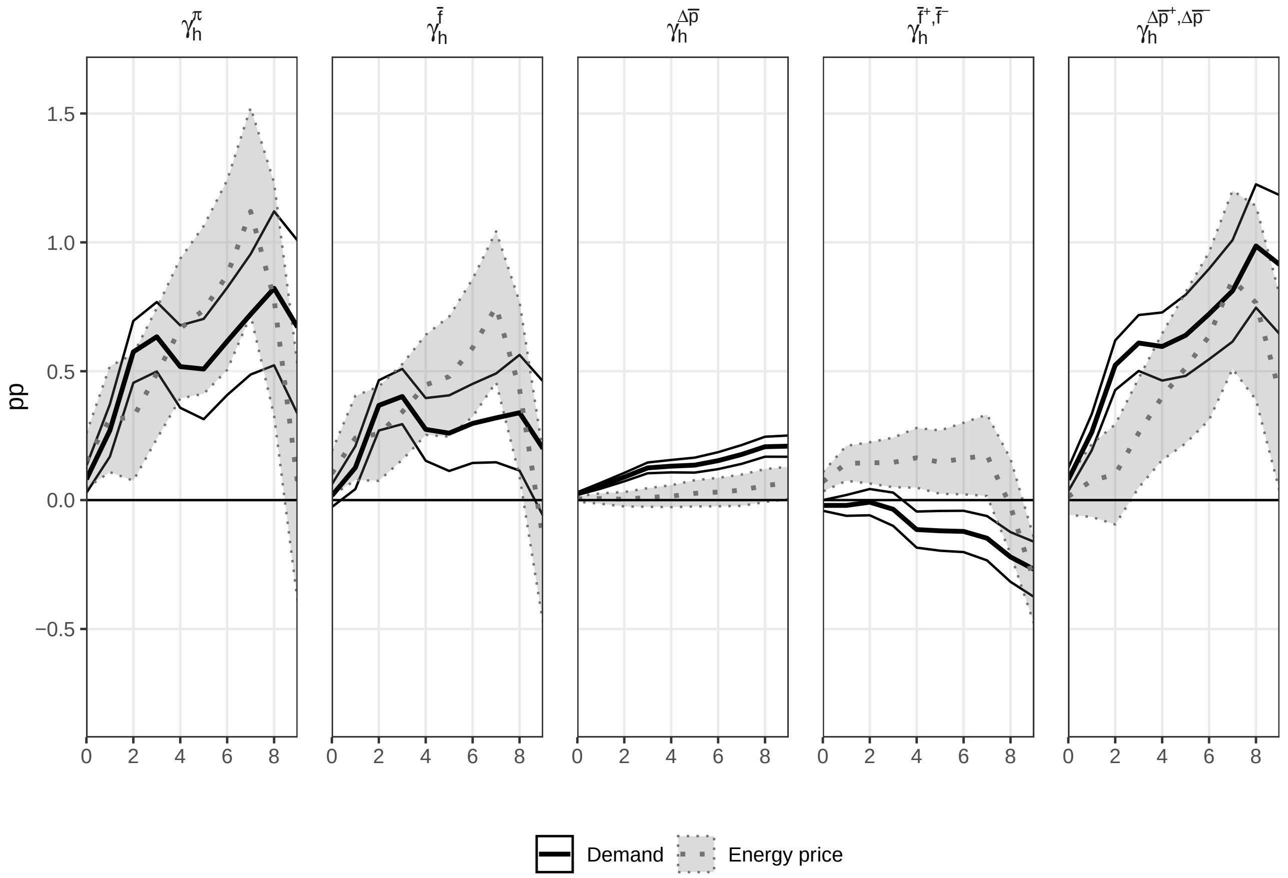
$$\tilde{\pi}_{cjt-1,t+h} = \alpha_{cj,m} + \delta_h I_{\pi_{high}} + \chi_h \, Shock_{c,t} + \gamma_h \, Shock_{c,t} \times I_{\pi_{high}} + \epsilon_{cj,t+h}. \tag{11}$$

where $\alpha_{cj,m}$ denotes month-ECOICOP4-country fixed effects, and $I_{\pi_{high}}$ is a dummy that takes the value 1 in the period of high inflation.[16]

Figure 10 depicts the response of the counterfactual inflation rates to a one-standard-deviation shock, calculated for the whole period, in the period of high inflation relative to response in the period of low inflation, estimated with the coefficients γ_h.

[16] Note that in this case, the counterfactual inflation rates are calculated by fixing the margins at the sample-wide averages from 2019 to 2023. All the regressions are weighted by yearly country-specific ECOICOP4 HICP weights.

Figure 10: Cumulative responses of Baltic counterfactual inflation rates to structural shocks in the periods of high inflation and low inflation



Notes: The first plot (γ_h^{π}) indicates the response of the sample-based inflation rate, the second plot ($\gamma_h^{\bar{f}}$) is that of counterfactual inflation with a constant frequency, the third plot ($\gamma_h^{\Delta\bar{p}}$) that of counterfactual inflation with a constant average size, the fourth plot ($\gamma_h^{\bar{f}^+,\bar{f}^-}$) that of counterfactual inflation with a constant frequency of price rises and cuts, and the last plot ($\gamma_h^{\Delta\bar{p}^+,\Delta\bar{p}^-}$) that of counterfactual inflation with a constant average size of price rises and cuts. The shaded areas represent a standard error based on calendar clusters (month-year).

Immediately after the shocks, the responses exhibited a quasi-identical pattern in the two periods. However, only one month later, a one-standard-deviation shock of either type had a more pronounced cumulative inflationary impact when inflation was high. Moreover, the responses are considerably steeper in that period, reflecting lower price rigidity and higher pass-through of the shock. Finally, the shocks had different effects on the counterfactual inflation rates, with the overall frequency varying across the two periods (see the middle plot). This is consistent with the predictions of SD models, which posit that the likelihood of price adjustments increases with the occurrence of larger aggregate shocks (Alvarez et al., 2019).

6 Conclusions

Our analysis compares consumer price rigidity in the Baltic states during periods of low inflation in 2019-2020 and high inflation in 2021-2023. We use the monthly price records collected by the statistical offices for CPI estimations to compile our statistics on the frequency and size of price changes in each period. The granularity of the data allows us to provide these statistics at the ECOICOP level 4, which is the lowest level of publicly observable CPIs. Our final sample covers approximately 65% of the ECOICOP4 categories, which account for about 90% of the HICP weights over the period; the prices of services are less well represented with about 50% coverage.

Aggregate statistics indicate that the average frequency of price changes increased during the period of high inflation by approximately 4 p.p. This rise was mainly due to a jump in the average frequency of price rises, which increased by 5 p.p., while the average frequency of price cuts declined by 1 p.p. The average frequency in the Baltic region during the period of low inflation was 21.2% and the average frequency of non-energy price changes was 16.2%, which is significantly higher than the 12.4% in the EA. This difference is attributed to price changes becoming more frequent for processed and unprocessed food items, as their frequencies were on average around 7 and 9 p.p. higher.[17] However, this difference mainly disappears after excluding sales and discounts, which suggests that discounts are much more important in explaining price flexibility in the Baltic states than they are in the EA.

Furthermore, the average size of the price changes increased from 1.4% in the period of low inflation to 4.2% in the period of high inflation because the share of price rises was larger. While the average size of price rises was similar in the two periods, the average size of price cuts grew by 0.5 p.p. in absolute value.

We study these contrasting dynamics in the size and frequency margins of inflation further by estimating fixed-effects regression models. We find that the frequency and average size of price changes followed similar trends to those of the frequency of price rises, but not to those of the frequency of price cuts or the average size of price rises and price cuts. Another piece of evidence is that the size distribution of price changes in each country shifted significantly to the right between the periods of low and high inflation. The shape of the distributions remained

[17] We additionally observe energy prices, which are not present in the EA's sample. The average frequency of price changes for this type of goods and services was about 60% in the period of low inflation and 64% during the period of high inflation.

largely the same though, suggesting that there was no significant additional occurrence of large price changes in the period of high inflation. In other words, what changed between the two periods was mainly the share of small to moderate price rises.

Finally, we analyse the role of aggregate shocks in explaining the significant adjustment in the frequency of price changes during the period of high inflation. We estimate country-specific structural shocks to energy prices and aggregate demand using BVAR models with monthly macroeconomic data from 2002M1 to 2023M9. The models successfully capture the impact of the COVID-19 lockdowns in 2020 and the energy price spike in 2022 that followed the Russian military aggression in Ukraine. We then assess the cumulative average response of inflation rates to the shocks using the local projection method (Jordà, 2005). Various counterfactual inflation rates allow us to determine whether it is the frequency or size margin that drives the fluctuations in inflation for each shock. We find that the average size margin mainly accounts for the changes in inflation following each type of shock in both periods, as in Gautier et al. (2024). Importantly, we find that the frequency margin responded significantly to both shocks in the period of high inflation, but was mostly muted in the period of low inflation. This implies that a Calvo (1983) price-setting assumption would be inconsistent with the pricing mechanisms during the period of high inflation, suggesting that SD models are more appropriate for explaining the data (Auclert et al., 2023).

