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Consumer price stickiness in the euro area during an inflation surge

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ChaMP is coordinated by a team chaired by Philipp Hartmann (ECB), and consisting of Diana Bonfim (Banco de Portugal), Margherita Bottero (Banca d'Italia), Emmanuel Dhyne (Nationale Bank van België/Banque Nationale de Belgique) and Maria T. Valderrama (Oesterreichische Nationalbank), who are supported by Melina Papoutsi and Gonzalo Paz-Pardo (both ECB), 7 central bank advisers and 8 academic consultants.

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Abstract

We use CPI micro data for nine euro area countries to document new evidence on consumer price stickiness in the euro area during the 2021-2024 inflation cycle. In 2022, the monthly frequency of price changes reached 12%, compared with an average of 8% over 2010–2019, roughly a four-percentage-point increase; it then fell quickly in 2023 and more slowly in 2024, ending close to its pre-pandemic level. The decline in the frequency of price changes was faster for food and non-energy industrial goods (NEIG) than for services, where frequencies remained elevated in 2024. The overall frequency rose mainly because there were more price increases, while the magnitude of the average size of the price increases or decreases changed only marginally during the surge. Products with a larger imported-energy cost share responded more strongly, and hazard-rate evidence shows that the probability of price adjustments increases with the gap between actual and optimal prices, consistent with state-dependent pricing and a steepening of the Phillips curve. To illustrate the implications of this state dependence, a macro model suggests that peak inflation would have been almost 1 percentage point lower if the frequency had not responded to the inflation surge.

JEL Classification: E31, E52, F33, L11

Keywords: Price rigidity, euro area, inflation surge, micro price data.

Non-technical summary

Understanding how often and how strongly consumer prices adjust during periods of large cost shocks is key to assessing inflation dynamics and the real effects of monetary policy. While prices are quite sticky when inflation is low (Gautier et al., 2024), less is known about how they adjust in response to large cost shocks. Using detailed micro data underlying the consumer price indices in nine euro area countries, this paper examines how price-setting behaviour changed during the inflation surge between 2021 and 2024. The analysis builds on around 190 million price quotes and provides a consistent comparison with the low and stable inflation period before 2020.

We find that the frequency of consumer price changes increased significantly during the peak of the inflation surge. On average, the share of prices that changed in a given month rose from around 8% before the pandemic to an average of 12% in 2022, peaking at nearly 16% in January 2023. This increase was driven mainly by more frequent price increases, while the average size of price increases or decreases changed only modestly. As inflation subsided in 2023 and 2024, the frequency of price changes gradually returned to its previous levels, particularly for food and non-energy industrial goods (NEIG). In contrast, the frequency of price changes in services remained higher than the average, consistent with more persistent, wage-related pressures in this sector.

A key contribution of the paper is to test whether the observed patterns are consistent with predictions of a state-dependent pricing model, under which firms are more likely to change prices in response to larger shocks. The results show that products with a greater share of input costs – particularly energy – showed larger increases in the frequency of price changes. Moreover, hazard-rate evidence indicates that the likelihood of a price change rises with the gap between the actual and the estimated optimal price, both findings consistent with state-dependent adjustment.

To further assess the mechanisms behind inflation dynamics, the paper decomposes inflation into two components: how often prices change (*extensive margin*) and how large those changes are (*intensive margin*). During the inflation surge, the extensive margin contributes more to inflation variation than it usually does in low-inflation periods, while the intensive margin continues to contribute at a similar level as in low-inflation periods. In a higher-inflation environment, firms increase their prices more frequently, which not only increases the size of price changes (because of a larger share of price increases among price changes) but this also raises the overall frequency of price adjustments. This latter phenomenon explains why the extensive margin played a larger role in inflation dynamics during the recent inflation surge.

Finally, a macroeconomic model explores what inflation dynamics would have looked like in the absence of this increase in price flexibility. The simulations show that inflation in the euro area would have been up to one percentage point lower at its peak if firms had not increased the frequency of price changes. As the frequency of price changes returned to its long-term levels by late 2024, the episode appears largely temporary in terms of price-setting behaviour, though services still display some persistence.

Overall, the study provides a comprehensive picture of how price-setting behaviour adapted during an exceptionally high-inflation episode and adds to the understanding of inflation dynamics in the euro area: when inflation is high, consumer prices become more flexible and respond faster to shocks, making inflation more responsive to monetary policy.

1 Introduction

When inflation is low and aggregate shocks are small, prices tend to be sticky. Gautier et al. (2024) documented for euro area countries that, on average, fewer than 9% of consumer prices other than prices for energy products were adjusted in a given month over the period 2010-2019. They also showed that patterns of price adjustment are broadly consistent with the predictions of a Calvo model, or a state-dependent model with large idiosyncratic shocks. These two models behave similarly when inflation is low and not very volatile (see Gertler and Leahy, 2008; Alvarez et al., 2017; Auclert et al., 2023), and yield very close predictions for price adjustment patterns, showing that the frequency of price changes is not closely correlated with inflation, and the average size of price changes is the main margin where prices are adjusted. When aggregate shocks are large, by contrast, state-dependent models predict that prices will be adjusted more frequently, implying that *"large shocks travel fast"* (Cavallo et al., 2024). This paper provides evidence for the first time on the stickiness of consumer prices in the euro area in the presence of large aggregate cost shocks. To do this we use national consumer price index (CPI) micro datasets as in Gautier et al. (2024), with updated information for nine euro area countries covering the full inflation cycle between 2021 and 2024.

Our first main finding is that the frequency of price changes in the euro area increased significantly as inflation rose in 2022-2023 before slowly returning to its long-term average. This contrasts with the period of low inflation, when the frequency of price changes in the euro area was lower and quite stable over time. The frequency of monthly price changes excluding sales, measured as the share of prices that changed within any given month, reached an average of 12.0% in 2022 and peaked at 15.7% in January 2023, while the average was 8.2% before 2020. Prices for more than two-thirds of the detailed product categories in our common sample changed significantly more often in 2022 than before 2020. This sharp increase in the frequency of price changes was common to all broad product categories, but it was stronger for food, which has more flexible prices than non-energy industrial goods (NEIG) or services. The frequency of price changes for food and NEIG then returned to close to its long-term average in 2024, while the frequency for services remained higher than its long-term average, reflecting how the response of services to the inflation surge was lagged and more persistent. We also use cross-section regressions at the product level and find that in 2022 and 2023, a higher share of imported energy inputs is associated with a stronger response of the frequency of price changes.[1] We document some cross-country heterogeneity, notably that the increase in the frequency of price changes in 2022 was greater in countries where the inflation surge was more pronounced, but overall the differences between countries were smaller than those between products.

Another key finding is that the average size of price changes excluding sales responded to the rise in inflation and increased from 1.5% before 2020 to 5.5% in 2022. This change was mainly driven by an increase in the fraction of price changes that were increases, since two-thirds of all price changes before 2020 were price increases, but by 2022 this fraction had increased to 82%. Overall, the inflationary episode was associated with a shift in the distribution of price changes, with price rises clearly

[1] Micro prices for energy are not available in all euro area countries and were excluded from the baseline analysis because only a few national micro price datasets cover them extensively.

predominating over price cuts. In contrast, the average sizes of price rises and price cuts reacted much less in the inflationary episode, and the higher moments of the price change distribution were also barely affected. As inflation came back down in 2023-2024, the share of price increases returned gradually to its average from when inflation was low, while there was no strong variation in the size of the price rises and price cuts taken separately. Overall, inflation in 2021-2024 was mainly driven by variation in the frequency of price increases rather than by changes in the size of those individual price increases.

We also find that the increase in the frequency of price changes during the inflation surge is consistent with the standard predictions of state-dependent models. In these models, the probability of a price change at a given firm depends on the price gap between the actual price and the optimal price that the firm would have set without frictions. When a large cost shock hits the economy, this price gap widens for many firms and the probability of a price change also increases. We investigate the degree of state dependence in consumer prices and provide three types of results showing the presence of state dependence in the adjustments of consumer prices. First, we derive micro-price-based hazard rates and document that they are V-shaped, meaning the probability of a price change increases as the absolute price gap widens. This is consistent with the existence of state dependence in all countries and in most sectors. Second, inflation can vary over time because of price adjustments on the extensive or intensive margin, that is through adjustments to the frequency of price changes or to the average size of price changes. A state-dependent model predicts that the extensive margin should contribute more to the variation in inflation when inflation is high. We therefore estimate product-level regressions that relate actual product-level inflation to counterfactual inflation rates for which either the frequency or the size of price changes is held constant over time. We find a stronger correlation between the extensive margin and inflation than before during the inflation cycle of 2021-2024, suggesting that variation in the frequency of price changes contributed significantly more to the variation in inflation during this inflation cycle. The intensive margin, which is the variation in the size of non-zero price changes, still played an important role in explaining the variation in inflation, as it did when inflation was low. We obtain the third set of results by investigating whether economic shocks were transmitted differently during the inflation surge. We estimate local projection regressions that link counterfactual inflation rates to energy shocks, and we find that the extensive margin was more responsive to shocks during the inflation surge than it was when inflation was low. This confirms that there is some degree of state dependence in consumer price setting in the euro area. We also use a macro model to illustrate some of the implications of this state dependence with simple counterfactual inflation dynamics by imposing or relaxing state dependence in price setting in the recent period. This simple setup lets us show that the quarterly inflation rate would have been 1 percentage point (pp) lower if the frequency had not responded to the inflation surge.

The main contribution of this paper is that it provides new evidence on price stickiness in the euro area when large aggregate cost shocks hit the economy. Several papers have documented in various contexts how prices respond to large aggregate shocks: Gagnon (2009) considers prices in the context of a large devaluation, Karadi and Reiff (2019) during large changes in VAT in Hungary, Gopinath et al. (2012) during the collapse in global trade in 2008-2009, Alvarez and Neumeyer (2020) in the Argentinian context of large increases in utility prices and a currency devaluation between 2012 and 2018, and Auer et al. (2021) after a large appreciation of the currency in Switzerland.[2] The existing evidence on price rigidity for the euro area has mainly been obtained with inflation being low and quite stable. Sources of evidence on price stickiness for the euro area as a whole include Dhyne et al. (2006) and Gautier et al. (2024). More recent country-specific evidence has been documented for consumer prices in Spain (Gutiérrez and Roldan-Blanco, 2024), Lithuania (Jouvanceau, 2023) and the Baltic countries (Fadejeva et al., 2024), and also for producer prices in Belgium (Gagliardone et al., 2025) and in France (Gautier et al., 2023a). Evidence for the United States in an environment of low inflation includes Bils and Klenow (2004), Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008), while Cavallo et al. (2024) and Montag and Villar (2025) provide some results for the surge in US inflation in 2021-2024. A notable finding is that the increase in the frequency of price changes appears earlier in the United States than in the euro area and is more pronounced.

Our second contribution is that we provide evidence on state dependence in consumer prices in the euro area.[3] In an environment where pricing is state-dependent, the prices that are farthest from their ideal target should experience higher frequencies of adjustment. To the best of our knowledge, we are the first to provide systematic and comprehensive empirical support for this hypothesis for consumer prices, covering several sectors and countries. Gagnon et al. (2012) and Karadi et al. (2023) have documented hazard rates using a similar methodology, but using only scanner price data from supermarkets in the US and Europe, while Gautier et al. (2023b) and Gagliardone et al. (2025) compute hazard rates relating individual prices to marginal cost information for gasoline prices in France and producer prices in Belgium. Wulfsberg (2016) and Nakamura et al. (2018) have also decomposed inflation into extensive and intensive margins to show that when inflation is high, the extensive margin may be more important for the dynamics of inflation. We apply a similar setup in the context of the recent inflation surge in the euro area.

More generally, this paper also contributes to a literature that examines the implications of state dependence for the real effects of monetary policy (Alvarez et al., 2016, 2022; Blanco et al., 2024a,b; Ghassibe and Nakov, 2025), the Phillips curve (Gertler and Leahy, 2008; Auclert et al., 2023), or optimal monetary policy environments of high inflation (Karadi et al., 2024). The statistics computed at the product-country level for nine euro area countries are made available to the research community, as are those obtained for a period of low inflation by Gautier et al. (2024) and can be used for calibrating macroeconomic models and deriving some further policy implications.[4]

Our paper is organised as follows. In section 2, we describe the underlying database, which consists of updated CPI micro datasets for nine euro area countries. Section 3 documents how the frequency of

[2] Another part of the related literature has documented patterns of price stickiness in a context of high steady-state inflation. Examples include high inflation in Argentina during the 1990s (Alvarez et al., 2019) and during the 1970s and 1980s in the United States (Nakamura et al., 2018) and Norway (Wulfsberg, 2016).

[3] See also Ascari and Haber (2022) who provide indirect evidence of state dependence using time series analysis for the United States.

[4] Data and replication files from Gautier et al. (2024) for the low inflation period can be accessed here.

price changes responded to higher inflation in the euro area. Section 4 investigates changes in the size of price changes. In section 5, we assess how much state-dependence in price setting has contributed to variation in the frequency of price changes and to inflation over the inflation cycle. Section 6 concludes.

2 Data

The starting point for our analysis is a sample of the CPI micro price datasets used in Gautier et al. (2024), which we have extended over the years 2020-2024 to cover the recent inflation cycle. We were able to compile results for nine countries in total, which together represent about 83% of the euro area HICP (Table 1). The countries are Austria, Estonia, France, Germany, Greece, Italy, Latvia, Lithuania and Spain.[5] The micro price datasets end in December 2024 for all but one country.[6]

Price setting statistics for the euro area are derived from a common sample of 166 product categories (defined in Gautier et al., 2024) that cover food, non-energy industrial goods (NEIG) and services, and together account for around 60% of the euro area HICP in terms of product coverage (see Table A1 for details on the product composition of the common sample). Our analysis is based on a total of more than 190 million price quotes covering the period 2010 to 2024. We compute the moments of price changes under two scenarios: one including price changes due to sales, and the other excluding them. For most countries in our sample (Austria, France, Germany, Italy, Latvia and Lithuania), we identify sales using the flag provided by the national statistical office in the micro-price datasets. For Spain and Greece, where this flag is missing, we apply a standard sales filter.

Like Gautier et al. (2024), we exclude energy from our analysis because the country-specific micro price datasets cover only a very small part of it.[7] Our results therefore reflect how the price adjustment for products excluding energy changed during the recent inflation surge. The corresponding inflation rate, which is HICP excluding energy, rose at the end of 2021 and then again more substantially in 2022. It reached a historical peak in March 2023, when inflation stood at 7.9% for the euro area as a whole and ranged from 6.9% in France and 7.0% in Italy to 8.3% in Germany and more than 15% in the Baltic countries (Figure 1). Quite a quick disinflation process started after March 2023, and then slowed in 2024. By the end of 2024, the inflation rate in the euro area excluding energy was about 2.7%.

The period 2020-2024 posed three measurement challenges for analysis of price-setting behaviour using euro area CPI micro data. First, the COVID-19 pandemic caused disruptions in price collection. Second, governments passed various tax changes and other fiscal measures because of the pandemic and to counter high inflation. Third, national statistical offices have increasingly constructed price indexes from scanner and web-scraping data, but confidentiality concerns mean that these individual

[5] Compared to that used in Gautier et al. (2024), the dataset lacks Belgium, Luxembourg and Slovakia, but includes Estonia.

[6] The only exception is Lithuania for which the latest data available were from March 2023. See Appendix A.1 for a description of the nine euro area country-specific datasets and how we accessed them.

[7] Nevertheless, as a robustness check, we provide some results for energy prices for a subset of available countries.

price quotes are often unavailable for research purposes. The remainder of this section briefly discusses the implications of these issues for our analysis.

The COVID-19 pandemic made it difficult to collect prices in the field because of the restrictions imposed during lockdowns. Furthermore, some products were temporarily out of stock, and so fewer price quotes were found in some countries and a larger share of prices were estimated, or imputed, in most countries. As Table A2 in the Appendix reports, the share of imputed prices peaked in the euro area at 32% of the total HICP in April 2020, when the first wave of the pandemic hit Europe. The share of imputations then fell to almost zero in the summer of 2020, before rising again to around 15% in the following winter. In line with the impact of the pandemic waning, price imputations also became less important in the course of 2021. For our analysis we simply exclude the data for April 2020 because the proportion of price imputations is so large, and we take the collected price quotations of the other pandemic months as they are, while bearing in mind that they may not reflect actual pricing decisions but rather assumptions about them by statistical institutes.[8]

There were several major VAT changes in 2020-2024, either in response to the COVID-19 pandemic or to the inflation surge of 2021-2023.[9] Some countries in our sample introduced temporary *sector-specific* cuts in VAT as an economic stimulus (see OECD, 2022), and there was also a temporary reduction in VAT on essential food items in Spain from January 2023 to December 2024 (Forteza et al., 2025). There were temporary reductions in overall VAT rates in Germany from July 2020 to December 2020, and several countries have similarly introduced price support measures more recently to cushion the impact of the sharp rise in energy prices (see Amores et al., 2025). Our analysis drops observations for any given country for the months when there was a major change in VAT.