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Appendix

Table A1: Micro datasets

	Estonia (EE)	Latvia (LV)	Lithuania (LT)
(1) General			
Source	Statistics Estonia	Statistics Latvia	Statistics Lithuania
Period	2019M1-2023M6	2019M1-2023M6	2019M1-2023M3
Total observations	$\approx$ 1M	$\approx$ 1M	$\approx$ 3.3M
Monthly observations (average)	$\approx$ 20k	$\approx$ 20k	$\approx$ 65k
Imputations	no	yes	yes
(2) Coverage			
Location	10 towns/counties	11 territories	6 main territories
ECOICOP4 weight coverage	$\approx$ 80%	100%	$\approx$ 90%
ECOICOP4 categories	189	205	230
(3) Level of detail			
Detailed ECOICOP categories	700	539	949
Example of a detailed category	01.1.1.1.101	01.1.1.101	01.1.1.1.00.00.00.01
Store identifier	no	yes	yes
Price detail	brand	target product	target product
Unit/quantity	yes	yes	yes
(4) Flags			
Price change indicator	no	yes	yes
Quality/quantity replacement	yes	yes	yes
Price discounts (sales)	yes, discount period	yes, discount period + 1	yes, first month

Table A2: List of the ECOICOP level 4 categories in the common sample

Product groups	ECOICOP4 categories
Energy	4522, 4530, 4541, 4549, 4550, 7221, 7222, 7223
NEIG	3110, 3121, 3122, 3123, 3131, 3132, 3211, 3212, 3213, 4310, 4410, 5111, 5113, 5119, 5121, 5122, 5201, 5202, 5203, 5311, 5312, 5313, 5314, 5315, 5321, 5322, 5323, 5401, 5402, 5403, 5511, 5521, 5522, 5611, 5612, 6110, 6121, 6129, 6131, 6139, 7130, 7211, 7212, 7213, 7224, 8202, 9111, 9112, 9119, 9121, 9141, 9142, 9149, 9311, 9312, 9321, 9322, 9331, 9332, 9342, 9511, 9513, 9521, 9522, 9541, 9549, 12121, 12131, 12132, 12311, 12312, 12321, 12322, 12329
Processed food	1111, 1112, 1113, 1114, 1115, 1116, 1117, 1118, 1127, 1128, 1132, 1134, 1135, 1136, 1141, 1142, 1143, 1144, 1145, 1146, 1151, 1152, 1153, 1154, 1162, 1163, 1164, 1172, 1173, 1174, 1175, 1181, 1182, 1183, 1184, 1185, 1191, 1192, 1193, 1194, 1199, 1211, 1212, 1213, 1221, 1222, 1223, 2111, 2112, 2121, 2122, 2123, 2131, 2133, 2201
Services	3141, 3142, 3220, 4110, 4321, 4324, 4329, 4420, 4430, 4441, 4442, 5330, 5621, 5622, 6211, 6212, 6220, 6231, 6239, 6300, 7230, 7241, 7242, 7243, 7311, 7321, 7322, 7341, 8101, 8109, 8304, 9150, 9350, 9412, 9421, 9422, 9423, 9425, 10101, 10102, 10400, 10500, 11111, 11112, 11120, 11201, 11203, 12111, 12112, 12113, 12313, 12401, 12402, 12621, 12701, 12702, 12703, 12704
Unprocessed food	1121, 1122, 1124, 1126, 1131, 1147, 1161, 1171

Note: The common sample of goods and services comprises the ECOICOP4 categories that are collected in at least two Baltic countries.

Table A3: Aggregate weighted statistics for the periods of low and high inflation (common sample, excluding discounts)

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	14.0	7.9	6.1	6.6	4.8	10.8	-9.8	69.4	100.0	7.3
All (non-energy)	8.2	5.3	2.9	11.7	5.5	11.6	-10.4	72.0	88.6	7.6
Energy	59.3	28.0	31.3	1.1	-0.7	4.7	-5.2	48.9	11.4	0.9
NEIG	4.7	3.1	1.6	20.7	5.3	11.7	-9.6	68.6	28.4	7.6
Processed food	8.7	6.2	2.5	10.9	4.3	10.1	-8.7	71.8	25.8	14.7
Services	7.7	4.7	2.9	12.5	7.3	12.5	-12.3	77.5	29.2	0.2
Unprocessed food	27.4	15.6	11.8	3.1	2.8	13.8	-12.7	61.0	5.3	11.8
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	17.9	12.7	5.2	5.1	7.7	11.9	-10.3	80.3	100.0	6.7
All (non-energy)	11.6	9.0	2.7	8.1	8.4	12.5	-10.9	82.5	87.8	6.9
Energy	63.2	39.6	23.7	1.0	2.8	7.4	-6.0	64.3	12.2	0.6
NEIG	7.9	6.1	1.8	12.2	8.3	12.7	-10.5	80.2	28.6	7.0
Processed food	14.2	12.0	2.2	6.5	8.1	11.3	-9.3	85.2	27.4	13.3
Services	9.2	6.7	2.5	10.4	9.6	13.2	-12.7	85.2	26.0	0.2
Unprocessed food	29.1	18.8	10.3	2.9	5.6	14.8	-13.2	69.3	5.7	11.4

Notes: The statistics are calculated from price changes without product replacements. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The common sample of goods and services is defined as the list of ECOICOP4 collected in at least 2 Baltic countries. The results are estimated using the common sample and the average values of yearly weights in the corresponding period and across countries.
The columns from left to right are: the special aggregate category, the frequency of price change, the frequency of price rises, the frequency of price cuts, the time in months between two consecutive price changes, the average size of price changes overall, the average size of price rises, the average size of price cuts, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the frequency of price changes due to discounts. Duration is given by $dur = -1/ln(1-\bar{f})$.

Table A4: Aggregate weighted statistics (full sample): low and high inflation periods, Estonia

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	18.4	9.5	8.9	4.9	0.1	17.0	-19.1	55.2	100.0	7.5
All (non-energy)	14.4	7.4	6.9	6.4	0.2	18.3	-20.6	55.6	89.6	7.8
Energy	52.6	26.9	25.7	1.3	-1.0	3.9	-4.9	50.9	10.4	1.1
NEIG	13.4	5.7	7.7	6.9	-3.7	22.7	-25.2	45.8	27.2	8.4
Processed food	21.6	11.9	9.7	4.1	0.3	16.9	-19.2	55.3	27.8	13.3
Services	2.9	2.0	0.9	34.3	6.2	13.4	-13.5	73.2	29.6	0.1
Unprocessed food	48.2	24.9	23.3	1.5	-0.1	18.1	-19.1	51.8	4.9	13.4
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	22.1	13.7	8.4	4.0	2.5	16.5	-20.1	63.1	100.0	7.5
All (non-energy)	18.0	11.2	6.8	5.0	2.6	17.6	-21.4	63.5	88.0	7.8
Energy	51.8	31.9	19.9	1.4	1.5	6.2	-7.1	59.7	12.0	0.8
NEIG	17.0	9.5	7.5	5.4	0.2	20.8	-24.8	56.4	27.8	9.1
Processed food	25.8	16.8	9.0	3.3	2.7	16.7	-19.8	62.7	28.8	12.6
Services	3.8	3.1	0.7	25.9	7.4	12.6	-16.6	82.2	25.8	0.2
Unprocessed food	48.8	28.1	20.7	1.5	2.3	18.0	-19.4	58.3	5.5	13.2

Notes: The statistics are calculated from price changes without product replacements. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The results are estimated using the full sample and yearly weights. The columns from left to right are: the special aggregate category, the frequency of price change, the frequency of price rises, the frequency of price cuts, the time in months between two consecutive price changes, the average size of price changes overall, the average size of price rises, the average size of price cuts, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the frequency of price changes due to discounts. Duration is given by $dur = -1/ln(1-\bar{f})$.

Table A5: Aggregate weighted statistics (full sample excluding discounts): low and high inflation periods, Estonia

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	10.8	6.2	4.6	8.8	2.6	9.3	-9.5	64.4	100.0	7.5
All (non-energy)	6.0	3.8	2.2	16.1	3.0	9.9	-10.1	65.9	89.6	7.8
Energy	51.7	26.6	25.1	1.4	-0.8	3.4	-4.4	51.3	10.4	1.1
NEIG	2.6	1.7	0.9	37.9	2.9	9.5	-9.1	65.5	27.2	8.4
Processed food	8.1	5.4	2.7	11.9	1.4	7.6	-8.7	63.0	27.8	13.3
Services	2.8	2.0	0.9	35.2	6.7	13.3	-12.7	74.6	29.6	0.1
Unprocessed food	32.9	18.1	14.7	2.5	0.6	14.0	-15.3	55.9	4.9	13.4
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	14.3	10.2	4.1	6.5	5.4	10.2	-10.3	75.0	100.0	7.5
All (non-energy)	9.2	7.2	2.0	10.4	5.9	10.7	-10.8	76.8	88.0	7.8
Energy	51.2	31.6	19.6	1.4	1.5	5.6	-5.6	60.2	12.0	0.8
NEIG	5.8	4.9	0.9	16.8	7.2	11.2	-10.3	80.3	27.8	9.1
Processed food	12.8	10.6	2.2	7.3	4.4	9.0	-9.2	73.7	28.8	12.6
Services	3.6	3.0	0.6	27.2	7.8	12.2	-15.2	83.2	25.8	0.2
Unprocessed food	33.6	20.9	12.7	2.4	3.0	14.4	-14.8	62.6	5.5	13.2

Notes: The statistics are calculated from price changes without product replacements and sales. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The results are estimated using the full sample and yearly weights.
The columns from left to right: the special aggregate category, the frequency of price change, the frequency of price increase, the frequency of price decrease, the duration between two consecutive price changes (in months), the average size of price change (overall), the average size of price increases, the average size of price decreases, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the frequency of price changes due to discounts. Duration is given by $dur = -1/ln(1-\bar{f})$.

Table A6: Aggregate weighted statistics (full sample): low and high inflation periods, Latvia

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	22.4	11.1	11.3	3.9	0.2	14.2	-14.8	52.3	100.0	7.8
All (non-energy)	19.7	10.0	9.6	4.6	0.4	15.3	-16.3	54.5	85.5	8.1
Energy	38.5	17.2	21.3	2.1	-1.5	3.8	-4.3	38.8	14.5	0.6
NEIG	17.8	8.3	9.6	5.1	-2.4	16.7	-18.3	46.4	24.6	6.6
Processed food	28.1	14.8	13.3	3.0	0.1	16.8	-17.6	52.2	24.2	19.6
Services	12.1	6.5	5.5	7.8	4.1	11.0	-10.5	67.1	31.3	0.3
Unprocessed food	34.5	17.1	17.4	2.4	-0.4	18.1	-18.5	49.7	5.4	14.6
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	27.6	16.7	10.9	3.1	2.7	14.4	-16.2	62.8	100.0	7.1
All (non-energy)	23.2	13.8	9.4	3.8	2.7	15.2	-17.5	62.8	84.1	7.3
Energy	51.2	32.1	19.1	1.4	3.0	8.8	-7.0	62.8	15.9	0.5
NEIG	20.5	11.2	9.3	4.4	-0.2	15.9	-18.7	54.7	23.4	6.0
Processed food	32.6	19.7	12.9	2.5	2.2	16.1	-18.2	60.5	27.7	18.1
Services	12.9	8.5	4.3	7.3	7.3	12.2	-12.2	78.4	26.9	0.2
Unprocessed food	36.4	20.2	16.2	2.2	1.3	17.9	-18.7	55.1	6.1	13.4

Notes: The statistics are calculated from price changes without product replacements. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The results are estimated using the full sample and yearly weights. The columns from left to right are: the special aggregate category, the frequency of price change, the frequency of price rises, the frequency of price cuts, the time in months between two consecutive price changes, the average size of price changes overall, the average size of price rises, the average size of price cuts, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the frequency of price changes due to discounts. Duration is given by $dur = -1/ln(1-\bar{f})$.

Table A7: Aggregate weighted statistics (full sample excluding discounts): low and high inflation periods, Latvia

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	14.7	8.2	6.5	6.3	5.2	10.8	-7.3	67.6	100.0	7.8
All (non-energy)	10.7	6.7	4.1	8.8	6.3	11.6	-7.9	72.5	85.5	8.1
Energy	38.1	17.1	21.0	2.1	-1.4	3.7	-4.0	39.1	14.5	0.6
NEIG	8.9	5.1	3.8	10.7	7.0	11.9	-7.7	71.3	24.6	6.6
Processed food	9.4	7.5	1.9	10.1	7.4	11.2	-6.1	78.6	24.2	19.6
Services	11.7	6.4	5.3	8.0	4.5	10.7	-9.6	68.7	31.3	0.3
Unprocessed food	19.1	11.6	7.5	4.7	5.3	14.4	-10.3	66.0	5.4	14.6
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	19.8	13.8	6.0	4.5	7.4	11.8	-8.6	77.6	100.0	7.1
All (non-energy)	13.9	10.3	3.5	6.7	8.2	12.3	-8.9	80.4	84.1	7.3
Energy	51.0	32.0	19.0	1.4	3.0	8.7	-6.9	63.0	15.9	0.5
NEIG	12.1	8.2	3.9	7.7	8.0	12.1	-8.8	77.5	23.4	6.0
Processed food	14.7	12.9	1.8	6.3	9.1	11.9	-7.4	85.4	27.7	18.1
Services	12.7	8.5	4.2	7.4	7.9	12.1	-10.8	80.2	26.9	0.2
Unprocessed food	22.1	15.2	6.9	4.0	6.0	14.6	-11.3	68.5	6.1	13.4

Notes: The statistics are calculated from price changes without product replacements and sales. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The results are estimated using the full sample and yearly weights.
The columns from left to right are: the special aggregate category, the frequency of price change, the frequency of price rises, the frequency of price cuts, the time in months between two consecutive price changes, the average size of price changes overall, the average size of price rises, the average size of price cuts, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the frequency of price changes due to discounts. Duration is given by $dur = -1/ln(1-\bar{f})$.

Table A8: Aggregate weighted statistics (full sample): low and high inflation periods, Lithuania

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	22.1	11.6	10.5	4.0	1.5	15.9	-17.8	58.5	100.0	5.9
All (non-energy)	14.3	8.0	6.3	6.5	1.8	17.4	-19.8	60.0	88.4	6.1
Energy	80.8	38.7	42.1	0.6	-0.4	5.0	-5.1	47.8	11.6	0.8
NEIG	13.9	7.1	6.9	6.7	-0.8	19.4	-21.8	51.0	32.1	7.1
Processed food	18.2	10.4	7.9	5.0	0.8	17.9	-20.2	58.3	24.8	11.0
Services	5.7	4.1	1.6	17.1	7.2	13.6	-14.9	78.0	26.2	0.2
Unprocessed food	41.1	22.2	18.9	1.9	0.6	16.6	-17.7	54.3	5.3	8.1
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	24.7	16.2	8.5	3.5	4.5	15.4	-18.1	68.6	100.0	5.0
All (non-energy)	17.3	11.7	5.6	5.3	4.8	16.5	-19.5	69.3	89.1	5.1
Energy	85.3	53.2	32.1	0.5	2.1	6.2	-6.4	63.5	10.9	0.4
NEIG	15.7	9.6	6.0	5.9	2.5	17.9	-21.7	61.7	33.9	5.8
Processed food	23.1	16.2	6.9	3.8	4.0	16.1	-19.7	68.8	25.4	9.0
Services	8.0	6.8	1.2	12.0	10.2	14.4	-13.7	85.5	24.4	0.2
Unprocessed food	42.4	25.6	16.8	1.8	3.0	17.0	-18.2	61.1	5.3	9.2

Notes: The statistics are calculated from price changes without product replacements. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The results are estimated using the full sample and yearly weights. The columns from left to right are: the special aggregate category, the frequency of price change, the frequency of price rises, the frequency of price cuts, the time in months between two consecutive price changes, the average size of price changes overall, the average size of price rises, the average size of price cuts, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the frequency of price changes due to discounts. Duration is given by $dur = -1/ln(1-\bar{f})$.

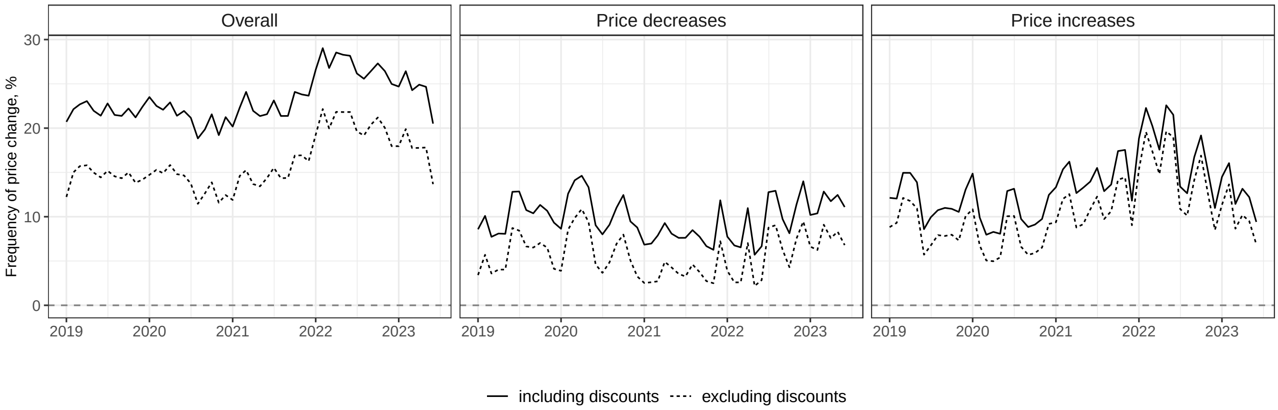
Table A9: Aggregate weighted statistics (full sample excluding discounts): low and high inflation periods, Lithuania