The national statistical offices in four countries shifted their price collection from on-site price collection to processing supermarket scanner data. France, Italy and Spain did this from 2020, and Austria did so from 2022. Although scanner data are a valuable source for measuring consumer price inflation, they are not included in the corresponding CPI research micro price datasets used in this paper for reasons of confidentiality. The number of food and non-durable goods available has thus fallen substantially in Italy and Austria, and to a lesser extent in France; see Figure A1 in the Appendix reporting the number of observations by country and broad sector relative to the number of observations in 2019. On top of this there was a specific structural break that affects online price quotes in Germany. Prices collected online are not part of the CPI research micro datasets in most euro area countries, but Germany is an exception and the share of online prices in the German dataset has increased significantly since 2020 (Figure A2 in the Appendix). As the frequency of price changes is higher for online prices, the gradual increase in the share of online prices also affects the evolution of the overall frequency of price changes from 2020 onwards, complicating the interpretation of the evolution of the frequency of price changes during the inflation surge.[10] We consequently drop online price data for

[8] Henkel et al. (2023) provide further details on how official price collection and price setting were affected by the COVID-19 pandemic in Germany, Italy and Latvia.

[9] See Table A3 in the Appendix for an overview.

[10] Note that information on online prices is only available for Germany and Austria. A detailed comparison of online and offline price setting in Germany for the period 2010-2019 can be found in Strasser et al. (2023). We provide an

Germany to keep the analysis consistent with that for other countries where online prices are either not included or do not change the sample composition as much as they do in Germany.

3 Frequency of Price Changes

This section provides evidence on the frequency of price changes during the 2021-2024 inflation cycle. We analyse the changes in terms of overall frequency (section 3.1), sectoral heterogeneity (section 3.2), and cross-country heterogeneity (section 3.3).

3.1 Aggregate Evidence

Figure 2 plots the aggregate frequency of price changes over time with price changes during sales included and again with them excluded.[11] The patterns for the two series are similar. The frequency of price changes was roughly flat before 2020 at around 8%, with an annual peak in each January (as already documented in Gautier et al., 2024). During the COVID-19 pandemic, the frequency of price changes was more volatile, possibly because of the problems with collecting prices during lockdowns (see Henkel et al., 2023). Then in January 2022, the frequency of price changes excluding sales started to increase until it peaked at a maximum of 15.7% in January 2023. The frequency of price changes remained high in 2023, but it gradually returned to the level observed before 2020. In 2024, the overall frequency of price changes was already close to its pre-2020 average, even if it was still quite elevated during the first quarter of 2024.

To estimate more precisely how the frequency of price changes varied during the inflation surge, we estimate the following regression for each product in a given country:

$$f_{jt} = \alpha_j + \sum_{y=2010}^{2024} \beta_j^y + \gamma_j X_{jt} + \epsilon_{jt}, \tag{1}$$

where f_{jt} is the frequency of price changes at date t (month-year) for a given product j at the COICOP 5-digit level in the given country, β^y are year-specific effects with the reference period 2019, and X_{jt} are month fixed effects to control for product-specific seasonality.[12] We chose 2019 as the reference year because it is the earliest year in our sample for which price data are available in all countries, allowing us to have the same reference period for all countries.[13]

update of the German results, together with those for Austria, in section A.2 in the Appendix.

[11]The frequency of price changes is first calculated at the country-level and (COICOP 5) product-level as the share of prices that change among all prices. In the next step, we compute the average frequency of price changes in the euro area using i) product-level euro area HICP weights and then ii) country weights of the euro-area HICP, both averaged over the period 2017-2024. We use a common average weighting structure so that our results are not perturbed by composition effects.

[12]Observations corresponding to the dates of major VAT changes are dropped from the sample as explained in section 2.

[13]In the Appendix, we also present results using the period 2010–2019 as our reference period. Results are broadly unchanged.

Table 2 shows the aggregate weighted results of these estimates ($\beta^y = \sum_j \omega_j \beta_j^y$), using HICP weights ($\omega_j$). We find that the frequency of price changes in 2020 and 2021 is only slightly higher than in 2019. However, in 2022 the frequency of price changes excluding sales was on average 4.3 percentage points (pp) higher than when inflation was low.[14] The frequency remains elevated in 2023 and in 2024 but is only higher by 2.5pp in 2023 and 0.8pp in 2024 on average than in 2019. This increase in the fraction of prices that change is similar whether or not we exclude price changes due to sales.[15] Overall, the frequency of price changes being larger during the inflation surge is consistent with the standard prediction of a state-dependent model, but it cannot be replicated by a Calvo model.

Across the literature, our results are consistent with those of Wulfsberg (2016) and Nakamura et al. (2018), who document for Norway and the United States respectively that the frequency of price changes increased by about 4pp to 5pp when inflation was high in the 1970s. More recently, Cavallo et al. (2024) document from online price data for several countries in the euro area, the UK and the US that the frequency of changes in prices for food and beverages increased substantially in 2022 and even more in 2023. Montag and Villar (2025) find a similar pattern from looking at consumer price quotes for the United States during the recent inflation surge. They document that price changes in the United States were more frequent during the inflation surge than before it. However, our results highlight that there are two important differences between the US and the euro area. First, the increase in the frequency of price changes seems to have started earlier in the US than in the euro area, in 2019-2020 rather than 2022. Second, the increase in the frequency of price changes is more moderate in the euro area and in each euro area country separately than in the US (+10pp in the US in 2022 vs a range between 3 and 6.5pp among EA countries and 4pp on average in the euro area). In contrast, the degree of price stickiness when inflation was low was found to be similar in both economies once sales are excluded (Gautier et al., 2024). During the recent period of high inflation, the nature of the shocks affecting prices as demand or supply shocks and the size of them may have been different in Europe and the US.[16] A product-level comparison (as carried out in Gautier et al., 2024) would be needed to understand better these differences in price flexibility on either side of the Atlantic.

3.2 Sectoral Heterogeneity and Product-Level Evidence

Looking at the different sectors underlying the CPI reveals a very similar pattern, as the frequency of price changes started to increase at the beginning of 2022 and then slowly decreased in 2023 and in 2024 (Figure C1 in the Appendix). However, the magnitude of the increase in the frequency and its persistence are quite heterogeneous across sectors. For food, the frequency of price changes was

[14] When using 2010-2019 as the reference period, the difference is slightly smaller at 3.6 pp (Table B5 in Appendix).

[15] Table B1 in the Appendix reports the average frequency of price changes (excluding sales) by year: it was 8.2% before the pandemic, 12.0% in 2022, 10.2% in 2023 and 8.6% in 2024. As a robustness check, we have also calculated the average frequencies using the full country-specific sample of products (instead of the common euro area sample) and the results for the euro area and individual countries are close to those found in our benchmark analysis, as the increase in the frequency of price changes was 4pp higher in 2022 than in 2010-2019, see Table B2).

[16] See, for instance, Bernanke and Blanchard (2025) and Arce et al. (2024) for a discussion of supply-driven and demand-driven determinants of inflation in the US and the euro area.

7pp higher in 2022 than in 2019 (Panel B of Table 2), and it remained 3.5pp higher in 2023 but returned to its low inflation average in 2024.[17] For NEIG and services, the increase in frequency in 2022 was smaller than that for food at only 3pp for NEIG and 3.5pp for services. These effects are still quite large, as the frequency of price changes excluding sales before 2020 was 5.9% in NEIG and 6.2% in services, and it increased to about 9% in 2022 and 8% in 2023. For services, the decline in the frequency in 2023-2024 is less pronounced than the declines in other sectors. The frequency is still higher than the low inflation average though, by 2.5pp in 2023 and 2pp in 2024. For NEIG, the frequency is higher by only 1.6pp in 2023 and 0.7pp in 2024. This longer persistence for services might reflect a lower degree of state dependence – price changes in services are more frequent in January in line with predictions of Taylor-type time-dependent models that feature a small degree of price change staggering, and this might induce a longer lag in the response of service prices. It can also reflect second-round effects from the initial inflation surge through stronger wage dynamics in 2023 and 2024. Overall, the frequency of price changes in all sectors increased in 2022 by about 50% of the frequency observed in the period of low inflation and then progressively decreased in 2023 and 2024.

Taking the product-level estimations in equation (1), we document that the frequency of price changes is significantly higher in 2022 than in 2019 for more than two-thirds of all products and this is still the case in 2023 for 60% of products, particularly in services. In contrast, the proportion fell to 38% in 2024, though it was still about 57% in services.[18] There were however very few products for which the fraction of price changes is significantly lower in 2022 than in 2019, and they total less than 3% of our sample products. Overall, the rise in the frequency of price changes in the euro area is widespread across products. By contrast, in 2024, there are more products with significantly lower frequency of price changes than in 2019 (13% of all products and 30% of food products).

To investigate further the sources of cross-sectoral heterogeneity in the response of frequency to the inflation surge, we run OLS regressions linking the year fixed effects estimated in equation (1) at the product level β_j^y to product-level characteristics. We use a product cost structure that is derived from Eurostat's symmetric input-output table for the euro area (as in Gautier et al., 2024), which gives us the labour share, the cost share of imported energy inputs and the cost share of other imported inputs.[19] We also control for products whose prices are regulated in a given year, using Eurostat's classification of administered prices between 2020 and 2024.[20] We estimate the following regression:

$$\beta_{j,c}^y = a + b_1 Labour_j + b_2 Energy_j + b_3 Import_j + b_4 Reg_{j,c}^y + u_{s,c} + v_{j,c}, \tag{2}$$

where $\beta_{j,c}^y$ are the year fixed effects estimated for the COICOP-5 product j in country c (capturing the product-specific variation in the frequency of price changes relative to the 2019 reference period),

[17] See also Table B1 in the Appendix for detailed statistics by year and broad product category.

[18] Detailed results are reported in Table B3 and B4 in the Appendix.

[19] We use the input-output matrix of the year 2022; if we used the input-output matrix of the year 2015 as in Gautier et al. (2024), the results would be very similar. By inverting the input-output table, we get the cumulated cost structure for each product group, which gives a more complete picture of the inputs that might influence price-setting behaviour (in this case we look at the "inputs of the inputs" over the production chain). We match product groups (classification of products by activity – CPA) to the COICOP-5 groups (see Gautier et al., 2024 for more details).

[20] Regulated prices are mostly for services like medical care, transportation, cultural services or social protection, or for other services such as administrative ones.

$Labour_j$ is the share of labour costs, $Energy_j$ is the share of imported energy and raw material inputs, $Import_j$ is the share of other imported inputs, and $Reg^y_{j,c}$ is a dummy variable for regulated prices in year y. As controls, we include interacted dummies $u_{s,c}$ between the broad sectors of food, NEIG and services, and countries.

Figure 3 plots the results for the cost share of imported energy inputs and the cost share of other imported inputs. We find that products with a higher cost share of energy inputs have a relatively higher frequency of price changes than usual in 2022, and to a lesser extent in 2023 and 2024. The correlation is positive and significant for all three years, whereas it is not different from 0 in 2020 or in 2021. This suggests that the large increase in the frequency of price changes in the years 2022 and 2023 was mainly driven by products that were affected more severely by the imported cost shock because their energy input share was larger. We can quantify the impact of this correlation with the increase in the total frequency, since the standard deviation of the imported energy cost share within our sample of products is 2pp and the estimated parameter estimate is about 0.8 in 2022, meaning that the frequency of price changes is on average 1.6pp higher for a product whose energy input share is one standard deviation larger than the average. The effects of other imported inputs are also positive and significant in 2021-2022 for the frequency of price increases, but these effects were less pronounced than the ones obtained for energy inputs. The final result is that cross-sectoral differences in labour cost shares are not closely correlated to the year-specific variation in the frequency of price changes (Figure C8 in the Appendix).

As a robustness exercise, we examine how much the exclusion of energy prices might affect our main conclusions about how the inflation surge impacted the aggregate frequency of price changes. As mentioned in the section on data, we have excluded the energy sector from our main analysis because micro price data for this sector are partially or entirely missing for most countries. However, we are able to examine how much the energy cost shock affected the frequency of price changes for the energy sector in Germany, Austria and Latvia.[21] We find that the frequency of price changes for petrol during the inflation surge was high, but similar to what it was before the pandemic (detailed results are reported in Appendix A.3). For gas, electricity and other heating energy, the frequency of price changes was affected differently across countries, which may reflect heterogeneity in government measures to compensate households for the energy price surge. Overall, including the energy sector increases the overall frequency of price changes and slightly affects its variation during the inflation surge, mainly because of changes in gas and electricity prices. Using data from Austria, Germany and Latvia — assuming they are representative of the other countries in our sample — we estimate that this would imply an increase of approximately 0.9pp in the overall frequency of price changes in 2022-2023 compared to the 2010–2019 period (see Appendix A.3 for details).

[21] For these three countries, petrol prices and heating energy prices for electricity or gas were available.

3.3 Country Heterogeneity

We also analyse developments in the frequency of price changes across our nine euro area countries. In contrast to the findings of Gautier et al. (2024) for the period of low inflation, we find that cross-country heterogeneity in the frequency of price changes is more pronounced in the euro area during the period of high inflation.[22] While the increase in the frequency of price changes is common to all euro area countries, the magnitude of the increase varies between countries. The country-specific frequency of price changes is highest in Estonia and Lithuania, where it is on average more than 6pp higher in 2022 than in 2019 (Table 2). The gap is between 4 and 6pp for most of the remaining countries, but it is only 3pp for France and Austria.[23] We also find some country heterogeneity in 2023 as frequencies are 2.5 to 3pp higher than the low inflation average in Austria, Germany, Greece, Italy, Lithuania and Latvia, but only 2pp higher in France and Spain. Frequencies are still higher in 2024 by about 2pp in Austria, Greece, Latvia and Italy, but by about 1pp in Germany, Spain and Estonia. In France, the frequency of price changes is even slightly lower in 2024 than in 2019.

A possible explanation for these cross-country differences during the inflation surge could be that there were differences in the size of the inflation shock. Inflation in the Baltic countries, where the frequency gap is above average in 2022, was much higher than in the rest of the euro area, as HICP inflation excluding energy was more than 10% on average in 2022 but only 5% in the euro area; see Figure 1. In contrast, inflation in France and Italy, where the frequency gap is quite small, was also below the average at about 4%. Figure C6 in the Appendix plots the increase in the frequency of price changes between 2019 and 2022 at the country level against the corresponding variation in the inflation rate (excluding sales), and we find a strong correlation between the two, suggesting that a large part of the country heterogeneity is driven by country differences in headline inflation.

4 The Distribution of Non-Zero Price Changes

The inflation surge had an impact not only on the frequency of price changes but also on their distribution. Figure 4 shows the product-level distribution of price changes excluding sales before 2020 and during the inflation surge in 2022-2023. It is clear that the distribution has shifted to the right, with more price increases during the inflationary episode. This section examines how the recent rise in inflation affected the distribution of non-zero price changes. We analyse the fraction of price increases and price decreases (section 4.1), the average size of them (section 4.2) and the higher moments (section 4.3).

[22] However, sectoral heterogeneity remains stronger than country heterogeneity (Figure C7) in the Appendix.

[23] Since supermarket prices collected on site have been replaced by scanner data in Austria, they are not included any more in the micro dataset (mainly in the food sector, see section 2). This negatively affects the frequency gap, as the frequency of price changes has increased more for food than for other products in the rest of the euro area (Table 2).

4.1 Fraction of Price Increases and Price Decreases

Zooming in on the recent increase in the frequency of price changes in the euro area, we find that it was mainly driven by a sharp increase in the frequency of price increases (Figure C2 in the Appendix). The frequency of price increases was 4.6pp higher in 2022 than in 2019, 2.3pp higher in 2023 and still 0.7pp higher in 2024 (Table 2).[24] In the low inflation environment we find a positive correlation between inflation and the frequency of price increases, and this correlation predicts a jump in the frequency of price increases in the period of high inflation. Price cuts, however, are slightly less frequent in 2022 than in 2019 and a little more frequent in 2024, but the change in the magnitude of these changes is very limited as it was 0.3pp smaller on average in 2022 than in 2019 and less than 0.2pp larger in 2023 and 2024. Overall, the share of price increases in all price changes increased by more than 13pp on average (last column of Table 2). When inflation was low, the share of price increases in price changes was around two thirds; when inflation was high in 2022, this share was around 80%. This increase in the share of price rises among price changes is consistent with the predictions of both state-dependent and time-dependent models in the presence of a large positive aggregate shock. However, this increase in the share of price rises was temporary since the share returned in 2024 close to its low inflation value and was only 1pp higher in 2024 than in 2019.

There is some sectoral heterogeneity, since the frequency of price rises, excluding sales, increased in 2022-2023 for all sectors, but the increase is stronger for food at 8pp more in 2022 than in 2019, while it was 3.4pp more for NEIG and services. We also find that products with a larger share of imported energy costs are those for which the frequency of price rises increased more strongly in 2022 (Figure 3). The frequency of price cuts remained more or less the same for services, but it decreased slightly for NEIG, by 0.3pp, and for food, by 1.0pp. Overall, the increase in the share of price rises in 2022 is very large for food and NEIG at around 20pp, but much more limited at 6pp for services, where it was initially higher than in other sectors.

There are also some differences between countries in how the inflation surge affected the frequency of price increases, but these differences are similar and somewhat smaller than those documented for the overall frequency of price changes. These differences are also smaller than the ones found between sectors; see Figure C3 in the Appendix reporting the average frequency of price increases and decreases by country.

4.2 Average Size of Price Changes

Since price rises are much more frequent in 2022 and 2023, we find a large increase in the average size of price changes, taking price increases and price decreases together, during the inflation surge (Figure 2). This increase is estimated to be around 3.7pp in 2022 (Table 2). The size of price changes (excluding sales) averaged 1.5% before 2020, but it reached 5.5% in 2022 and 3.9% in 2023, before returning to 1.8% in 2024 (Table B6 in the Appendix).[25] However, considering price increases and

[24] See Table B1 in the Appendix, which shows the average frequency of price increases and decreases by year.