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\bar{f}^{discount}$
Low inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	16.3	9.0	7.3	5.6	4.2	11.8	-11.0	65.9	100.0	5.9
All (non-energy)	7.8	5.1	2.7	12.3	4.8	12.8	-12.0	68.6	88.4	6.1
Energy	80.4	38.5	42.0	0.6	-0.4	4.5	-4.6	47.6	11.6	0.8
NEIG	5.0	3.2	1.8	19.6	4.2	12.7	-11.0	63.9	32.1	7.1
Processed food	8.7	5.9	2.8	11.0	3.6	12.3	-12.3	67.2	24.8	11.0
Services	5.5	4.0	1.5	17.8	8.0	13.3	-13.6	80.4	26.2	0.2
Unprocessed food	32.7	18.5	14.2	2.5	2.1	13.5	-12.9	58.3	5.3	8.1
High inflation	%	%	%	$m.$	%	%	%	%	%	%
All-items	19.2	13.6	5.6	4.7	6.9	12.2	-11.4	76.9	100.0	5.0
All (non-energy)	11.2	8.8	2.4	8.4	7.6	13.0	-12.1	78.6	89.1	5.1
Energy	85.0	53.1	31.9	0.5	2.3	5.9	-5.1	64.1	10.9	0.4
NEIG	7.5	5.8	1.7	12.8	7.0	12.7	-11.5	76.1	33.9	5.8
Processed food	14.8	12.1	2.7	6.3	6.7	12.2	-12.3	78.6	25.4	9.0
Services	7.8	6.7	1.1	12.3	10.5	14.2	-13.1	86.6	24.4	0.2
Unprocessed food	33.2	21.1	12.1	2.5	4.2	14.2	-13.1	65.3	5.3	9.2

Notes: The statistics are calculated from price changes without product replacements and sales. The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. The results are estimated using the full sample and yearly weights.

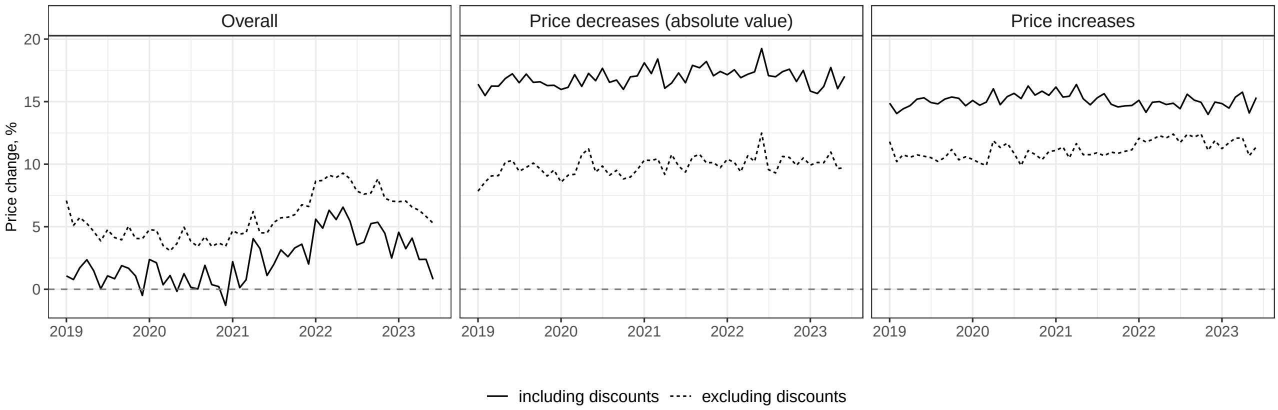
The columns from left to right are: the special aggregate category, the frequency of price change, the frequency of price rises, the frequency of price cuts, the time in months between two consecutive price changes, the average size of price changes overall, the average size of price rises, the average size of price cuts, the share of positive price changes in all price changes, the weighted share of special aggregates in all items, the frequency of price changes due to discounts. Duration is given by $dur = -1/ln(1-\bar{f})$.

Figure A1: Average overall frequency of price changes (common sample), %



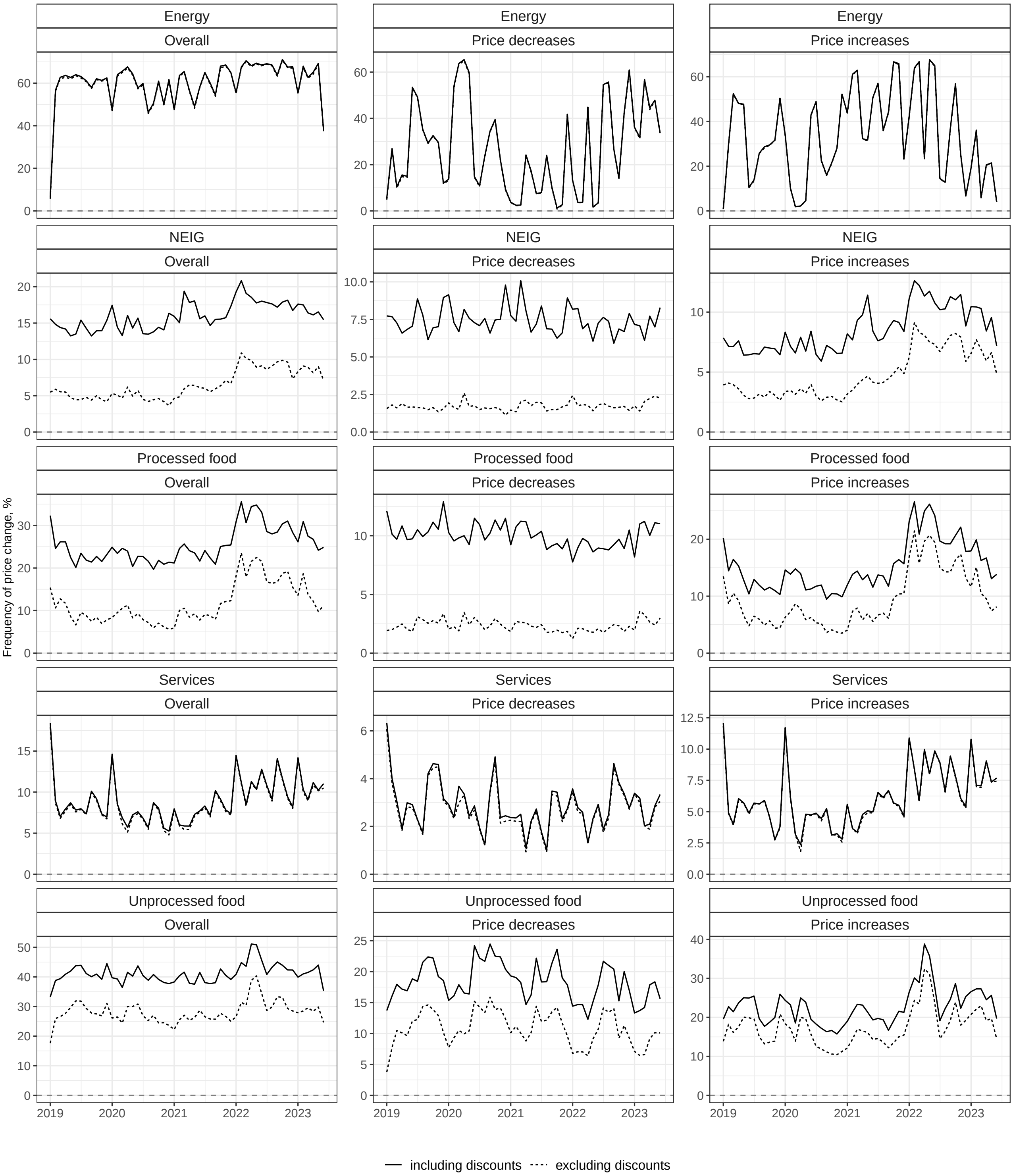
Notes: The plot shows the frequency of price adjustments during 2019-2020 in the three Baltic states for the common sample of ECOICOP4 categories. The results are estimated using the average values of yearly weights in the corresponding period and across countries.

Figure A2: Average size of price changes (common sample), %



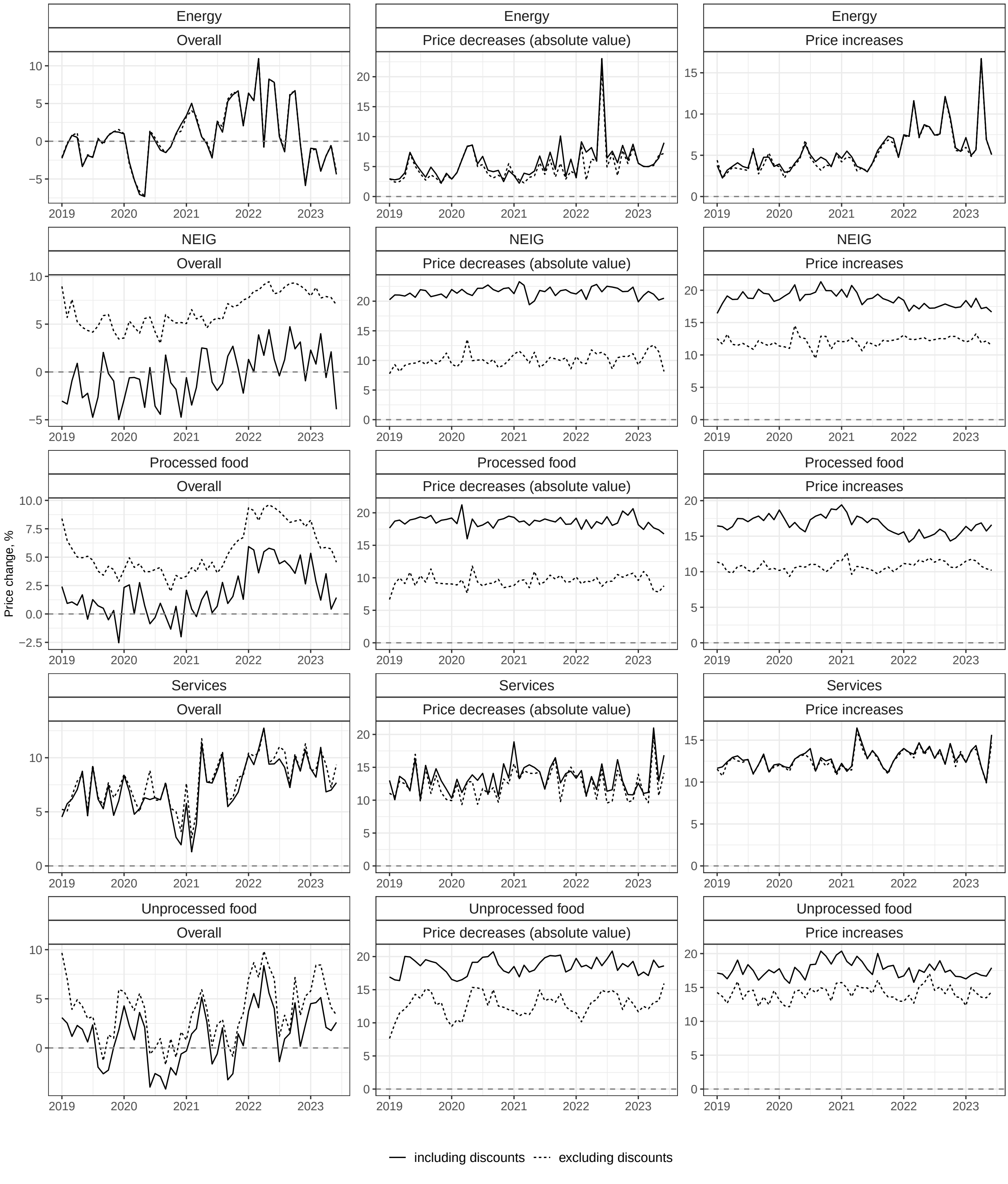
Notes: The plot shows the size of price changes during 2019-2020 in the three Baltic states for the common sample of ECOICOP4 categories. The results are estimated using the average values of yearly weights in the corresponding period and across countries.

Figure A3: Average overall frequency of price changes (common sample): by special aggregates, %



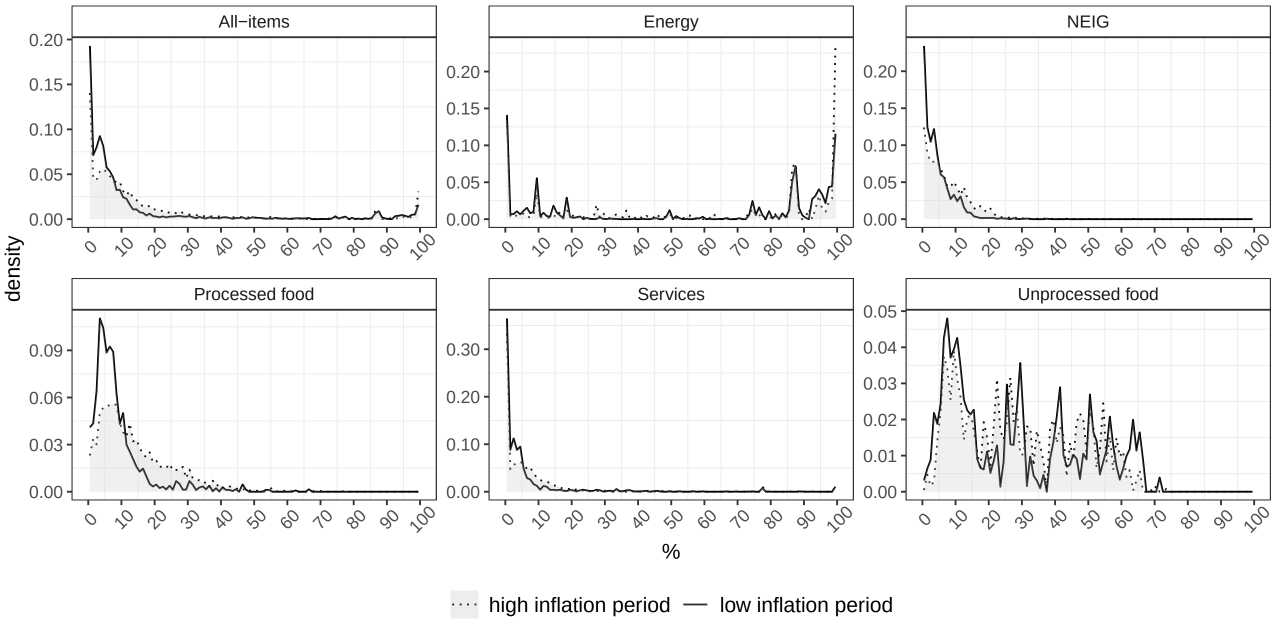
Notes: The plot shows the frequency of price adjustment during 2019-2020 in the three Baltic states for the common sample of ECOICOP4 categories. The results are estimated using the average values of yearly weights in the corresponding period and across countries.

Figure A4: Average size of price changes (common sample): by special aggregates, %



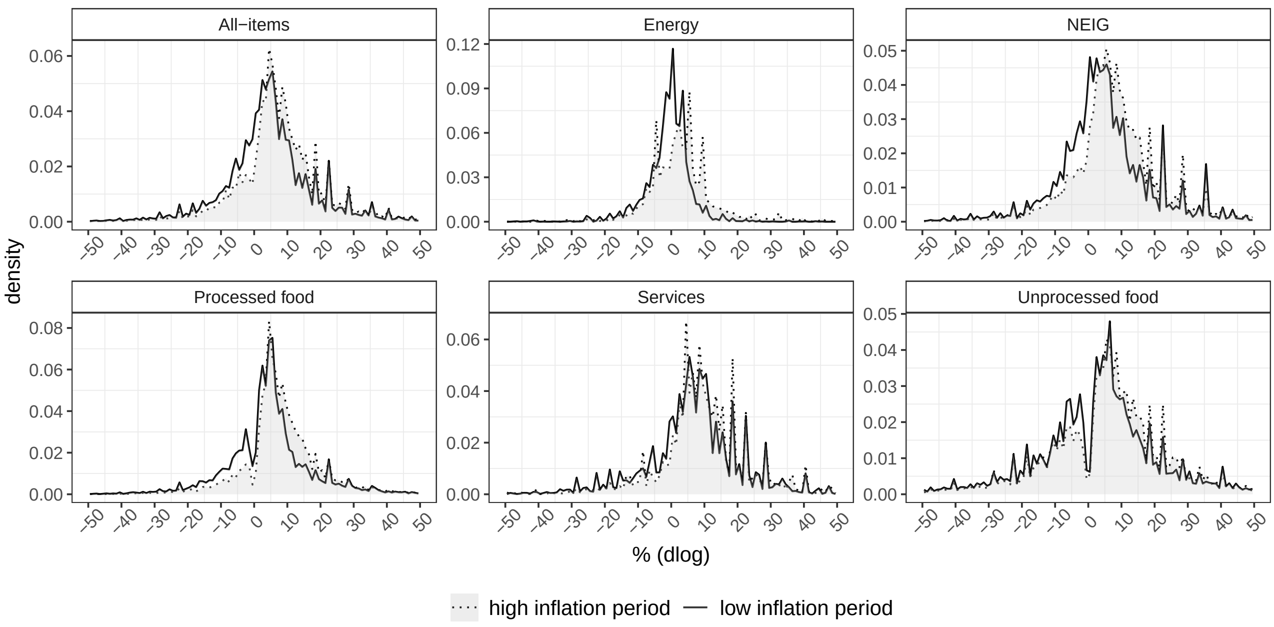
Notes: The plot shows the size of price changes during 2019-2020 in the three Baltic states for the common sample of ECOICOP4 categories. The results are estimated using the average values of yearly weights in the corresponding period and across countries.