[25] Table B7 reports similar estimates for the size of price changes using full product samples of every country.

price decreases separately reveals only small differences in the average size of the price rises and falls over the period 2021-2024, since the average size of price increases in 2022 was only 1pp higher than in 2019, and the difference for price cuts was even smaller. This finding would be more consistent with the predictions of a state-dependent model than with those of a time-dependent model. In a typical Calvo model, firms adjust the size of price changes in response to shocks since they cannot adjust their frequency, and so a large aggregate shock would translate into larger price increases.

There are differences between product categories, as the overall increase in the average size of price adjustments was greater for food at 4.6pp and for NEIG products at 4.9pp than it was for services at 2.2pp (Table 2 and Figure C4). The average size of the price changes was larger for food and NEIG mainly because the share of price increases was larger. At a more granular level, we find that the average size of price changes was larger for 65% of the products in 2022 than in 2019 and for 47% of them in 2023, but this proportion drops to about 20% in 2024.[26] We find large increases in all euro area countries in the size of the average price change (Figure C5), which are mostly driven by an increase in the share of price increases.

4.3 Higher Moments of the Price Change Distribution

During the episode of high inflation (2022-2023), the distribution of price changes shifted to the right. This shift was observed for all product categories (Figure C11 in the Appendix) and for all countries. It affected the average size of price changes but not the higher moments of the price change distribution. Table B8 in the Appendix reports aggregate moments calculated from the product level distributions of price changes. We find that the standard deviation decreased slightly from 18.1 before 2022 to 17.7 in 2022–2023. The skewness remains relatively stable on average over the two periods, as it is close to zero in both cases at 0.01 before 2022 and -0.02 in 2022–2023. This stability suggests that the distribution of price adjustments has remained symmetric over time. Kurtosis values above 5 in both periods indicate a leptokurtic distribution with relatively heavy tails compared to those of a normal distribution. Across product categories, the kurtosis is lower for goods at about 3 to 4 than for services, for which it is more than 7, but we do not find strong evidence that the kurtosis has varied with the inflation surge.

5 Evidence on State Dependence in Price Setting

A key result that emerges during the 2021-2024 inflation cycle is that the frequency of price changes in the euro area is more correlated with inflation than it was during the period of low inflation. This would support the view that there is some inherent state dependence in consumer price adjustments. This section documents further evidence of state dependence in consumer prices, from hazard rates

[26] Figures C9 and C10 in the Appendix plot the parameter estimates of equation (2) linking year fixed effects for the size of price changes and cost structure, and we find a small and mostly insignificant relationship between cross section differences in product cost structures and the evolution of the average size of price changes in the years 2022, 2023 and 2024.

(section 5.1), counterfactual inflation rates (section 5.2), and differences in the response to energy cost shocks (section 5.3). We also illustrate the implications of this state dependence from a simple calibrated macro model (section 5.4).

5.1 Hazard Rates

One way of investigating the degree of state dependence in consumer prices is to examine the shape of the hazard rate of price adjustment. The hazard rate is the probability of a price change occurring as a function of the price gap between the observed price and the frictionless reset price, which is the optimal price that would have been set in the absence of price rigidities. In a typical state-dependent model, this probability is an increasing function of the price gap, so that the larger the gap is in absolute values, the more likely it is that a price change will occur (Alvarez et al., 2022). However, the price gap can be challenging to measure empirically because the frictionless price is a theoretical value that needs to be estimated.

To circumvent this problem, we follow the existing literature (Gagnon et al., 2012 and Karadi et al., 2023) and proxy the frictionless price for each product category with the average reset price across all the prices that are revised in the same month.[27] We then calculate the price gap as the log difference between each price observation and this average price. To deal with persistent heterogeneity across outlets, our final measure of the price gap subtracts the average price gap calculated across outlets and over time (see Appendix D for details).

The vertical axis in Figure 5 shows the average frequency of price changes, while the horizontal axis shows the estimated price gap, which is the percentage difference between the outlet price and its optimal price.[28] The probability of a price rise is shown in black and the probability of a price fall is shown in grey. As predicted by state-dependent models, we find that the frequency of price adjustment increases with the price gap, so that the larger the difference is between a price and its optimal reset price, the more likely the outlet is to adjust its price in the next period. For comparison, Karadi et al. (2023) also find from scanner data on supermarket products in the US and Europe that hazard rates are V-shaped in price gaps, though the slope of their hazard function is steeper than in our case.[29]

[27] Conceptually, the average competitor price serves as a valid proxy for the outlet's optimal reset price if the following premises hold: (i) for each homogeneous product, supply and demand disturbances are well reflected by the price choices of competitors, and (ii) the local supply and demand conditions faced by each outlet do not affect the optimal price of its product. See Eichenbaum et al. (2011), Gautier et al. (2023b) or Gagliardone et al. (2025) for other estimation approaches that use direct measures of costs to approximate the price that would have been set in the absence of price rigidities. For each country covered in our study, we use the most disaggregated level of product definition available, which may be below the COICOP-5 level (see Appendix D for robustness analysis).

[28] We measure the hazard rates over a period of low inflation since we can consider that this period represents the economies in the steady state. Large shocks will affect the distribution of price gaps, but should not affect the hazard rate which captures the policy function of retailers. The periods used are: France 1994-2019, Austria 2000-2019, Greece 2002-2019, Germany 2005-2019, Spain 2008-2019, Lithuania 2010-2019, Italy 2011-2019, Latvia 2017-2019 and Estonia 2019.

[29] This difference in slopes may arise because their study mainly covers food products, a category with particularly high adjustment rates, while our sample includes products from many different sectors. In addition, we estimate the frictionless price at a less disaggregated product level (COICOP-5), which could introduce measurement problems that

We further observe that the shape of the hazard rate is asymmetric around zero. There is a greater probability of upward adjustment with negative gaps, which means the observed price is below the frictionless price, than of downward adjustment with a positive gap of the same size. So if the price of a product is 20% below its optimal price for example, the probability of the average outlet adjusting it upwards is about 14.3%, but if the price is 20% above the optimal price, the probability of downwards adjustment is only 11.7%. The proportion of outlets adjusting prices in response to a negative price gap, caused by rising costs for example, is therefore higher everywhere than the proportion of outlets adjusting prices in response to positive price gaps of the same size. An asymmetric profit function could rationalise this asymmetry in the hazard rate (Cavallo et al., 2024).[30] When such profit asymmetries exist, retailers have more to lose by selling at a price that is lower than their desired price than by selling at a price that is too high. If a retailer sets a price that is too low, it will sell a lot of units, but at a margin that is very low and possibly negative.

Figure D1 in the Appendix plots the average size of price changes as a function of the price gap. As expected, the overall size of the price changes increases with the size of the gap. However, while a state-dependent model would predict a one-to-one relationship between the size of the price change and the size of the price gap, we find that this relationship is somewhat weaker.

We also present hazard rates by sector and country. Figure D2 in the Appendix shows that the slopes of the hazard rates are steeper for food than they are for other sectors.[31] The hazard rate pattern for food is very similar to that found by Karadi et al. (2023) from food scanner data. The V-shape of the hazard rate for NEIG is less pronounced and less asymmetric, while the hazard rate for services suggests the degree of state dependence is lower than for other sectors, although the frequency of price changes still increases with the price gap.[32] All things being equal, this would imply that a shock would take longer to be transmitted to prices for services than in another sector that has the same frequency but a steeper hazard rate. On the country dimension, we find state dependence and asymmetric responses to price gaps to be common features across countries (Figure D3 in the Appendix).

5.2 Counterfactual Decomposition

Time-dependent models predict that firms mainly adjust their prices along the intensive margin, assuming the frequency of price changes is constant and that the size of the price changes is the main margin of price adjustment. State-dependent models in contrast predict that firms mainly adjust their prices along the extensive margin as prices are adjusted more frequently, but the size of changes remains fairly constant.

could reduce the slope of the hazard rates. Appendix D shows robustness checks on hazard rates for those countries for which we have more disaggregated product definitions. The results are qualitatively similar.

[30] Luo and Villar (2021), Karadi et al. (2023) and Gagliardone et al. (2025) also document this asymmetry of hazard rates in different contexts.

[31] This result is also consistent with the ranking of kurtosis across broad sectors which is shown to capture state-dependence in standard price stickiness models; see Alvarez et al. (2024) for evidence on French data.

[32] Luo and Villar (2021) report similar sectoral patterns based on hazard-rate estimates from US CPI data.

To examine how the variation in the frequency and size of price changes over time contributed to the variation in inflation in 2010-2024, we define two counterfactual inflation rates. One counterfactual inflation rate $\pi_{jt}^{\bar{f}}$ assumes that the frequency of price adjustments is constant over time and is equal to its product-specific average $f_{j.}$. As before, j refers to a country-product (COICOP-5) pair such that

$$\pi_{jt}^{\bar{f}} = f_{j.} \times dp_{jt} \tag{3}$$

Similarly, we define a counterfactual inflation rate where retailers only vary the probability of price changes over time and the size of the price changes is equal to its product-specific average ($dp_{j.}$):

$$\pi_{jt}^{\bar{dp}} = f_{jt} \times dp_{j.} \tag{4}$$

For low and stable inflation, Gautier et al. (2024) find that the inflation rate recomposed from micro data is highly correlated with counterfactual inflation assuming a constant frequency as in equation (3), whereas inflation rates recomposed at the product-level have a much lower correlation with counterfactual inflation rates assuming a constant size for price changes as in equation (4).

To assess the extent to which this relationship changed during the 2021-2024 inflation cycle, we estimate regressions that relate product-level recomposed inflation rates to these two counterfactual inflation rates following Wulfsberg (2016), but interact counterfactual inflation with dummy variables for the different periods of our sample. The estimated equation can be written as:

$$\pi_{jt} = a + b_1^H \pi_{jt}^{\bar{dp}} 1_H + b_1^L \pi_{jt}^{\bar{dp}} 1_L + b_2^H \pi_{jt}^{\bar{f}} 1_H + b_2^L \pi_{jt}^{\bar{f}} 1_L + \epsilon_{jt}, \tag{5}$$

where 1_L is a dummy variable equal to 1 when inflation is low and stable as in 2010-2020, and 1_H is a dummy variable equal to 1 when inflation is higher and more volatile than usual, as in 2021-2024. Table 3 reports the regression results. We find that when inflation is low, the intensive margin is much more correlated with recomposed inflation than the extensive margin is and the estimated coefficients are close to those reported in Gautier et al. (2024). Moreover, the coefficient associated with the intensive margin is estimated much more precisely than that associated with the extensive margin, though the t-statistics for both coefficients are large. The intensive margin also contributes more to the variation in recomposed inflation. When inflation is more volatile in 2021-2024, we find that the coefficient associated with the intensive margin remains high and is quite similar to what it was when inflation was low. In contrast, the coefficient associated with the extensive margin is much larger, and its magnitude is now comparable to that of the intensive margin. In column (2), we decompose the effects by year and find that the correlation with the extensive margin reaches its peak in 2022 and decreases somewhat in 2023 and 2024, though it remains much higher than in the period of low inflation. The correlation for the intensive margin is also highest in 2022, but the increase from that in the period of low inflation is much more limited.[33]

[33]Figure C12 in the Appendix plots the weighted average of the counterfactual inflation rates. When inflation is low, the intensive margin is very well correlated with inflation, while the extensive margin is flat. During the recent inflation surge, the extensive margin is more correlated with inflation, though the intensive margin continues to play a key role in variation of inflation.

These results are also broadly similar across sectors; see columns (3) to (5). The coefficients for food and NEIG that are associated with the extensive margin increase during the inflation surge and peak in 2022 before decreasing in 2023 and 2024. For services, however, this coefficient increases in 2022 but then remains at a similar level in 2023 and 2024, indicating that the contribution of the extensive margin to inflation is comparatively more persistent.

Overall, our results are consistent with there being some state dependence in price setting. However, the intensive margin still plays an important role in inflation dynamics during the inflation surge. The average size of price changes increases, though mainly because of an increase in the share of price rises among price changes, which then contributes to the movement of the intensive margin in line with inflation.

5.3 Frequency Response to Aggregate Shocks

Large shocks should be transmitted to prices more quickly in the presence of state dependence because price changes are more frequent (Alvarez et al., 2019; Cavallo et al., 2024). Similarly to Gautier et al. (2024), we investigate how the response of the frequency and size of price changes to aggregate shocks differs in a period of high inflation from the response observed in a context of low and stable inflation. To do this we compute product-level counterfactual inflation rates, as in the previous section, assuming a variable frequency or a variable size for price changes. We then use local projections to relate these counterfactual inflation rates to oil supply news shocks, as obtained by Kanzig (2021).[34] To assess how the environment of high inflation affects the response, we interact the shock with a dummy variable for periods when inflation is high or low. We estimate the following equation:

$$\pi^*_{j,t-1,t+h} = \alpha_{jm,h} + \sum_{k=0}^{3} (\delta_{k,h} D_k + \gamma_{k,h}\, S_t \times D_k) + \beta_h S_t + \epsilon_{j,t}, \tag{6}$$

where $\pi^*_{j,t-1,t+h}$ is the cumulative counterfactual inflation rate between periods $t-1$ and t+h ($*$ is for the different counterfactual inflation rates used in this exercise), and $\alpha_{jm,h}$ are country-product-month fixed effects. The set of dummy variables D_k represents different time periods, so D_0 is the periods of low inflation before March 2020 and after June 2023, D_1 is the pandemic period from March 2020 to December 2021, and D_2 is the period of high inflation from January 2022 to June 2023.[35] S_t are oil supply news shocks as obtained by Kanzig (2021). Our coefficient of interest is $\gamma_{2,h}$, which captures how the transmission differs when inflation is high or low.

We expect the oil supply shock to be transmitted more quickly and strongly to prices when inflation is high. In the state-dependent model, the frequency of price changes will increase in response to a

[34] Kanzig (2021) uses high-frequency oil supply surprises as an instrument in a proxy VAR to identify oil supply news shocks. This oil supply news shock is normalised to increase the real oil price by 10%. In the Appendix, we report some robustness results obtained using Baumeister and Hamilton (2019) oil supply shocks identified using a structural VAR model.

[35] The periods of low and high inflation are defined using the monthly HICP (excluding energy) inflation. On average, monthly inflation in the euro area was 0.1% during the period of low inflation and 0.6% during the period of high inflation.

shock that positively affects marginal costs, producing a larger effect on inflation. In both the Calvo and the menu cost models, it should be the size that responds to such a shock, since the share of price rises should be higher than before the shock.

We can decompose this effect using counterfactual inflation rates to examine how much the frequency and the size of price changes, taken separately, have contributed to higher inflation. To do this, we consider two counterfactual inflation rates $\pi^*_{j,t-1,t+h}$ constructed in a similar way to those presented in the previous section. The first counterfactual inflation rate assumes that only the frequency of price changes can vary, while the size of price changes is constant. The specific response of this counterfactual inflation rate should capture the state-dependent effect. The second counterfactual inflation rate assumes that the frequency is constant and that only the size of price changes drives the additional inflation effect. This means that following a supply shock that increases oil prices, the share of price rises might be larger even if the frequency remains constant.

Figure 6 plots the counterfactual inflation rate responses to an oil supply shock that raises oil prices. We find that the overall inflation response is explained by a response in the size of price changes (middle panel), and also by a response in their frequency (left panel). However, the frequency response is smaller than that of the size of price changes. As in the low inflation environment, the size effect is almost entirely driven by the share of price rises (right panel of Figure 6). Overall, we find a specific response from the frequency to the larger shock, which was not the case in the low inflation environment, suggesting that there is some state dependence. However, this response is quantitatively limited.[36]

5.4 Macroeconomic Implications of the Higher Frequency of Price Changes

In general equilibrium, price changes being more frequent when inflation is high has critical implications for the propagation of shocks. This section provides an illustration of these possible consequences by estimating an off-the-shelf model proposed by Gasteiger and Grimaud (2023) that allows the frequency of price changes to be endogenous in a tractable setup. More details on the model are provided in Appendix E. The model is rooted in a standard New-Keynesian framework with Calvo (1983) pricing under trend inflation. Its main innovation is to endogenise the share of firms that update prices from the present value of pricing decisions, using a discrete choice logit framework (Matějka and McKay, 2015). In this model, firms are more likely to update their prices during inflationary shocks in order to maintain profitability. This dynamic underpins the state-dependent behaviour observed in the model, where the frequency of price changes in response to inflationary shocks is higher than the frequency in response to disinflationary shocks.[37]

[36] Using an alternative oil supply shock measure (Baumeister and Hamilton, 2019) gives similar results (Figure C13 in the Appendix).

[37] This model is simpler than standard state-dependent pricing frameworks and easier to incorporate into a general equilibrium model because it abstracts away selection effects at the idiosyncratic level. In doing so, it provides a reduced-form approximation of aggregate price-setting frequency dynamics and allows us to perform an estimation under full information methods; see Ascari et al. (2025) for an estimation of quantitative model over euro area business cycle. Gasteiger and Grimaud (2023) show how their aggregate price-setting mechanism can be mapped as a reduced-form

We estimate the model using non-linear Bayesian methods and filter shocks using the euro area HICP, detrended GDP growth, the Krippner (2013) shadow rate, and the time series of the frequency of price changes excluding sales obtained from our micro data (Table E1 in Appendix E). Figure 7 (panel d) shows that the model can replicate reasonably well the quarterly aggregate share of constant prices.

We then conduct counterfactual general equilibrium simulations to assess the impact of state-dependent price setting for inflation. One key advantage of this framework is its flexibility, particularly because it includes a single additional parameter γ that extends the Calvo (1983) model. The parameter is identified through the estimation and captures the elasticity of the price-resetting frequency to the difference between the present value of price resetting and the present value of maintaining the same price. When the parameter $\gamma \to 0$, the model becomes isomorphic to a fully time-dependent pricing model.[38] This property allows us to assess the role of state dependence by running three simulations.

In the first case, $\gamma = 9.4$ is at the posterior mode and the state-dependent pricing mechanism is active, allowing the model to match the observed paths of inflation, output, and the policy rate by construction. In the second case, we remove state dependence by setting $\gamma \to 0$ and re-simulate the model with the same sequence of shocks. In the third case, we multiply γ by 3 to enhance the state dependency in the model. This counterfactual exercise isolates and quantifies the effects of state dependence, and specifically the extensive margin of price adjustments, on inflation dynamics and the Phillips curve in a general equilibrium framework.

The results of this simulation highlight the importance of state dependence during periods of high inflation (Figure 7). The frequency of price changes remained stable before 2022 and state dependence was negligible, but from 2022 onwards, the sharp increase in the price-resetting frequency (panel b) amplified the inflation dynamics in the state-dependent model (panel a). The time-dependent or Calvo counterfactual shows that inflation would have peaked almost 1pp lower on a quarterly basis if the frequency had not responded to the surge in inflation. The increase in the size of the price changes would also have been larger in a Calvo counterfactual (panel c) than the one we observe under a state-dependent model where the increase in the size is driven by an increase in the share of price rises. The counterfactual with higher state dependence further illustrates this mechanism, as inflation rises more at the extensive margin (panel b) and less at the intensive margin (panel c), implying a frontloaded but shorter-lived aggregate price response.

In a general equilibrium setting, these non-linear dynamics underline the non-linear nature of the Phillips curve under state dependence. When inflation is high, state dependence becomes crucial, steepening the Phillips curve and amplifying the accelerating behaviour of inflation dynamics. Additional simulations in Figure E1 further illustrate this point. With random demand shocks, the Phillips curve remains linear in the Calvo framework, but exhibits convexity in the state-dependent model. Similarly, the Phillips curve is linear with supply shocks in the Calvo case, but becomes non linear with state-dependent price setting.[39]

representation of the Logit framework proposed by Costain and Nakov (2019).

[38] At the other extreme, as $\gamma \to +\infty$, the model converges to a pure menu cost framework, where in each period all or none of the homogeneous firms reset their prices, reflecting an extreme form of state dependence.

[39] More sophisticated models investigating non linearities in the Phillips curve with state-dependent price stickiness

6 Conclusion

This paper provides new evidence on price stickiness in the euro area during the 2021-2024 inflation cycle. Our analysis is based on more than 190 million price quotes that underlie the official CPI for nine euro area countries in the period 2010-2024.

We document that the frequency of price changes increased by an average of about 4pp during the inflation surge in 2022. The average size of non-zero price changes was also larger, and the fraction of price rises increased to 80% from 60% in the period of low inflation, but the average size of price rises did not increase much. Overall, the higher inflation during the inflation surge reflected more frequent price increases rather than price increases being larger (when prices were adjusted). These findings are consistent with the standard predictions of a state-dependent model. We provide further evidence to support the presence of state dependence in price adjustment, as the hazard rates estimated on consumer prices are V-shaped, as predicted by a menu cost model, and we also show that the extensive margin of price adjustment is much more closely correlated with inflation when inflation is high, while the correlation for the intensive margin remains similar. We calibrate a model that allows for frequency of price changes to be endogenous, and we show that inflation would have peaked almost 1pp lower on a quarterly basis if the frequency had not responded to the surge in inflation.

Finally, we show that the frequency of price changes progressively came back to its average low inflation value during the period of disinflation in 2023-2024. This return was faster for food products and much slower for services, for which second-round effects might be stronger and state-dependence weaker. However, we do not find evidence at the end of 2024 that the frequency of price changes in the euro area is significantly higher than its average value in periods of low and stable inflation. This confirms that retailers facing a large but transitory shock in their marginal costs increased the frequency of their price changes, accelerating the transmission of the shock to prices, but this increase in the frequency of price changes then proved to be temporary.

have been recently developed by Ascari et al. (2025); Blanco et al. (2024b); Ghassibe and Nakov (2025); Karadi et al. (2024). These papers also discuss more broadly the implications of such non linearities for the transmission of monetary policy shocks and optimal monetary policy.

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List of tables

Table 1: CPI micro database with country-specific period

Country	Code	Period	% of products[a] (total)	% of products[a] EA (common sample)	% of EA HICP[b]	Number of obs.[c] total (millions)	Number of obs.[c] by month (thousands)
Austria	AT	2000M01-2024M12	95.3	57.8	3.4	9.5	31.8
Estonia	EE	2019M01-2024M12	69.6	54.2	0.2	1.4	19.9
France	FR	1994M07-2024M12	83.0	57.2	20.2	45.2	124.5
Germany	DE	2005M01-2024M12	89.7	58.6	28.0	79.2	335.5
Greece	GR	2002M01-2024M12	66.1	53.1	2.2	10.2	36.9
Italy	IT	2011M01-2024M12	63.1	56.5	16.9	33.9	203.0
Latvia	LV	2017M01-2024M12	92.4	57.2	0.3	2.0	20.5
Lithuania	LT	2010M01-2023M03	82.8	58.2	0.5	8.4	53.6
Spain	SP	2008M02-2024M12	57.1	54.2	11.3	2.9	14.1
Total				57.0	83.0	192.6	528.7

Notes: **(a):** % of products covered by the national micro price dataset, expressed in terms of euro area product weights at the COICOP-5 level (2017-2024 average). For the euro area, we report the coverage of the common product sample. **(b):** Country weights in euro area HICP (2017-2024 average). **(c):** Total number of monthly observations (in millions/thousands).

Table 2: Product-specific estimation of year effects on the frequency and size of price changes

Period	Frequency of price changes			Size of price changes			
	All	Increases	Decreases	All	Increases	Decreases	% inc.
Panel A: Average β^y in pp.							
2020	0.47	0.14	0.33	-0.16	0.41	0.03	-2.96
2021	0.57	0.66	-0.10	0.98	0.27	0.25	3.22
2022	4.30	4.63	-0.33	3.72	1.10	0.41	13.38
2023	2.47	2.32	0.15	2.11	1.14	0.43	6.38
2024	0.81	0.67	0.14	0.70	0.96	0.29	1.05
Panel B: By sector - average β^y in pp.							
2022							
Food	6.99	8.03	-1.04	4.62	1.23	1.37	19.24
NEIG	3.04	3.38	-0.33	4.87	0.84	-0.13	17.71
Services	3.53	3.38	0.15	2.15	1.23	0.17	5.79
2023							
Food	3.48	3.23	0.25	1.72	1.12	0.84	6.39
NEIG	1.54	1.55	-0.01	2.63	0.76	-0.17	8.83
Services	2.53	2.32	0.21	1.95	1.46	0.65	4.35
2024							
Food	-0.34	-0.22	-0.13	0.68	0.78	0.68	-1.08
NEIG	0.34	0.28	0.06	0.28	0.92	0.06	0.31
Services	1.98	1.60	0.38	1.58	1.01	0.19	3.11
Panel C: By country - average β^{2022} in pp.							
Austria	3.17	2.99	0.17	3.40	1.08	-0.84	7.59
Estonia	6.13	6.31	-0.18	3.03	0.99	2.97	13.13
France	3.06	3.94	-0.88	3.69	1.19	0.03	16.05
Germany	5.19	5.30	-0.11	4.45	1.19	0.87	13.64
Greece	5.88	5.57	0.32	5.55	-2.21	1.52	19.26
Italy	4.11	4.07	0.05	2.88	2.20	-0.64	8.92
Latvia	5.08	5.25	-0.27	4.75	2.67	-0.36	13.80
Lithuania	6.44	6.68	-0.24	2.78	-0.04	-0.43	11.64
Spain	4.21	4.85	-0.64	2.57	-0.05	1.08	13.52

Notes: The table shows the weighted average of the estimated year effects on the frequency and size of price changes (reference period = 2019), and the effect in 2022 by broad product categories and by country (regression presented in equation 1). Frequency and size estimates exclude price changes due to sales.

Table 3: Correlation between extensive/intensive margins and inflation

		All sectors		Food	NEIG	Services
		High vs Low	Year			
		(1)	(2)	(3)	(4)	(5)
Extensive margin	2010-2020	0.533***				
		(22.07)				
	2021-2024	1.017***				
		(39.25)				
	2010-2019		0.578***	0.797***	0.315***	0.756***
			(32.74)	(19.54)	(14.01)	(27.10)
	2020		0.275***	-0.0558	0.228**	0.300*
			(3.133)	(-0.295)	(2.469)	(1.708)
	2021		0.876***	1.177***	0.573***	0.960***
			(11.09)	(12.77)	(8.696)	(7.563)
	2022		1.095***	2.154***	0.751***	1.206***
			(29.73)	(33.87)	(12.86)	(23.70)
	2023		0.974***	1.618***	0.655***	1.174***
			(20.89)	(11.80)	(10.07)	(17.26)
	2024		0.933***	1.086***	0.603***	1.123***
			(16.88)	(7.368)	(9.263)	(14.87)
Intensive margin	2010-2020	0.801***				
		(134.1)				
	2021-2024	0.925***				
		(86.28)				
	2010-2019		0.808***	0.900***	0.719***	0.784***
			(137.0)	(120.8)	(82.99)	(57.82)
	2020		0.716***	0.714***	0.662***	0.762***
			(29.70)	(20.11)	(21.65)	(12.54)
	2021		0.797***	0.824***	0.734***	0.804***
			(36.44)	(34.92)	(22.90)	(12.50)
	2022		1.075***	1.158***	1.012***	0.891***
			(41.41)	(37.33)	(27.31)	(15.01)
	2023		0.954***	1.084***	0.862***	0.845***
			(42.19)	(47.34)	(25.97)	(15.18)
	2024		0.807***	0.846***	0.715***	0.919***
			(45.80)	(48.51)	(33.25)	(16.85)
	Constant	-0.124***	-0.121***	-0.0574	-0.0870***	0.0284
		(-6.194)	(-6.146)	(-1.288)	(-4.374)	(0.785)
	Observations	192,508	192,508	68,418	79,087	45,003
	R-squared	0.755	0.763	0.828	0.742	0.742

Notes: The table reports the results of regressing the product-level inflation rates (as constructed from our micro datasets, excluding sales) on counterfactual inflation rates assuming a constant frequency of price changes (intensive margin) or a constant size of price changes (extensive margin) (regression presented in equation 5). Estimation results are aggregated using euro area HICP weights (2017-2024 average).

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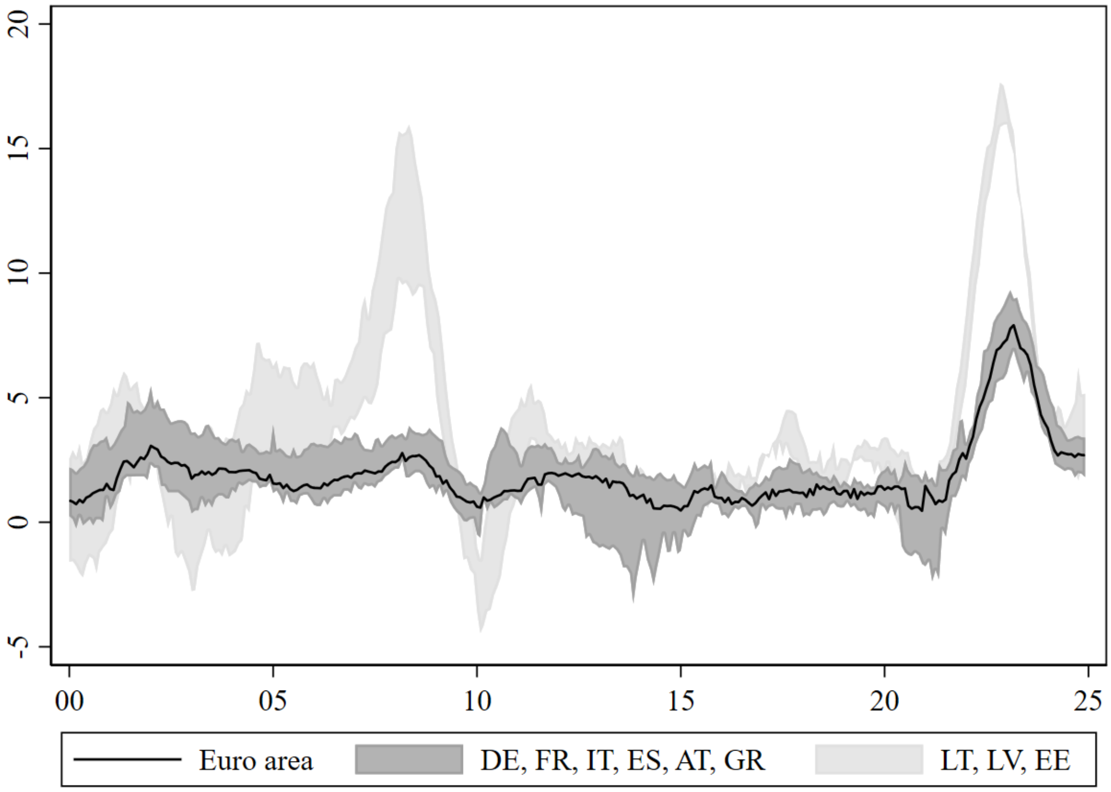
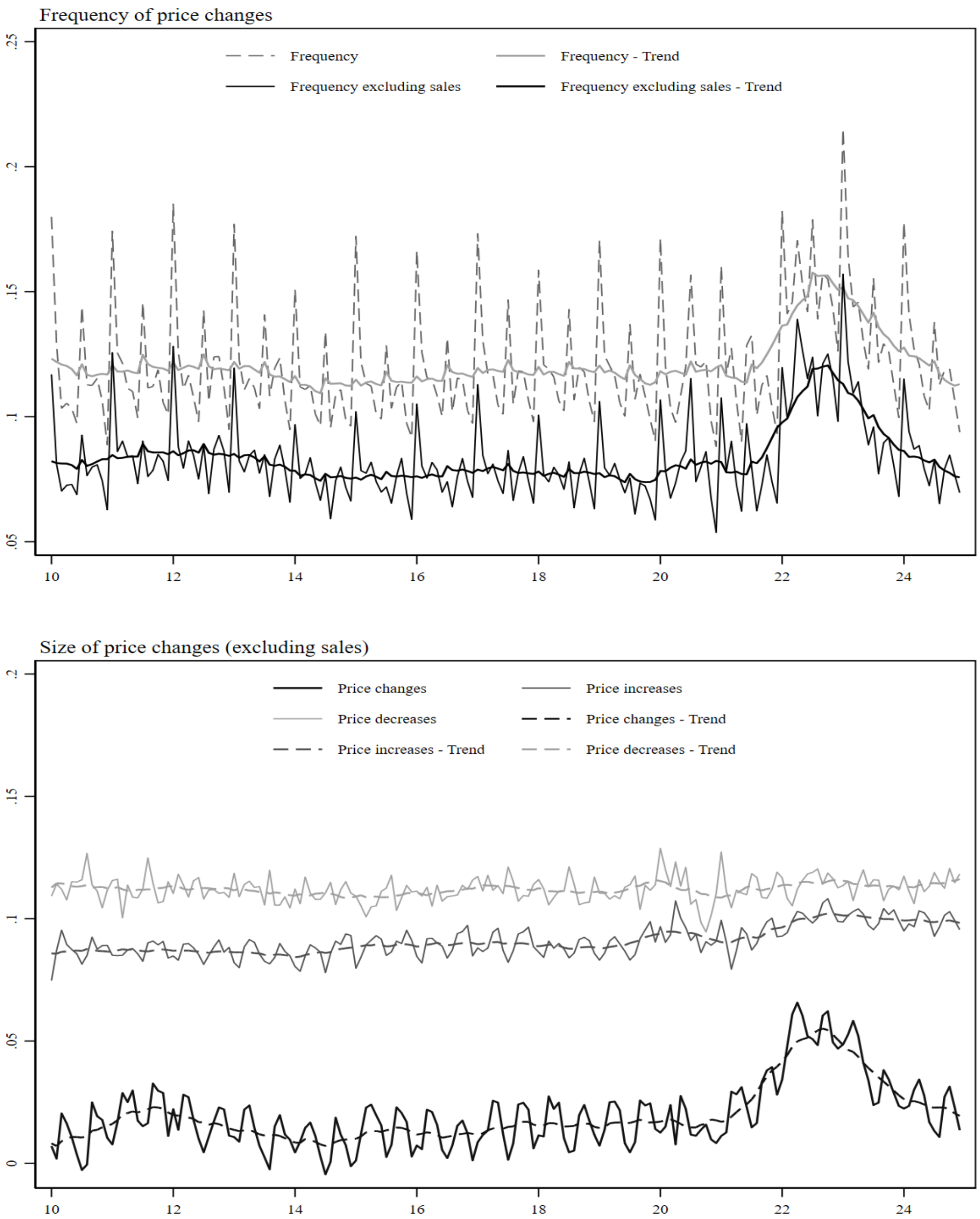
Figure 1: Inflation (HICP excluding energy) in the euro area