Figure A5: Weighted distribution of the frequency of price changes in the Baltics (common sample, excluding discounts)



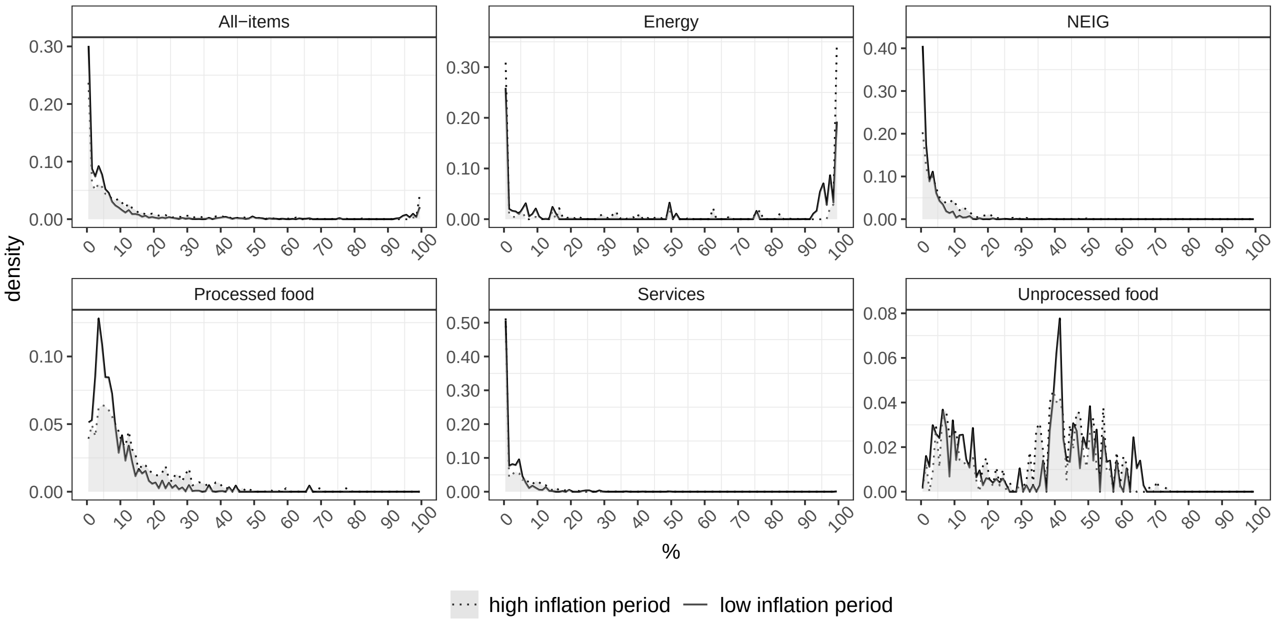
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the common sample of goods, we first estimate for each country the frequency of price changes in each month at the detailed item level (see Table A1), and then calculate average frequencies at the ECOICOP level 4. Next, using the mean values of the weights of the corresponding country in each of the two periods, we aggregate distributions to the country and specific product group level. The weighted distribution for the Baltics is estimated by averaging the distributions obtained for each country.

Figure A6: Weighted distribution of the size of price changes in the Baltics (common sample, excluding discounts)



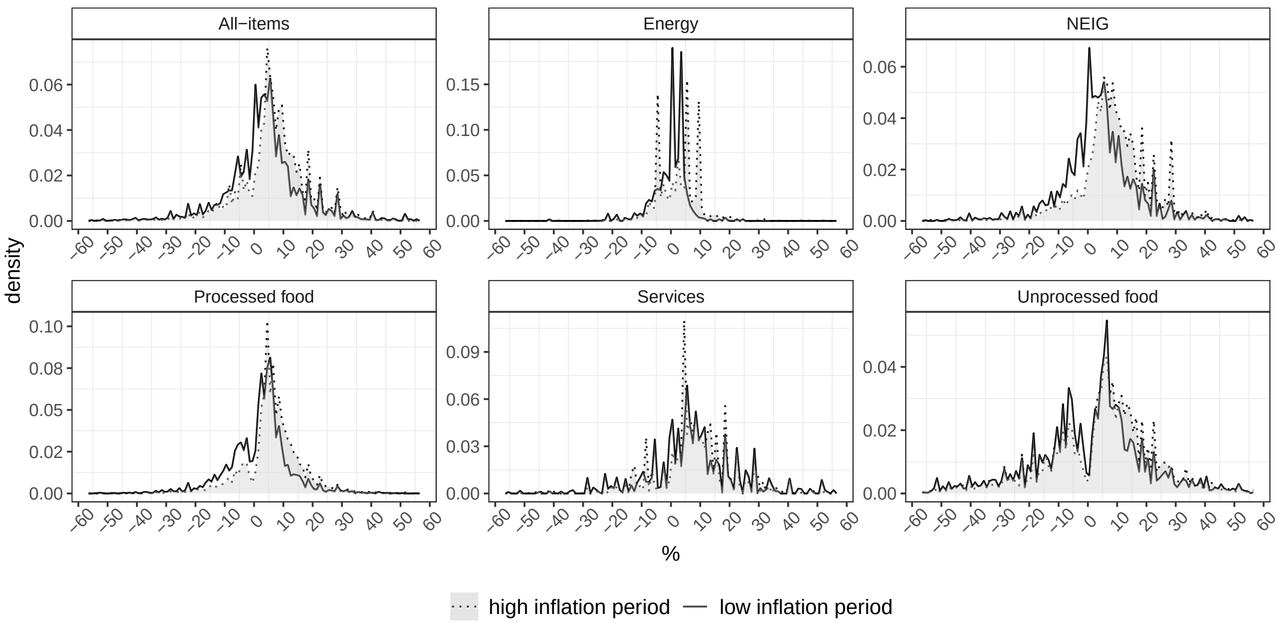
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the common sample of goods, the distribution of size changes is obtained for each country and ECOICOP level 4 category using the arithmetic mean of price changes at the detailed item level (see Table A1). Next, using the mean values of the weights of the corresponding country in each of the two periods, we aggregate ECOICOP4 distributions to the country and specific product group level. The weighted distribution for the Baltics is estimated by averaging the distributions obtained for each country.

Figure A7: Weighted distribution of the frequency of price changes (full sample excluding discounts): low and high inflation periods, Estonia



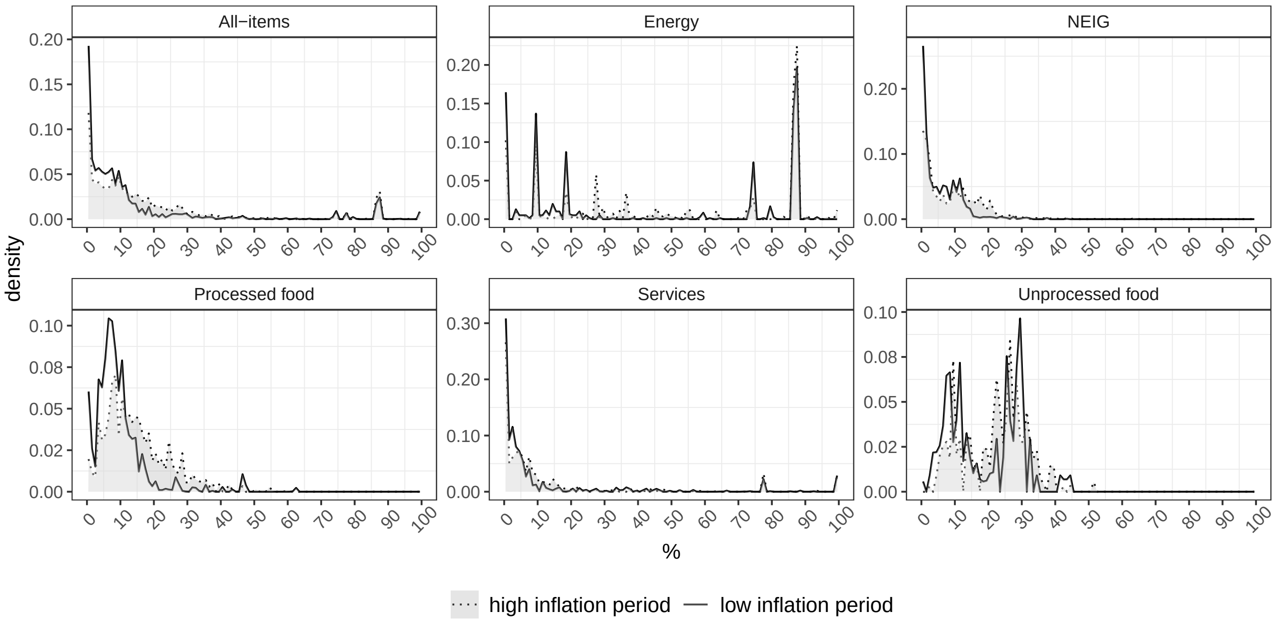
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the country specific sample of goods, we first estimate the frequency of price changes in each month at the detailed item level, and then calculate average frequencies at the ECOICOP level 4. Next, using the mean values of yearly ECOICOP4 weights in the corresponding period, we aggregate distributions to the country and special aggregate level.