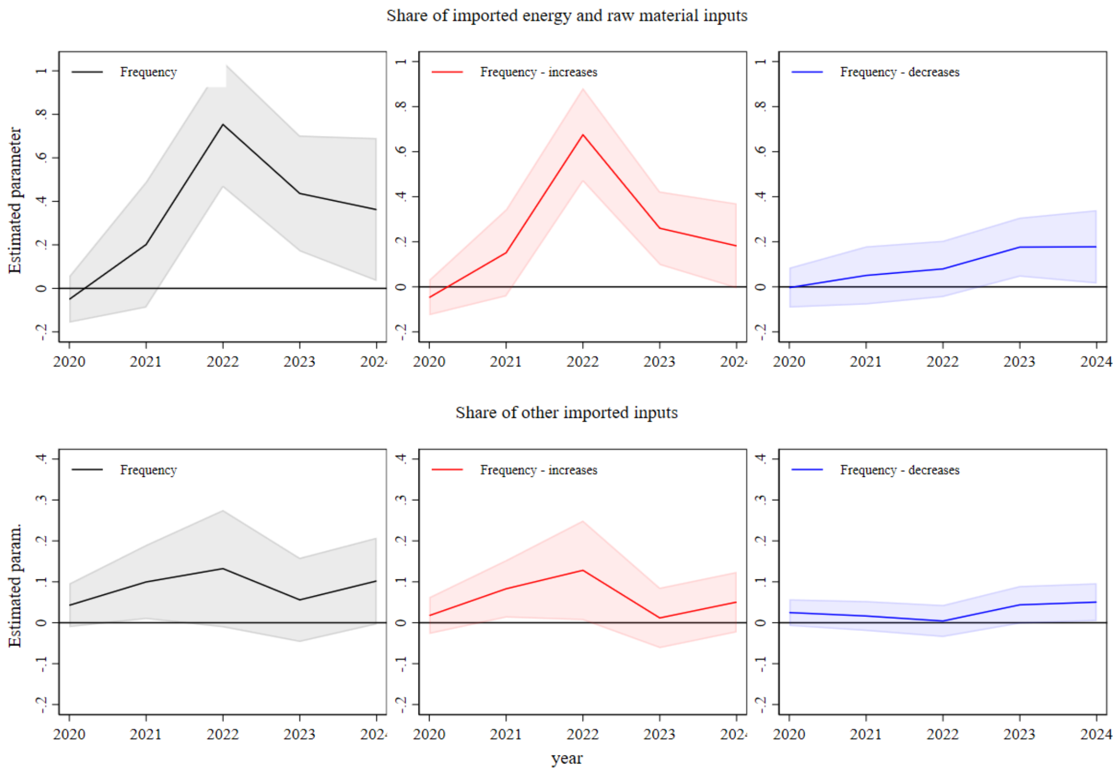
Notes: The graph shows year-over-year inflation rates of the HICP excluding energy for the euro area as a whole and for the nine countries for which CPI micro data are available. The shaded areas correspond to the minimum and maximum inflation rate by country group. Source: Eurostat and authors' calculations.

Figure 2: Frequency and size of price changes in the euro area over time



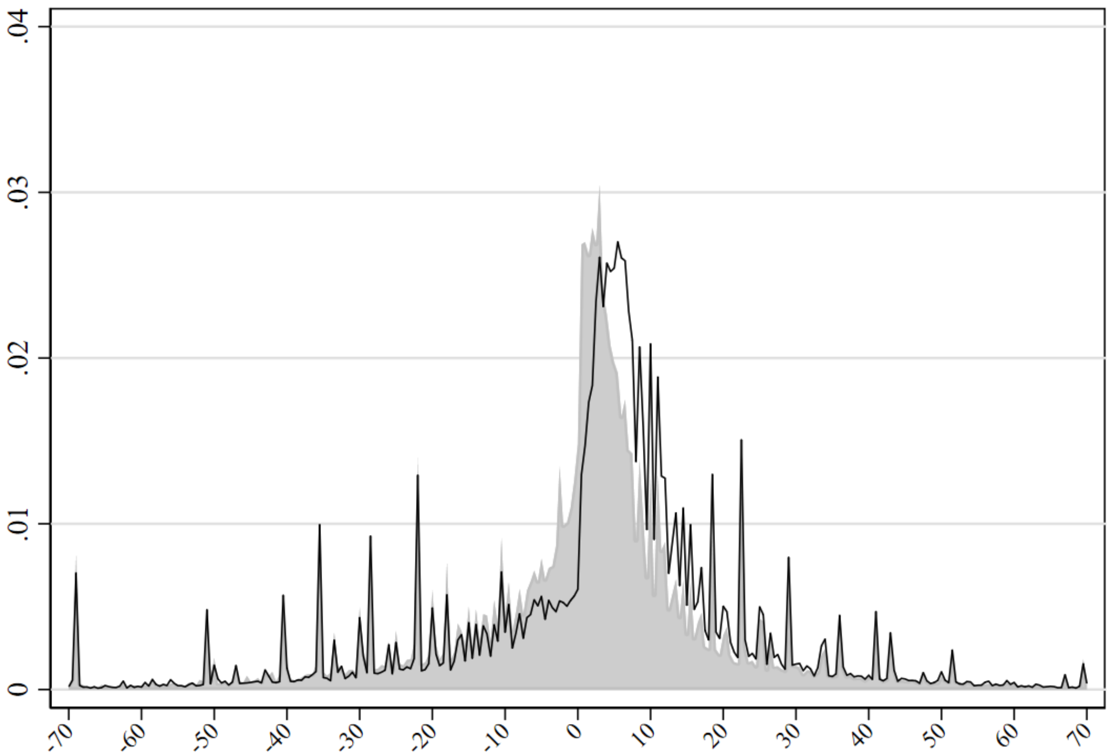
Notes: The top panel shows the frequency of price changes including and excluding sales. The lower panel shows the average size of price changes, price increases and price decreases. Trends are obtained by applying a moving average with a +/- 6-period window. Country-level statistics are controlled for VAT changes by replacing the country statistics by their average values during the VAT changes.

Figure 3: Cross-sectoral frequency of price changes in 2020-2024 and product-level cost structure



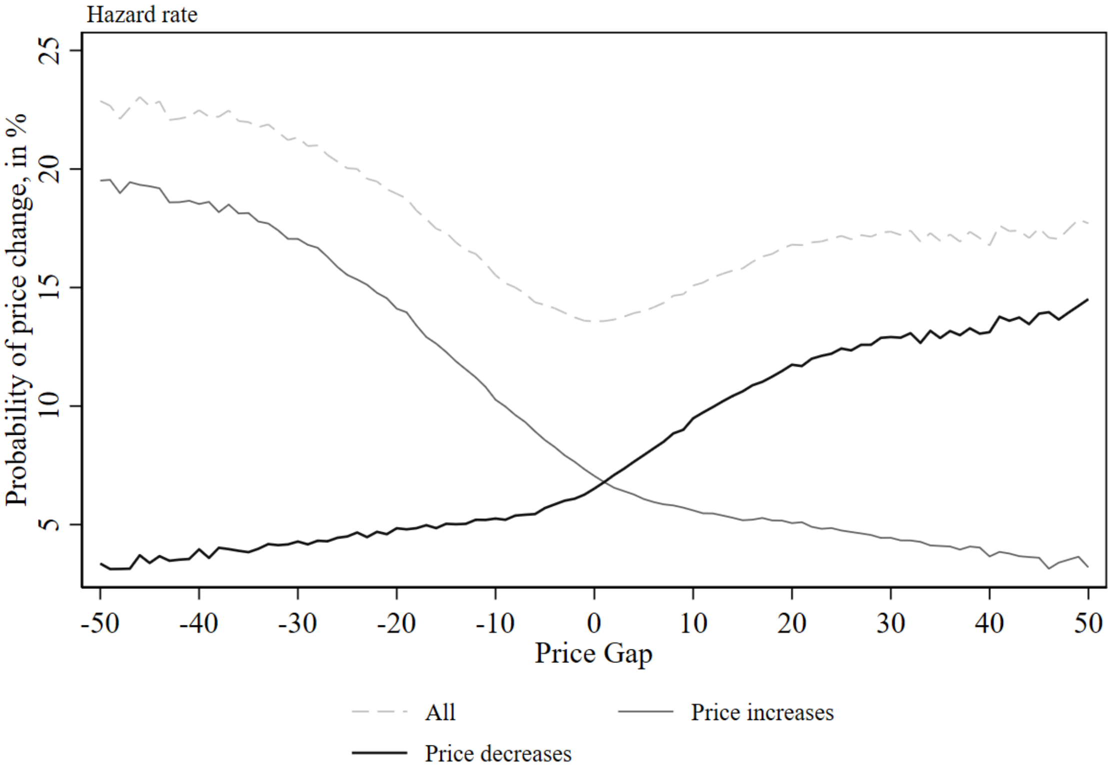
Notes: The figure shows the estimates of an OLS regression relating the year fixed effects estimated in equation (1) at the product level β_j^y, which captures how the frequency differs in year t from that in year 2019, to the product-level cost structure constructed from EA input-output matrices (equation (2)). This OLS equation is estimated for each set of year fixed effects (2020, 2021, 2022 and 2023) and for each variable (total frequency, frequency of price increases/decreases) separately. The top panel shows the results using the share of energy inputs as an exogenous variable, while the lower panel reports the results for the share of other imported inputs in the total costs.

Figure 4: Distribution of price changes in the euro area before and after 2022



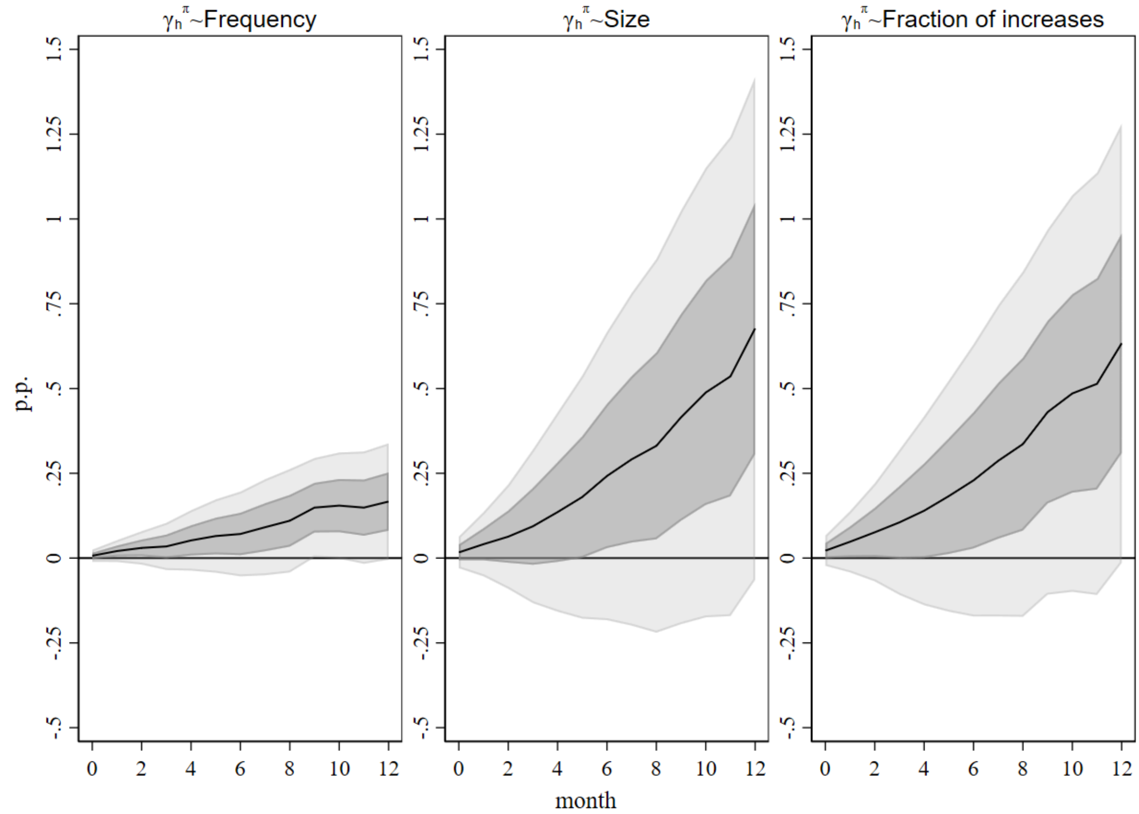
Notes: The graph shows the distribution of price changes (excluding sales) in the euro area for two different periods: before 2022 (grey area) and 2022-2023 (solid line). We first calculate a bin histogram for every product-country pair (at COICOP-5 level), excluding zeros and keeping only non-zero price changes. These histograms are then aggregated using product-level and country-level euro area HICP weights (average 2017-2024) to obtain the aggregate euro area distribution of price changes.

Figure 5: Adjustment hazard rates for the euro area



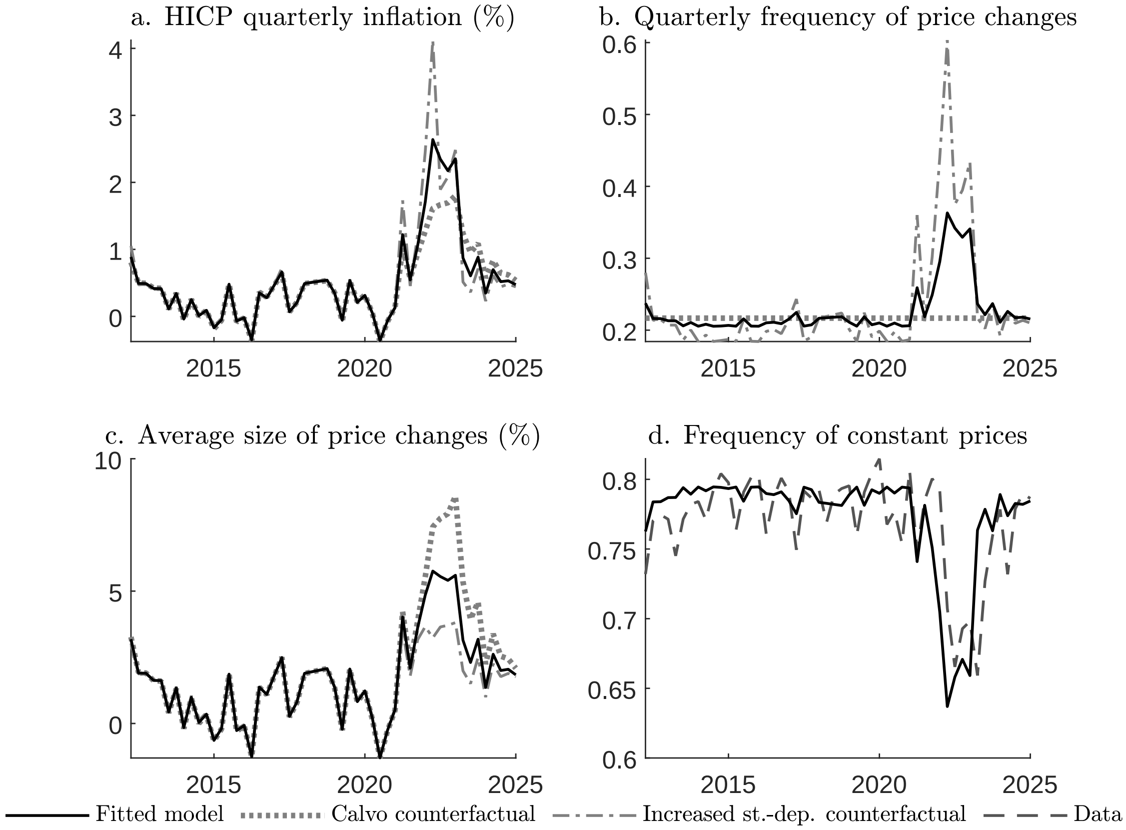
Notes: Hazard rates are first calculated at the country level and then aggregated using euro area HICP weights (average of country-level weights over the period 2017-2024). They represent the probability of price changes (grey dashed line), price increases (grey solid line) or price decreases (black solid line) as a function of the price gap.

Figure 6: Counterfactual inflation rate responses to a negative oil supply shock: high inflation period relative to low inflation period



Notes: This graph plots the estimated response of product-specific counterfactual inflation rates (excluding sales) to a negative oil supply shock following Kanzig (2021) in the high inflation period from January 2022 to June 2023 in comparison to the period before 2020. The left panel plots the response of a counterfactual inflation rate assuming a constant size of price changes (extensive margin), the centre panel the response of a counterfactual inflation rates assuming a constant frequency (intensive margin) and the right panel the response of a counterfactual inflation rate assuming that only the fraction of price increases varies.

Figure 7: Counterfactual simulations varying the degree of state dependency



Notes: The fitted model with $\gamma = 9.4$ at the posterior mode features dynamics for HICP, GDP and the policy rate that are by construction equal to the empirical dynamics. The quarterly frequency of price changes and the average price change are endogenous in the model. The difference between the data and the state-dependent model in Panel (d) is generated by the observation errors. The Calvo model is the same model under the same aggregate shock with the state-dependence shut down ($\gamma \to 0$). The version with increased state-dependence is the same model under the same aggregate shock with γ at three times the posterior mode.