Figure A8: Weighted distribution of the size of non-zero price changes (full sample excluding discounts): low and high inflation periods, Estonia



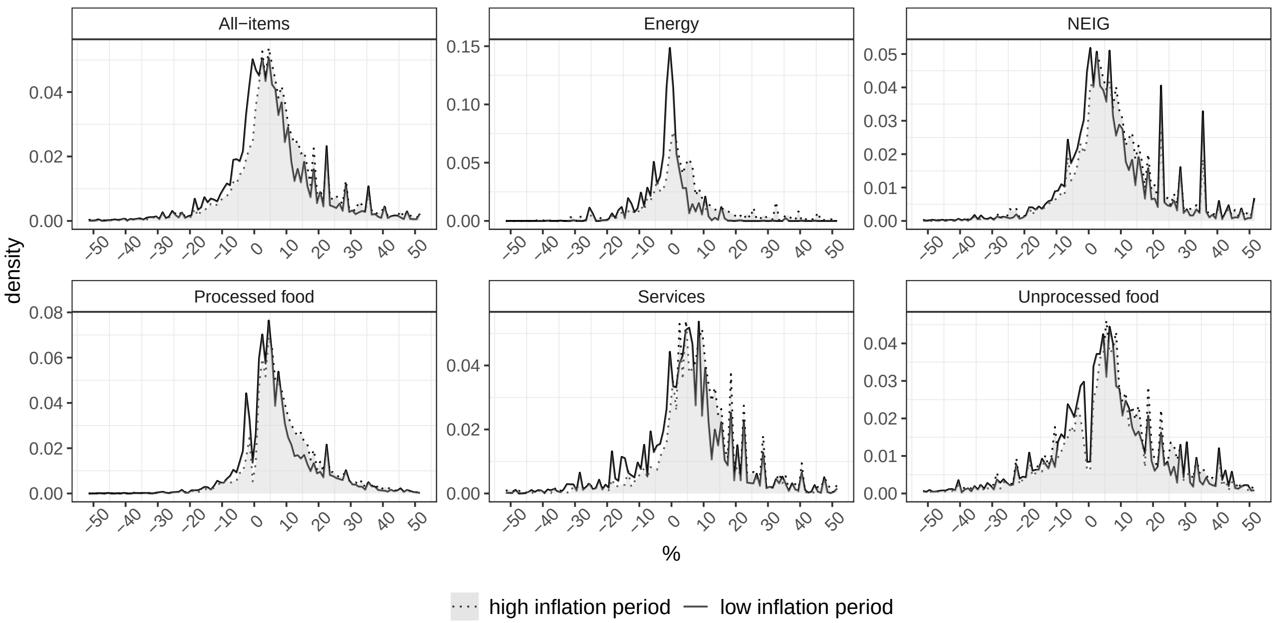
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the country specific sample of goods, the distribution of size changes is obtained for each ECOICOP level 4 category using the arithmetic mean of price changes at the detailed item level. Next, using the mean values of yearly ECOICOP4 weights in the corresponding period, we aggregate ECOICOP4 distributions to the country and specific product group level.

Figure A9: Weighted distribution of the frequency of price changes (full sample excluding discounts): low and high inflation periods, Latvia



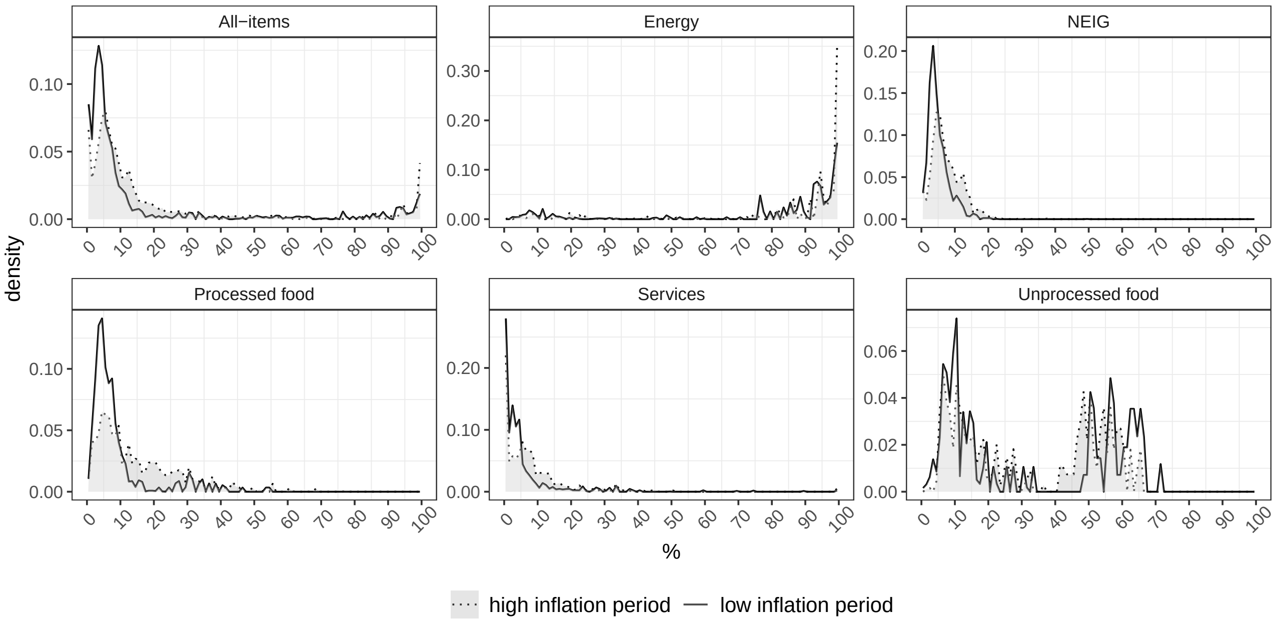
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the country specific sample of goods, we first estimate the frequency of price changes in each month at the detailed item level, and then calculate average frequencies at the ECOICOP level 4. Next, using the mean values of yearly ECOICOP4 weights in the corresponding period, we aggregate distributions to the country and special aggregate level.

Figure A10: Weighted distribution of the size of non-zero price changes (full sample excluding discounts): low and high inflation periods, Latvia



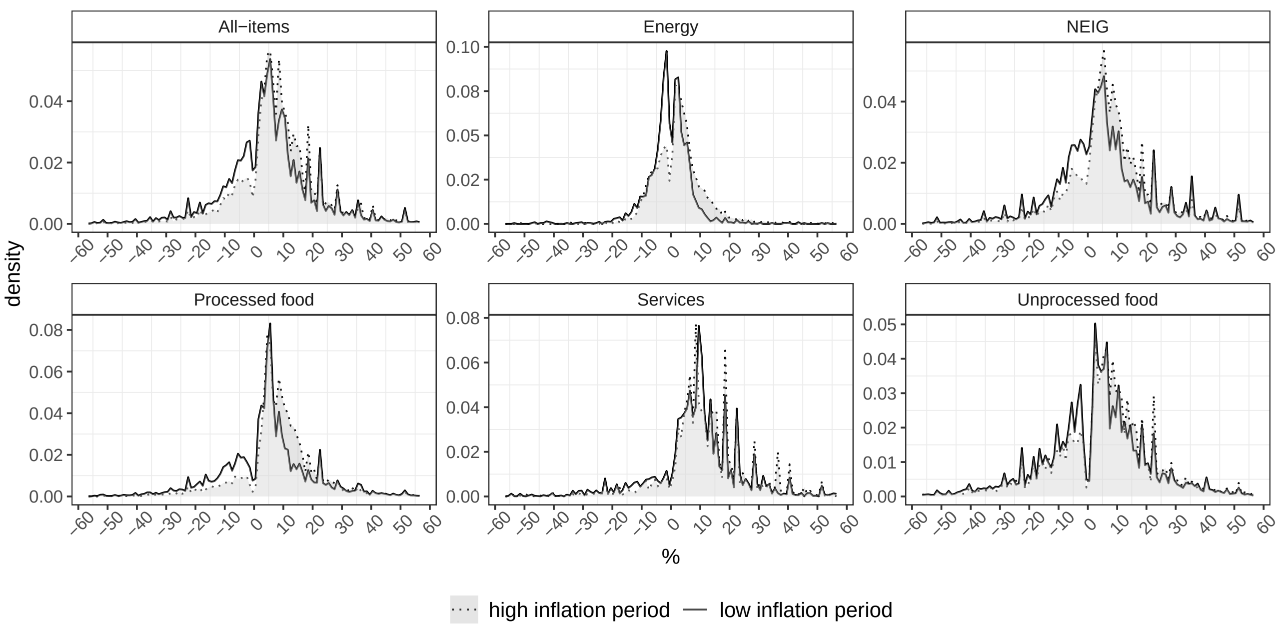
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M6. Using the country specific sample of goods, the distribution of size changes is obtained for each ECOICOP level 4 category using the arithmetic mean of price changes at the detailed item level. Next, using the mean values of yearly ECOICOP4 weights in the corresponding period, we aggregate ECOICOP4 distributions to the country and specific product group level.