Online Appendix

A Data and Methods

A.1 Update of National CPI Micro Datasets

This section provides information on changes in our underlying country-specific micro datasets in relation to Gautier et al. (2024). The main change is that the time period has been updated to 2020-2024 for most countries. Belgium, Luxembourg and Slovakia are missing from our country sample, while Estonia has been added.

Austria. The dataset has been provided by Statistics Austria to the Oesterreichische Nationalbank (OeNB) under a confidentiality agreement and therefore cannot be made available to researchers outside the OeNB. The dataset has been updated for the period January 2018 to December 2024. For the years 2000-2021, the dataset contains information on 100%, or at least 88.8% after cleaning, of the Austrian CPI. Some prices from 2022 onwards have been collected from scanner data for items in the COICOP classes 01, 02, and occasionally 12.1.[1] These scanner data are not included in the Austrian dataset. Consequently the dataset lacks information on food items as of 2022 and covers only about 84-88% (73-79% after cleaning) of the Austrian CPI from then on. The micro dataset contains information on outlet types as of 2006 and allows for a distinction between online and offline prices. Online price observations are included in outlet type "online and catalogue"; a more granular distinction is not available.

Estonia. The dataset has been provided to Eesti Pank by Statistics Estonia for research purposes and cannot be shared. The dataset covers the period January 2019 to December 2024 and provides some 20,000 raw price observations for each month, before any imputations and further adjustments by Statistics Estonia. Prices of goods and services are collected for 716 detailed consumption categories, covering 189 COICOP-5 categories and about 80% of the official CPI. Flag variables indicate replacements and price reductions due to sales. There is no separate flag in the dataset for prices collected online, though some product descriptions include URLs as a source. Nevertheless, the share of these observations is very marginal at 0.2%, and 85% of them are for services.

France. The French CPI micro dataset has been provided by the Institut National de la Statistique

[1] See section "2.5.1 Erhebungsform" of the standard documentation on CPI and HICP by Statistics Austria.

et des Études Économiques (INSEE). The dataset has been extended to cover the period October 2019 to December 2024. From January 2020 onwards, INSEE has used scanner data to calculate the CPI. As these scanner data are private data provided by large retailers, they cannot be used for purposes other than the construction of the CPI (see Leclair, 2019). Scanner data are collected for some broad categories such as processed food products, cleaning products and hygiene and beauty products. Some prices in the French CPI micro datasets are still collected for these products if they are not sold by supermarkets or hypermarkets. This means we can still calculate price rigidity statistics for these items after 2020, but the number of prices is much more limited as there are about half as many observations for these specific products as there were before 2020. Prices collected online through web-scraping are not included in the CPI research dataset.

Germany. The German CPI micro dataset is provided by the Research Data Centres (RDC) of the Federal Statistical Office and the statistical offices of the Länder and is publicly available for research purposes.[2] The dataset has been extended from that of Gautier et al. (2024) by adding the periods January 2005 to December 2009 and January 2020 to December 2024. In January 2005 (base year 2005), January 2010 (base year 2010), January 2015 (base year 2015) and January 2022 (base year 2020), the price survey is updated with a new survey ID, which does not allow the price change statistics to be calculated for these four months. We clean the dataset beforehand by excluding imputed prices and those product categories with fewer than three observations. Moreover, we drop prices collected from internet stores because of structural changes.[3] The final dataset contains roughly 770 distinct COICOP-10 groups and around 79 million observations.[4]

Greece. The Greek CPI micro data have been provided to the Bank of Greece by the Hellenic Statistical Authority under a confidentiality agreement and cannot be shared. The dataset has been updated for the period January 2020 to December 2024. The dataset does not, in general, contain online prices. In January 2023, a new data handling method was introduced for the Attica region resulting in new outlet ID's. As a result the price change statistics cannot be calculated for that month and region. Price change statistics for January 2023 consequently refer to all the other regions.

Italy. The Italian CPI micro data have been made available to the Banca d'Italia under an agreement between the Istituto Nazionale di Statistica (ISTAT) and Banca d'Italia in the PRISMA network. The data are confidential and cannot be shared with researchers outside the bank. The dataset has been extended to run from January 2019 to December 2024. From 2020 onwards, processed food prices have mainly been collected from scanner data, which significantly reduces the number of comparable food categories available in the Italian CPI micro dataset and introduces a bias in the sample composition in 2020 as supermarkets are dropped as an outlet type in the dataset. The sample of processed food in the Italian dataset is limited at 16% of the processed food that was covered in 2015-2019 and only represents prices in small shops. Few products are available for unprocessed food, as most prices of unprocessed products are collected every two months and are therefore not included in the Italian

[2] See "Verbraucherpreisindex für Deutschland", EVAS 61111, 2005 - 2024, DOI: 2005 to 2024.

[3] See section A.2.

[4] Note that the number of observations is nearly halved in December 2024, since a lot of prices were imputed in this month in light of the preparation of the base year 2025 (see the Meta Data Report 2024, p. 2, in German).

CPI micro dataset. Prices collected online through web-scraping are also not included in the research dataset.

Latvia. The Latvian CPI micro data are available to Latvijas Banka under a contract with Centrālā Statistikas Pārvalde (CSP), the Central Statistical Office of the Republic of Latvia. The micro data are confidential and cannot be shared with researchers outside the bank. The dataset has been updated for January 2020 to December 2024. The dataset might contain a limited number of online prices though, but these cannot be identified. By the end of 2024, the share of online prices in the Latvian CPI was only about 4% of the total prices registered, and they were mainly used as a way to automatise the price collection for services.

Lithuania. The database is provided to Lietuvos Bankas by Valstybės duomenų agentūra, the Statistical Office of Lithuania. The data may only be used for research purposes and may not be distributed. The database has been updated for the period January 2019 to March 2023. It has now added a flag to the previous dataset used in Gautier et al. (2024) that indicates whether a price was carried forward in two consecutive months, and so imputed, during the COVID-19 pandemic (see Jouvanceau, 2023 for more details).

Spain. The dataset has been made available to the Banco de España (BdE) by the Instituto Nacional de Estadística (INE), the Spanish national statistical institute; no researcher outside the BdE may use these data. The dataset has been updated for the period March 2018 to December 2024. The sample covers municipalities from 17 provinces, and contains 188 of the 479 items used by INE to calculate the CPI, and around 10,300 price observations per month out of the 220,000 monthly observations used on average by INE. The 17 provinces out of the 50 Spanish provinces and two autonomous cities are: La Coruña, Álava, Asturias, Badajoz, Barcelona, Cantabria, Comunidad de Madrid, Illes Balears, La Rioja, Las Palmas, Murcia, Navarra, Sevilla, Toledo, Valencia, Valladolid and Zaragoza. Since January 2018, our sample has covered 25 provinces, 203 items and 19,600 price observations per month. The eight additional provinces are Cádiz, Málaga, Burgos, León, Albacete, Alicante, Pontevedra and Bizkaia. From 2020 onwards, some prices have been collected from scanner data. However, the establishments affected by this change are not included in the sample, either before or after the scanner data started to be used, and so the coverage of the dataset remains unaffected by this change. Prices collected online through web-scraping are equally not included in the research dataset.

Table A1: HICP coverage of the common product sample

Special aggregate	HICP total share in % (EA 2017-2024)	Share not covered in %	Share covered in %	No. of COICOP-5s covered
Food	19.9	2.5	17.4	59
Processed food	15.3	2.5	12.8	49
Unprocessed food	4.6	0.0	4.6	10
NEIG	26.4	7.9	18.4	66
Durables	9.2	5.2	4.0	23
Semi-durables	10.4	0.7	9.7	30
Non-durables	6.8	2.1	4.6	13
Energy	10.0	10.0	0.0	0
Services	43.8	20.4	23.4	41
Housing services	10.7	9.7	1.1	4
Transport services	7.3	1.5	5.8	9
Communication services	2.7	2.7	0.0	0
Recreational services	15.3	2.7	12.7	16
Miscellaneous services	8.5	4.3	4.2	12
Total	**100.0**	**40.8**	**59.2**	**166**

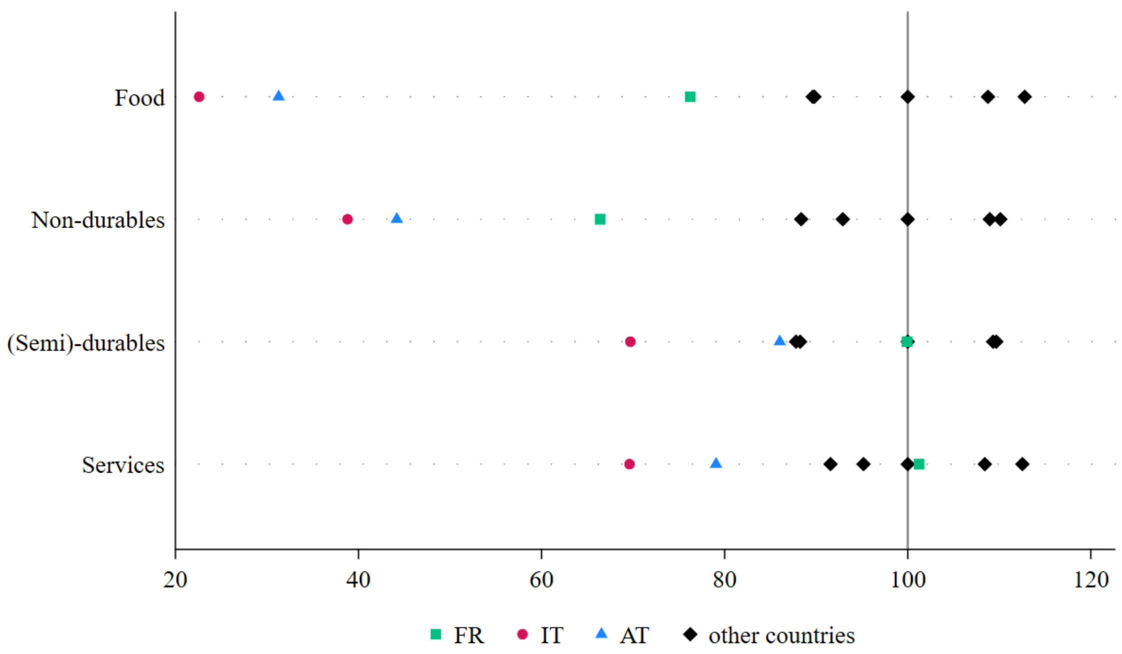
Notes: The micro dataset covers the country-specific periods as indicated in Table 1 and is set up such that 166 COICOP-5 products are available at least in 3 of the 4 largest countries (Germany, France, Italy and Spain) in 2022. 'HICP total share' corresponds to euro area HICP weights calculated on average over the period 2017-2024. 'Share not covered' corresponds to the share (euro area HICP weights) of products missing in our common sample of COICOP-5 products. 'Share covered' corresponds to the share (euro area HICP weights) of products included in our common sample of COICOP-5 products.

Table A2: Share of imputed prices in the euro area HICP due to the COVID-19 pandemic

All-items HICP	2020 M4	2020 M5	2020 M6	2020 M7	2020 M11	2020 M12	2021 M1	2021 M2	2021 M3	2021 M4	2021 M5	2021 M6	2021 M7	2021 M8
Austria	31	21	4	3	18	25	20	13	13	15	12	1	0	0
Estonia	7	5	3	2	2	2	1	0	3	3	1	0	0	0
France	47	42	26	1	15	16	5	9	8	15	15	3	2	2
Germany	27	13	8	3	9	10	23	23	14	13	11	3	1	1
Greece	32	20	4	2	11	11	10	7	9	8	2	2	0	0
Italy	40	27	12	9	15	12	11	10	13	13	8	7	7	9
Latvia	8	7	3	1	3	4	9	8	7	4	3	1	0	0
Lithuania	26	15	3	1	5	11	17	17	11	7	3	0	0	0
Spain	37	21	13	3	8	6	7	7	5	5	4	4	4	7
Euro area														
All-items	32	22	11	3	11	11	13	13	10	11	9	3	3	3
Food	11	8	7	2	4	4	2	2	2	5	4	1	1	1
NEIG	43	19	9	2	5	5	17	15	4	6	4	2	2	2
Services	41	34	15	5	20	20	19	20	21	21	16	6	4	5

Notes: This table reports the imputed share in the HICP (in % of the consumption expenditure) due to the COVID-19 pandemic for the periods April to July 2020 and November 2020 to August 2021 for individual countries and a selection of special aggregates for the euro area. From September 2021, the publication of this information was discontinued given that imputations reached low levels. Source: Eurostat, Methodology: COVID-19 and HICP.

Figure A1: Share of number of observations by broad category, 2019=100



Notes: The graph shows the average number of observations per product category and country between 2020 and 2023 relative to the number of observations in 2019. Note that for Austria, the number of observations for food items declines significantly for the period 2022-2023 because of the introduction of scanner data.

Table A3: Overview of major value-added tax changes

Country	Period	Specific VAT measure
Estonia	2024M1	Increase in the standard VAT rate from 20% to 22%.
France	2014M1	Increase in the standard VAT rate from 19.6% to 20% and in the intermediate VAT rate from 7% to 10%.
Germany	2007M1	Increase in the standard VAT rate from 16% to 19%, while the reduced rate stayed at 7%.
	2020M7-2020M12	Temporary VAT cut; the standard rate was lowered from 19% to 16%, and the reduced rate, which mainly applies to food (excluding beverages), newspapers and books, was lowered from 7% to 5%.
	2020M7-2023M12	Temporary VAT cut for restaurants from 19% to 7% for restaurant services (on-site, excluding drinks), affecting COICOP-5 groups 11.1.1.1 and 11.1.1.2.
Greece	2005M4	Increase in the VAT rates from 8% to 9% (intermediate rate) and from 18% to 19% (standard rate).
	2010M3	Increase in the VAT rates from 9% to 10% (intermediate rate) and from 19% to 21% (standard rate).
	2010M6	Increase in the VAT rate from 10% to 11% (intermediate rate) and from 21% to 23% (standard rate).
	2011M1	Increase in the VAT rate from 11% to 13% (intermediate rate).
	2015M8	Change in the VAT rate applying to some products from 13% (intermediate rate) to 23% (standard rate).
	2016M7	Increase in the VAT rate from 23% to 24% (standard rate).
	2019M6	Change in the VAT rate applying to some products from 24% (standard rate) to 13% (intermediate rate).
Italy	2013M10	Increase in the standard VAT rate from 21% to 22%.
Spain	2012M09	Increase in the standard and intermediate VAT rate.
	2023M1-2024M12	Temporary VAT cut; the rate was reduced for bread, flour, milk, cheese, eggs, fruits, vegetables, legumes, tubers and cereals from 4% to 0% (2% between 2024M10 and 2024M12) and for vegetables oils and pasta from 10% to 5% (7.5% between 2024M10 and 2024M12).

Notes: This table lists only major VAT changes in our sample which affected a broad range of products.
Sources: National tax authorities.

A.2 Offline vs. Online Price Setting: The Special Case of Germany

As E-Commerce has been increasing as a share of all commerce in Europe over the past decade, national statistical institutes have increasingly integrated prices from online shops into their official price collection (see Eurostat, 2020). Most countries run bulk web scraping, which is an automated way of retrieving a large number of price observations from online shops and further processing these data for index compilation. In contrast, targeted web scraping of pre-defined products is a way of automating price collection. In both cases, web-scraped data are typically not part of national CPI micro datasets because of their large volume and their different nature from traditionally collected on-site prices. Similarly, only the Austrian and German CPI micro databases among the country-specific datasets on which our study is based contain an indicator variable that allows distinction to be made between prices from online and offline stores.

In Germany, a specific outlet-type weighting is applied at the lowest elementary index level, mostly for food and NEIG. The different outlet types include discounters, supermarkets, specialised stores, department stores, and internet trade (see Destatis, 2023).[5] This means the outlet-type indicator allows online and offline prices to be distinguished in the micro dataset. Strasser et al. (2023) provide a detailed analysis of online and offline price setting in Germany in 2010-2019 at the lowest available product level. They find that online prices in Germany tend to change more often, but by a smaller amount, than their offline counterparts. This finding is consistent with menu costs generally being lower in online markets.

Updated results on online and offline prices show that the recent development of online prices in Germany is a special case in our datasets. The upper side of Figure A2 shows the share of online prices in the micro datasets for Germany and Austria over time. Note that the level shifts in the share of online prices coincide with the regular base year updates of the CPI in both countries, which are typically associated with major sample revisions.[6] In Germany, the share of online prices in total observations has increased sharply, from roughly 14% in 2010 to around 24% in 2024%.[7] In contrast, the share of online prices in Austria remains broadly constant over time, within a narrow range of 1.7% to 2.7%. Here the recent increase in the share of online prices is due to the general loss of observations following the introduction of scanner data in Austria; an adjusted share would indicate a slight decrease.