Figure A11: Weighted distribution of the frequency of price changes (full sample excluding discounts): low and high inflation periods, Lithuania



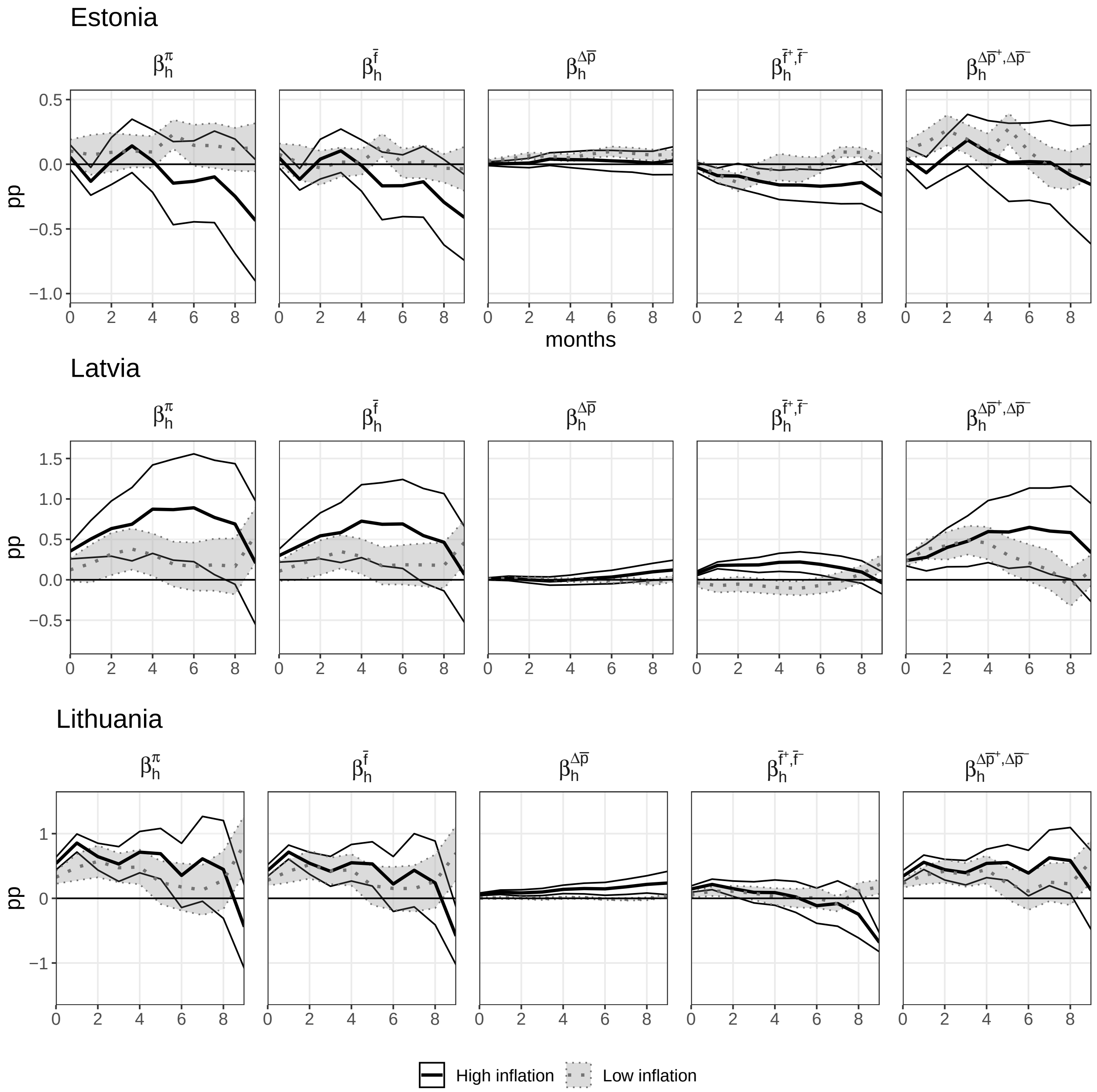
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M3. Using the country specific sample of goods, we first estimate the frequency of price changes in each month at the detailed item level, and then calculate average frequencies at the ECOICOP level 4. Next, using the mean values of yearly ECOICOP4 weights in the corresponding period, we aggregate distributions to the country and special aggregate level.

Figure A12: Weighted distribution of the size of non-zero price changes (full sample excluding sales): low and high inflation periods, Lithuania



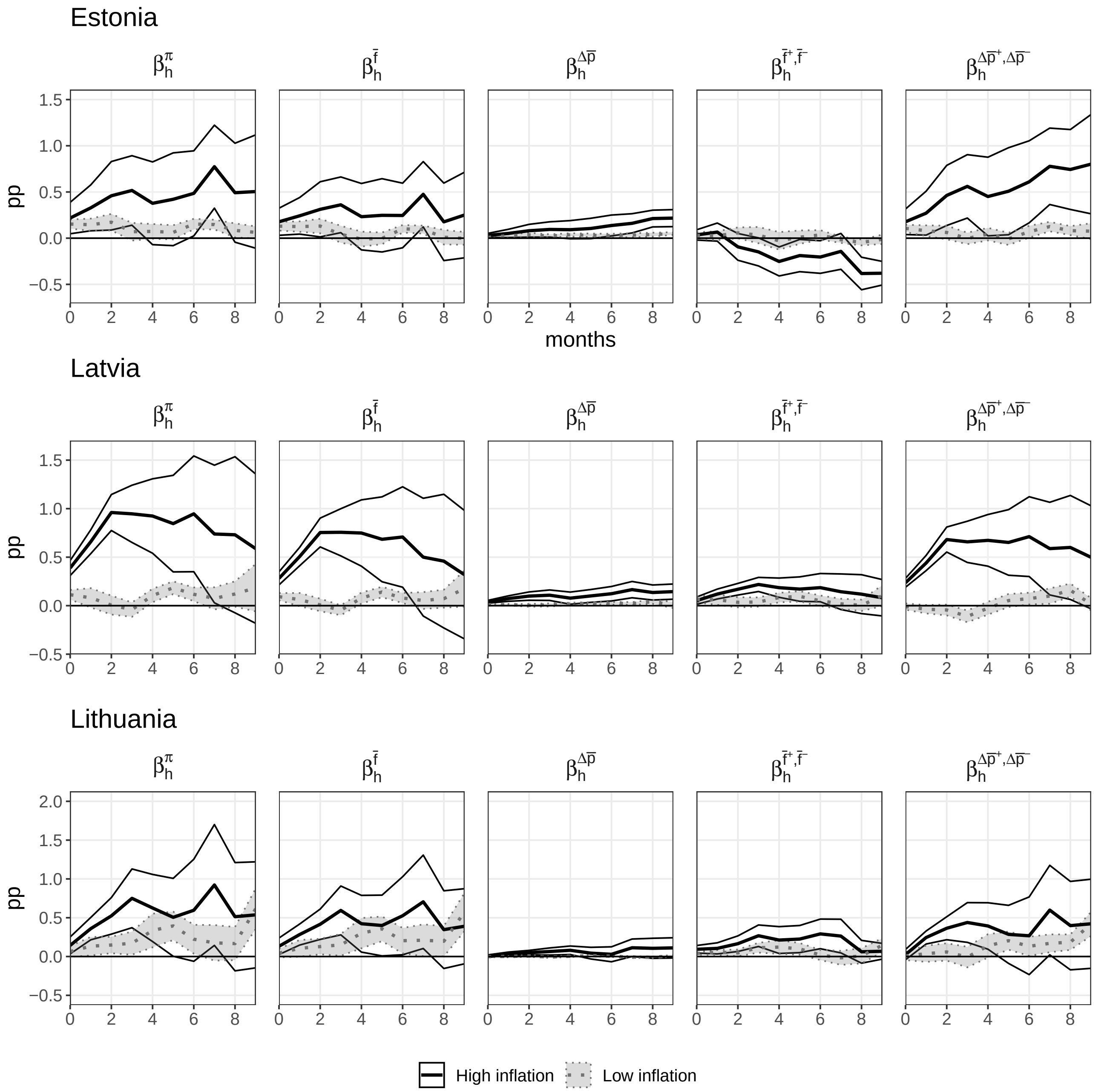
Notes: The low inflation sample covers 2019M1 to 2020M12, and the high inflation sample 2021M1 to 2023M3. Using the country specific sample of goods, the distribution of size changes is obtained for each ECOICOP level 4 category using the arithmetic mean of price changes at the detailed item level. Next, using the mean values of yearly ECOICOP4 weights in the corresponding period, we aggregate ECOICOP4 distributions to the country and specific product group level.

Figure A13: Cumulative responses of counterfactual inflation rates to a 1SD positive energy price shock



Notes: The header of column 1 (β_h^{π}) indicates the inflation response, that of column 2 ($\beta_h^{\bar{f}}$) that of counterfactual inflation with a constant frequency, that of column 3 ($\beta_h^{\Delta\bar{p}}$) that of counterfactual inflation with a constant average size, that of column 4 ($\beta_h^{\bar{f}^+,\bar{f}^-}$) that of counterfactual inflation with a constant frequency of price increases and decreases, and that of column 5 ($\tilde{\pi}_{jt}^{\Delta\bar{p}^+,\Delta\bar{p}^-}$) that of counterfactual inflation with a constant average size of price increases and decreases. The shaded areas represent a standard error based on calendar clusters (month-year).

Figure A14: Cumulative responses of counterfactual inflation rates to a 1SD positive aggregate demand shock



Notes: The header of column 1 (β_h^{π}) indicates the inflation response, that of column 2 ($\beta_h^{\bar{f}}$) that of counterfactual inflation with a constant frequency, that of column 3 ($\beta_h^{\Delta\bar{p}}$) that of counterfactual inflation with a constant average size, that of column 4 ($\beta_h^{\bar{f}^+,\bar{f}^-}$) that of counterfactual inflation with a constant frequency of price increases and decreases, and that of column 5 ($\tilde{\pi}_{jt}^{\Delta\bar{p}^+,\Delta\bar{p}^-}$) that of counterfactual inflation with a constant average size of price increases and decreases. The shaded areas represent a standard error based on calendar clusters (month-year).