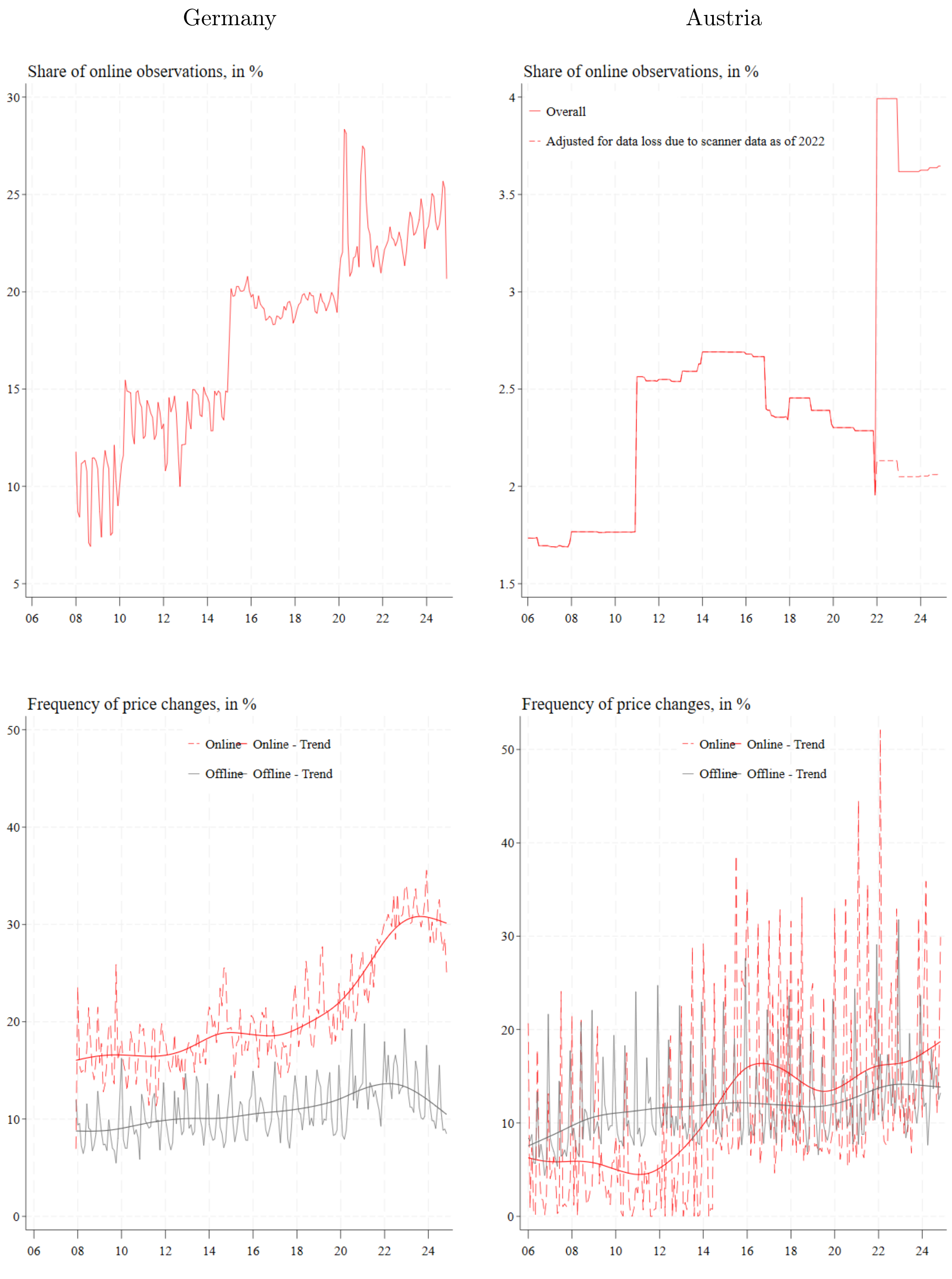
The increase in the share of online prices also affects the frequency of price changes for non-energy industrial goods in Germany. As shown in the lower left side of Figure A2, online prices tend to change more often than offline prices, but the frequency increases significantly over time. In Austria too, the frequency of online prices increases only in the base years, and their increase during the period of high inflation is of a similar magnitude to that of offline prices. Overall, the share of online prices increasing over time in Germany, together with an increase in the frequency of price setting in online stores, may reflect a change in the sample composition, which should be avoided when analysing the effect of the period of high inflation on price setting. We therefore exclude German online prices from our analysis, which also makes Germany more consistent with the other countries in our sample.

[5]Note that the Destatis "internet trade" outlet type also captures the "mail order" distribution channel. The share of the "mail order" channel is expected to be quite small, also in comparison to previous base years (2005 and 2010), with Destatis changing its external communication for this outlet type from "internet trade/mail order" to "internet trade" as of the base year 2015.

[6]In Germany, the general lockdown during the pandemic is also evident. See country-specific notes in section A.1.

[7]Note that the increasing share of online prices does not affect the official CPI, as outlet-specific weights are used in calculating that. These weights are kept constant in each base year period.

Figure A2: Offline and online price setting for non-energy industrial goods (NEIG)



Notes: The graphs in the first row show the percentage share of price quotations collected from online stores out of the total number of observations used in this study. The graphs in the second row show the frequency of price changes for non-energy industrial goods sampled in online and offline stores. Trends are derived by applying a HP filter. Price changes due to VAT changes and CPI base year introductions in Germany are imputed using adjacent observations (2020M7, 2021M1, 2010M1, 2015M1, 2022M1). For Austria, an adjusted share of online prices is calculated relative to the average number of total observations in the five years before the introduction of scanner data (2017-2021).

A.3 Robustness Exercise - Frequency of Price Changes Including Energy Prices

We exclude the energy sector from our analysis in the main body of our paper because energy-related micro prices are not included in the research datasets in most of our sample countries. This may be because energy prices are regulated and centrally collected or, as in France, because transport fuel prices are not collected locally but from a comprehensive dataset collected by an official online price platform. While the role of rising energy prices in the recent inflation surge is undisputed, the following robustness check shows that developments in the energy sector do not alter the main findings of our analysis of how the frequency of price changes has been affected by the inflation surge.

The robustness exercise covers countries where data coverage of the energy sector is highest and covers nearly all types of energy products. These countries are Austria, Germany and Latvia where the HICP coverage rate of energy is 97.6%, 100% and 93.2%, respectively. In the remaining countries, the coverage rates are below 10% in Spain, France, Greece and Italy and about 50% in Lithuania and Estonia.

Figure A3 shows the aggregate frequency of price changes for the energy sector in Austria, Germany and Latvia, and the underlying contributions from electricity, gas, transport fuels and other components such as liquid fuels, solid fuels or heat energy. Overall, the contributions to a change in the frequency of price changes for energy products mainly stem from electricity and gas, as contributions from transport fuels and others remain rather constant over time. Figure A3 also reveals some country heterogeneity related to electricity and gas. In Austria, we find an average increase of around 30pp in the frequency of energy prices during the period of high inflation, with electricity accounting for around 60% of this change on average. In Germany, the frequency of energy prices increased by only 6pp in 2022. In Latvia, the change to the contributions from electricity prices is of around 10-15pp starting in 2020. While the gas and electricity markets are more regulated, the observed country heterogeneity goes hand in hand with a different speed and effectiveness of national adjustment strategies across countries and a different degree of dependence on Russian gas and electricity imports (see also Adolfsen et al., 2022).[8]

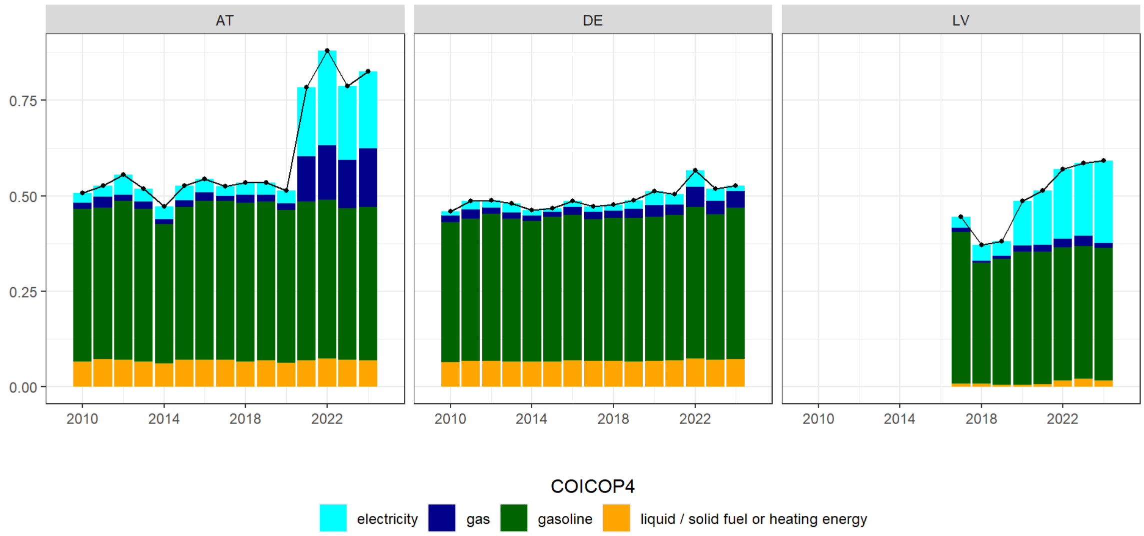
To put these findings into perspective, we perform a back-of-the-envelope calculation to evaluate the relative contribution of energy prices to the overall frequency of price changes. First, we note that the energy sector accounts for around 10% of the euro area HICP basket. Second, we assume that the energy price developments observed in Austria, Germany and Latvia are representative of the EA energy sector.[9] Using average 2017-2024 EA country weights, we obtain that the frequency of price changes in the energy sector was about 9pp higher in 2022-2023 compared to the low inflation

[8] In light of Russia's invasion of Ukraine, the German authorities pushed for alternatives to Russian gas such as imports from Norway, while Austria's scope of action was more limited due to long-term importing contracts with Russian suppliers. Similarly, Latvia's (and more generally the Baltic countries') dependence on both Russian gas and electricity imports had just increased due to geopolitical tensions that, among other things, had resulted in suspensions of imports from Belarus in 2020.

[9] One caveat here is that energy price policies implemented during that period were very heterogenous across countries.

period. This would imply an increase of approximately 0.9pp in the overall frequency of price changes in 2022-2023 compared to the 2010–2019 period.[10] Given that the increase in aggregate frequency (excluding energy) during the high inflation period was of about 4pp in 2022 (see Table 2), including energy would thus imply an increase of about 5pp. These findings do not alter our main conclusions and rather suggest that our results excluding energy prices are a quantitative lower bound.

Figure A3: Aggregate frequency of energy price changes and a component-breakdown at the COICOP-4 level for Austria, Germany and Latvia



Notes: The figure shows the aggregate frequency of energy price changes and a component-breakdown at the COICOP-4 level for Austria, Germany and Latvia (with COICOP-5 components in parentheses) for *electricity* (CP04510), *gas* (CP04521, CP04522), *transport fuels* (CP07221, CP07222, CP07223), and *others* consisting of liquid fuels (CP04530), solid fuels (CP04541, CP04549), and heat energy (CP04550). Contributions range from 0 to 100% (rescaled to [0,1]).

[10]If we consider only 2022, the contribution would be slightly higher at 1.2pp. At the country level, the contribution estimates (2022-2023 vs 2010-2019) range from 0.6pp in Germany to 1.8pp in Latvia and 3.1pp in Austria.

B Additional Tables

Table B1: Frequency of price changes in the euro area by subperiod: common euro area sample

Period	Including sales				Excluding sales			
	All	Up	Down	% Up	All	Up	Down	% Up
Total								
2010-2019	12.0	6.6	5.4	63.0	8.2	5.0	3.2	67.2
2020	11.9	6.4	5.5	60.9	8.0	4.8	3.2	65.7
2021	11.8	6.7	5.0	65.6	8.0	5.1	2.9	71.2
2022	15.7	10.8	4.9	74.8	12.0	9.4	2.6	81.7
2023	14.2	8.7	5.5	69.3	10.2	7.1	3.2	74.7
2024	13.2	7.2	6.0	61.9	8.6	5.3	3.3	66.4
Food								
2010-2019	19.1	10.3	8.8	55.1	13.4	7.6	5.8	58.5
2020	17.7	9.6	8.1	54.0	11.6	6.6	5.0	57.9
2021	18.0	10.1	7.8	57.5	11.8	7.2	4.6	63.2
2022	26.0	18.1	7.9	71.2	20.0	15.4	4.6	79.0
2023	22.7	13.6	9.2	61.5	16.3	10.6	5.7	66.5
2024	18.8	10.3	8.5	56.0	12.5	7.2	5.4	59.0
NEIG								
2010-2019	12.4	5.4	7.0	49.0	5.9	3.2	2.7	57.8
2020	13.2	6.0	7.2	47.1	6.7	3.6	3.0	58.0
2021	13.0	6.7	6.3	54.4	6.9	4.3	2.6	65.7
2022	14.9	8.7	6.2	61.9	8.9	6.6	2.3	76.0
2023	13.9	7.0	6.9	55.4	7.5	4.8	2.7	67.1
2024	12.8	5.9	7.0	50.0	6.3	3.5	2.7	58.5
Services								
2010-2019	6.4	4.7	1.7	80.0	6.2	4.6	1.6	81.1
2020	6.6	4.4	2.2	76.9	6.4	4.3	2.1	77.7
2021	6.2	4.3	1.9	80.4	6.0	4.2	1.8	81.6
2022	8.6	7.1	1.5	87.6	8.5	7.0	1.5	88.1
2023	8.0	6.3	1.7	86.2	7.9	6.3	1.6	87.0
2024	7.5	5.7	1.8	84.5	7.3	5.6	1.8	85.1

Notes: The table shows the average frequency of price changes, increases, decreases and the share of price increases calculated by subperiod using the common sample of products for the euro area (166 COICOP-5 products). All statistics are aggregated using euro area HICP weights (average product-level and country-level weights over the period 2017-2024).

Table B2: Frequency of price changes in the euro area by subperiod: country-specific product samples

Period	Including sales				Excluding sales			
	All	Up	Down	% Up	All	Up	Down	% Up
Total								
2010-2019	10.6	6.0	4.6	66.2	7.7	4.8	2.9	69.7
2020	10.5	5.9	4.6	64.9	7.5	4.6	2.9	69.0
2021	10.6	6.3	4.3	69.1	7.7	5.1	2.7	73.7
2022	14.4	10.1	4.2	77.0	11.6	9.0	2.5	82.4
2023	13.1	8.3	4.7	72.7	10.1	7.2	2.9	77.0
2024	11.8	7.0	4.8	69.7	8.9	5.8	3.1	72.8
Food								
2010-2019	18.1	10.1	8.0	56.9	12.9	7.6	5.3	60.0
2020	17.0	9.6	7.4	56.8	11.5	6.9	4.6	60.5
2021	17.3	10.1	7.2	60.2	11.6	7.4	4.2	65.7
2022	24.3	17.2	7.1	73.0	18.8	14.7	4.1	80.3
2023	21.6	13.3	8.3	63.7	15.8	10.6	5.2	68.4
2024	18.3	10.5	7.8	59.1	12.6	7.6	4.9	61.9
NEIG								
2010-2019	12.0	5.5	6.5	51.5	6.4	3.7	2.8	59.6
2020	12.6	6.0	6.5	50.5	7.0	4.0	3.0	60.1
2021	12.6	6.9	5.7	57.4	7.4	4.9	2.5	67.4
2022	14.8	9.2	5.6	65.3	9.6	7.4	2.3	77.3
2023	13.4	7.1	6.4	58.2	7.9	5.2	2.7	68.3
2024	12.5	6.0	6.5	52.9	6.8	3.9	2.8	60.2
Services								
2010-2019	6.3	4.4	1.9	79.3	6.1	4.3	1.8	80.3
2020	6.2	4.1	2.2	77.3	6.0	4.0	2.0	78.2
2021	6.3	4.2	2.1	80.3	6.2	4.1	2.1	81.2
2022	9.6	7.5	2.1	85.9	9.4	7.4	2.0	86.4
2023	9.0	6.9	2.1	85.6	8.9	6.8	2.1	86.2
2024	9.2	6.4	2.8	83.5	9.0	6.3	2.7	84.1

Notes: The table shows the average frequency of price changes, increases, decreases and the share of price increases calculated by subperiod using the country-specific product samples (but excluding energy). All statistics are aggregated using euro area HICP weights (average product-level and country-level weights over the period 2017-2024).

Table B3: Share of products for which frequency/size is significantly **higher** than in 2019

Period	Frequency of price changes			Size of price changes			
	All	Increases	Decreases	All	Increases	Decreases	% inc.
% of products significantly higher than in 2019							
2020	13.8	13.1	12.6	4.7	14.1	8.3	3.1
2021	23.6	25.2	9.6	19.1	15.9	8.6	21.6
2022	68.4	73.1	9.1	65.4	40.0	14.7	59.2
2023	58.9	62.2	20.8	46.9	41.2	14.8	31.2
2024	38.0	35.9	22.2	19.9	33.6	15.5	11.9
By product category							
2022							
Food	67.6	75.8	12.9	78.4	49.7	26.2	75.9
NEIG	72.3	79.5	5.4	76.1	38.5	12.4	70.5
Services	65.8	66.1	9.8	47.6	37.5	7.9	38.6
2023							
Food	48.6	49.3	32.3	37.8	43.8	25.6	34.9
NEIG	56.5	66.6	14.6	48.4	35.5	15.7	40.0
Services	67.9	67.4	18.1	51.9	44.2	5.4	21.5
2024							
Food	21.2	19.6	26.7	9.8	36.4	25.5	14.9
NEIG	28.5	25.2	20.8	23.2	28.6	19.6	13.5
Services	57.2	55.5	20.2	24.1	35.8	3.0	8.6
By country in 2022							
Austria	35.3	40.0	21.6	32.0	27.2	4.6	16.8
Estonia	70.5	72.8	3.2	44.1	26.3	6.4	50.9
France	62.9	76.1	9.1	78.0	42.8	26.6	79.1
Germany	70.6	72.4	12.9	68.9	39.5	14.3	61.6
Greece	58.1	77.1	18.0	45.9	2.3	6.5	65.2
Italy	81.2	81.3	3.2	74.6	70.9	10.8	44.5
Latvia	79.6	80.8	7.4	52.5	44.6	4.8	37.8
Lithuania	80.0	83.2	5.1	54.0	13.1	9.3	59.1
Spain	64.7	64.7	2.4	33.5	8.9	7.5	43.5

Notes: The table shows the weighted share of products for which the product-level estimates of year effects (equation (1)) are significantly higher at 5% than in 2019. All statistics are aggregated using euro area HICP weights (average product-level and country-level weights over the period 2017-2024).

Table B4: Share of products for which frequency/size is significantly **lower** than in 2019

Period	Frequency of price changes			Size of price changes			
	All	Increases	Decreases	All	Increases	Decreases	% inc.
% of products significantly lower than in 2019							
2020	13.5	12.0	14.5	6.6	9.8	10.3	11.2
2021	11.3	9.6	18.5	4.1	8.9	10.0	5.1
2022	2.6	0.3	18.7	0.2	5.0	8.8	1.2
2023	1.5	0.3	12.7	0.6	5.4	8.3	4.3
2024	12.7	10.6	11.7	7.2	3.8	8.3	12.3
By product category							
2022							
Food	4.5	0.0	38.3	0.0	5.7	3.0	0.0
NEIG	2.7	0.0	20.4	0.6	3.9	15.4	0.5
Services	1.1	0.6	4.1	0.1	5.3	7.2	2.7
2023							
Food	2.5	0.0	25.5	2.2	7.5	7.8	9.1
NEIG	1.8	0.5	9.2	0.0	7.3	8.1	2.5
Services	0.7	0.2	6.9	0.0	2.4	9.0	2.3
2024							
Food	30.2	27.4	24.7	16.5	6.9	10.1	21.4
NEIG	13.0	9.1	11.0	6.8	1.0	6.4	16.6
Services	0.5	0.5	3.5	1.2	3.9	8.7	2.5
By country in 2022							
Austria	0.5	0.3	3.6	0.0	1.4	2.6	2.9
Estonia	0.0	1.4	4.4	1.4	1.3	3.7	1.5
France	2.0	1.0	42.3	0.6	7.7	16.2	1.5
Germany	2.2	0.0	10.6	0.0	3.7	7.1	1.8
Greece	0.0	0.0	4.4	1.2	34.3	4.5	0.0
Italy	0.0	0.0	6.0	0.0	0.0	9.6	0.5
Latvia	0.6	0.1	7.8	0.3	0.4	4.5	0.0
Lithuania	3.7	0.0	8.8	0.0	13.0	2.9	0.1
Spain	8.7	0.0	20.1	0.4	4.6	1.2	0.0

Notes: The table shows the weighted share of products for which the product-level estimates of year effects (equation (1)) are significantly lower at 5% than in 2019. All statistics are aggregated using euro area HICP weights (average product-level and country-level weights over the period 2017-2024).

Table B5: Product-specific estimation of year effects on the frequency and size of price changes (Reference period 2010-2019)

Period	Frequency of price changes			Size of price changes			
	All	Increases	Decreases	All	Increases	Decreases	% inc.
Panel A: Average β^y in pp.							
2020	-0.29	-0.30	0.02	0.03	0.48	0.06	-1.94
2021	-0.18	0.21	-0.40	1.22	0.38	0.13	4.33
2022	3.58	4.20	-0.62	3.98	1.24	0.31	14.39
2023	1.74	1.89	-0.15	2.33	1.21	0.35	7.48
2024	0.09	0.24	-0.16	0.93	1.04	0.15	2.21
Panel B: By sector - average β^y in pp.							
2022							
Food	5.84	7.53	-1.69	4.78	1.39	1.68	21.19
NEIG	2.95	3.32	-0.37	5.08	0.90	-0.25	17.99
Services	2.58	2.70	-0.12	2.55	1.41	-0.22	6.86
2023							
Food	2.32	2.72	-0.40	1.87	1.26	1.15	8.30
NEIG	1.45	1.50	-0.05	2.84	0.83	-0.26	9.11
Services	1.58	1.64	-0.06	2.23	1.49	0.30	5.58
2024							
Food	-1.50	-0.72	-0.78	0.09	0.93	0.99	0.82
NEIG	0.26	0.23	0.03	0.49	1.00	-0.03	0.59
Services	1.02	0.91	0.11	1.87	1.14	-0.37	4.49
Panel C: By country - average β^{2022} in pp.							
Austria	2.80	2.74	0.06	3.05	1.09	-0.23	7.63
Estonia	6.13	6.31	-0.18	3.03	0.99	2.97	13.13
France	2.29	3.53	-1.24	3.43	1.40	0.41	15.64
Germany	4.21	4.64	-0.42	4.82	1.08	0.32	14.18
Greece	5.80	5.68	0.11	7.92	-0.88	2.50	25.99
Italy	3.10	3.45	-0.35	2.86	1.84	-0.68	10.96
Latvia	5.98	4.91	-0.02	5.07	2.93	0.05	15.05
Lithuania	5.32	5.90	-0.60	2.60	-1.70	-0.63	13.95
Spain	4.42	5.11	-0.69	3.66	1.15	0.89	16.27

Notes: The table shows the weighted average of the estimated year effects on the frequency and size of price changes (reference period = 2010-2019), and the effect in 2022 by broad product categories and by country. Frequency and size estimates exclude price changes due to sales.

Table B6: Size of price changes in the euro area by subperiod: common euro area product sample

Period	Including sales				Excluding sales			
	All	Up	Down	% Up	All	Up	Down	% Up
Total								
2010-2019	1.9	12.3	15.7	63.0	1.5	8.8	11.3	67.2
2020	2.0	13.3	16.4	60.9	1.6	9.3	11.2	65.7
2021	3.6	13.2	16.5	65.6	2.7	9.3	11.5	71.2
2022	6.6	12.7	16.3	74.8	5.5	10.2	11.9	81.7
2023	4.7	13.3	16.0	69.3	3.9	10.2	11.6	74.8
2024	2.4	14.5	17.0	61.9	1.8	10.2	12.1	66.4
Food								
2010-2019	1.7	14.6	16.4	55.1	1.0	9.5	10.5	58.5
2020	1.9	16.5	18.4	54.0	1.3	10.5	11.2	57.9
2021	3.3	16.3	19.3	57.5	1.8	10.2	12.1	63.2
2022	7.3	14.8	19.3	71.2	5.7	11.3	12.9	79.0
2023	3.8	15.9	18.6	61.5	2.9	11.1	12.2	66.5
2024	1.9	16.4	18.3	56.0	1.1	10.8	12.2	59.0
NEIG								
2010-2019	-0.2	16.4	21.3	49.0	-0.6	10.2	13.8	57.8
2020	-0.0	16.7	21.8	47.1	-0.5	10.0	13.1	58.0
2021	2.7	16.4	21.2	54.4	1.5	10.1	13.6	65.7
2022	6.5	15.9	21.5	61.9	4.5	11.2	13.8	76.0
2023	3.8	16.6	21.0	55.4	2.3	11.2	13.6	67.1
2024	0.7	17.6	21.0	50.0	-0.1	11.3	13.9	58.5
Services								
2010-2019	3.7	7.5	10.7	80.0	3.6	7.2	9.8	81.1
2020	3.6	8.2	10.6	76.9	3.5	7.7	9.7	77.7
2021	4.5	8.3	10.6	80.4	4.4	7.9	9.4	81.6
2022	6.1	8.7	10.1	87.6	6.1	8.5	9.6	88.1
2023	6.0	8.8	10.2	86.2	5.9	8.6	9.5	87.0
2024	5.3	8.4	10.2	84.5	5.2	8.2	9.5	85.1

Notes: The table shows the average size of price changes, increases, decreases and the share of price increases calculated by subperiod using the common sample of products for the euro area (166 COICOP-5). All statistics are aggregated using euro area HICP weights (average product-level and country-level weights over the period 2017-2024).

Table B7: Size of price changes in the euro area by subperiod: country-specific product samples

Period	Including sales				Excluding sales			
	All	Up	Down	% Up	All	Up	Down	% Up
Total								
2010-2019	2.2	11.4	14.7	66.2	1.9	8.6	11.1	69.8
2020	2.4	11.9	14.8	64.9	2.1	8.8	10.5	69.0
2021	3.7	11.9	15.2	69.2	3.0	8.8	11.1	73.7
2022	6.3	11.7	14.8	77.0	5.5	9.7	11.1	82.4
2023	4.7	12.1	14.7	72.7	4.2	9.6	11.1	77.0
2024	3.3	12.7	15.3	69.8	3.0	9.9	11.9	72.9
Food								
2010-2019	1.8	14.3	16.5	56.9	1.2	9.7	10.9	60.1
2020	2.1	15.9	18.2	56.8	1.5	10.3	11.2	60.5
2021	3.4	15.6	19.2	60.2	2.0	9.8	12.1	65.7
2022	7.1	14.0	18.9	72.9	5.6	10.7	12.6	80.2
2023	3.9	15.1	18.2	63.7	3.0	10.7	11.9	68.4
2024	2.1	15.7	18.2	59.1	1.3	10.2	11.8	61.9
NEIG								
2010-2019	-0.1	15.0	20.2	51.5	-0.4	9.7	13.4	59.6
2020	0.2	15.0	20.2	50.4	-0.1	9.3	12.2	60.1
2021	2.7	14.8	19.7	57.4	1.6	9.4	12.7	67.4
2022	6.0	14.3	19.8	65.2	4.4	10.3	12.8	77.3
2023	3.6	15.1	19.7	58.3	2.3	10.5	13.0	68.4
2024	0.7	15.9	19.5	52.9	0.1	10.4	13.1	60.2
Services								
2010-2019	3.8	7.8	10.5	79.3	3.7	7.5	9.7	80.3
2020	3.9	8.2	10.0	77.2	3.8	7.9	9.3	78.2
2021	4.4	8.4	10.6	80.3	4.3	8.0	9.6	81.3
2022	6.1	9.0	9.9	85.9	6.1	8.9	9.4	86.4
2023	5.8	8.8	10.1	85.5	5.8	8.7	9.5	86.2
2024	5.3	9.7	11.8	83.6	5.3	9.5	11.3	84.2

Notes: The table shows the average size of price changes, increases, decreases and the fraction of price increases calculated by subperiod using the country-specific product samples (but excluding energy). All statistics are weighted using euro area HICP weights (average product-level and country-level weights over the period 2017-2024).

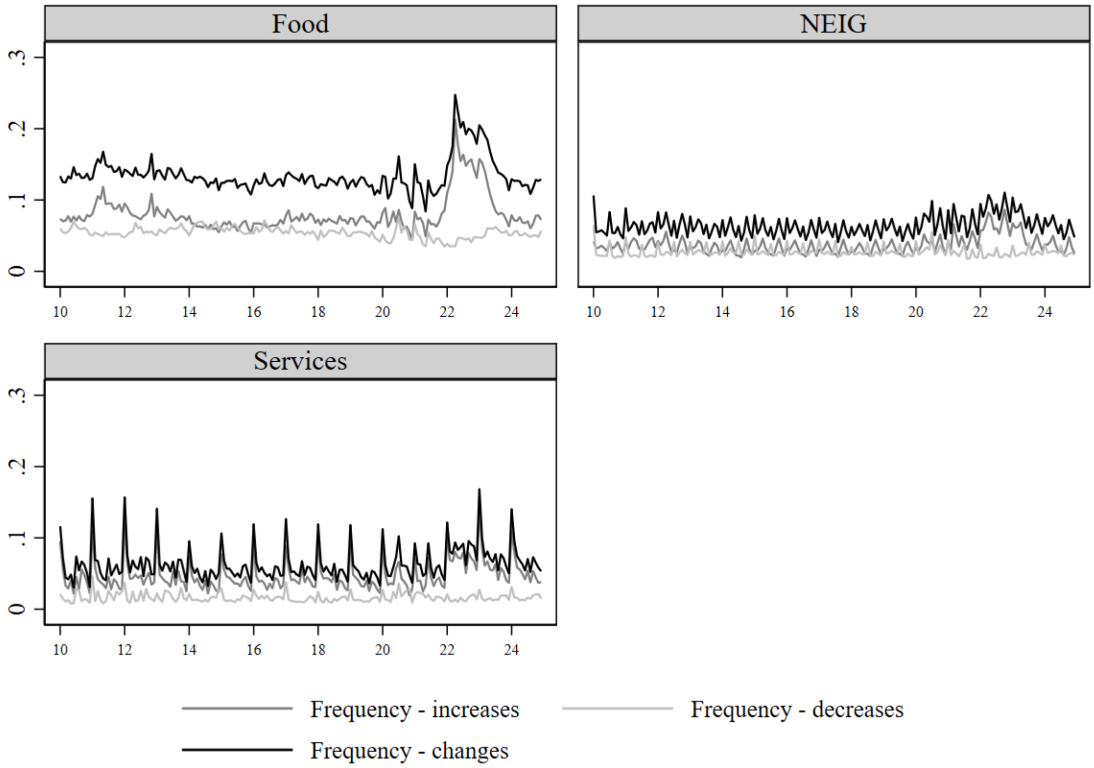
Table B8: Size of price changes in the euro area: higher moments

Period	Standard Dev.	Skewness	Kurtosis
Total			
Pre 2022	18.13	0.01	5.22
2022-2023	17.68	-0.02	5.16
Unprocessed Food			
Pre 2022	23.80	-0.02	3.23
2022-2023	22.35	-0.12	3.55
Processed Food			
Pre 2022	18.57	-0.03	4.20
2022-2023	18.96	-0.39	4.47
NEIG			
Pre 2022	22.99	0.05	3.83
2022-2023	22.79	-0.06	3.77
Services			
Pre 2022	11.74	0.01	7.72
2022-2023	11.08	0.24	7.21

Notes: The table shows higher moments of the distribution of price changes. The standard deviation, skewness and kurtosis of non-zero price changes are computed for each COICOP-5 country pair and then aggregated using euro area HICP weights. For each product, the distribution is computed for the period before 2022 and for the period 2022-2023.

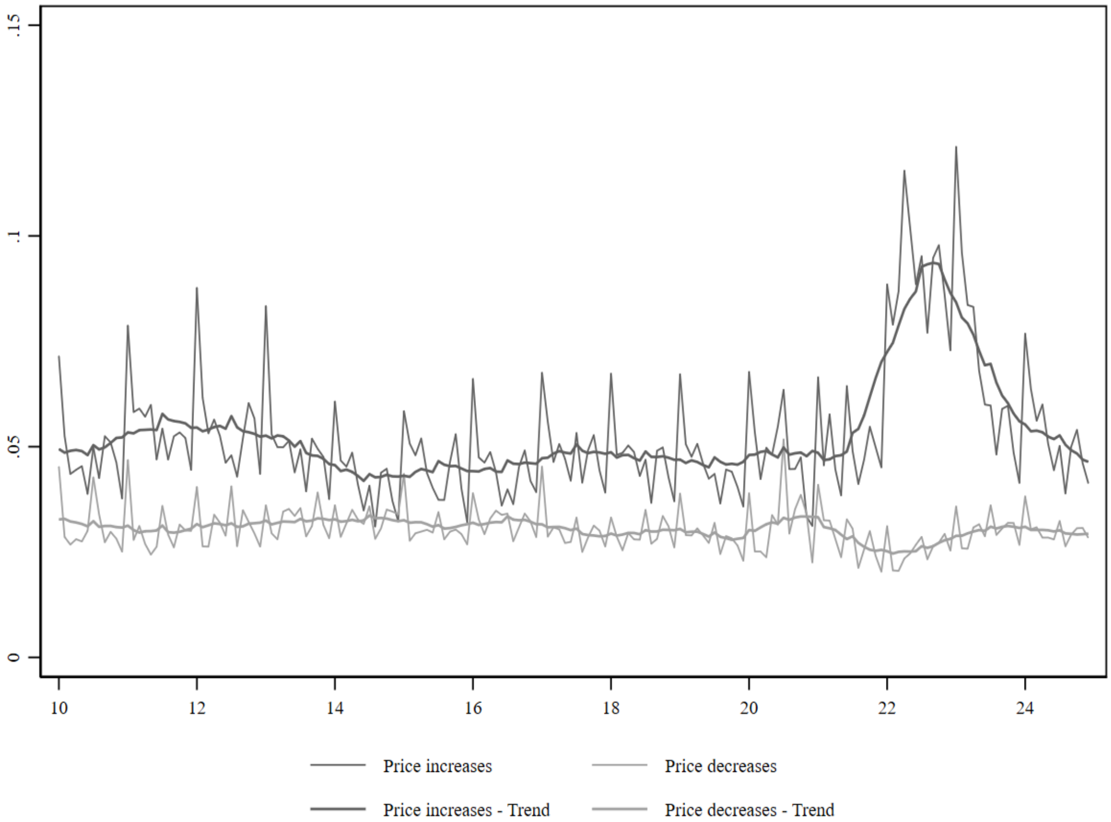
C Additional Figures

Figure C1: Frequency of price changes in the euro area by sector



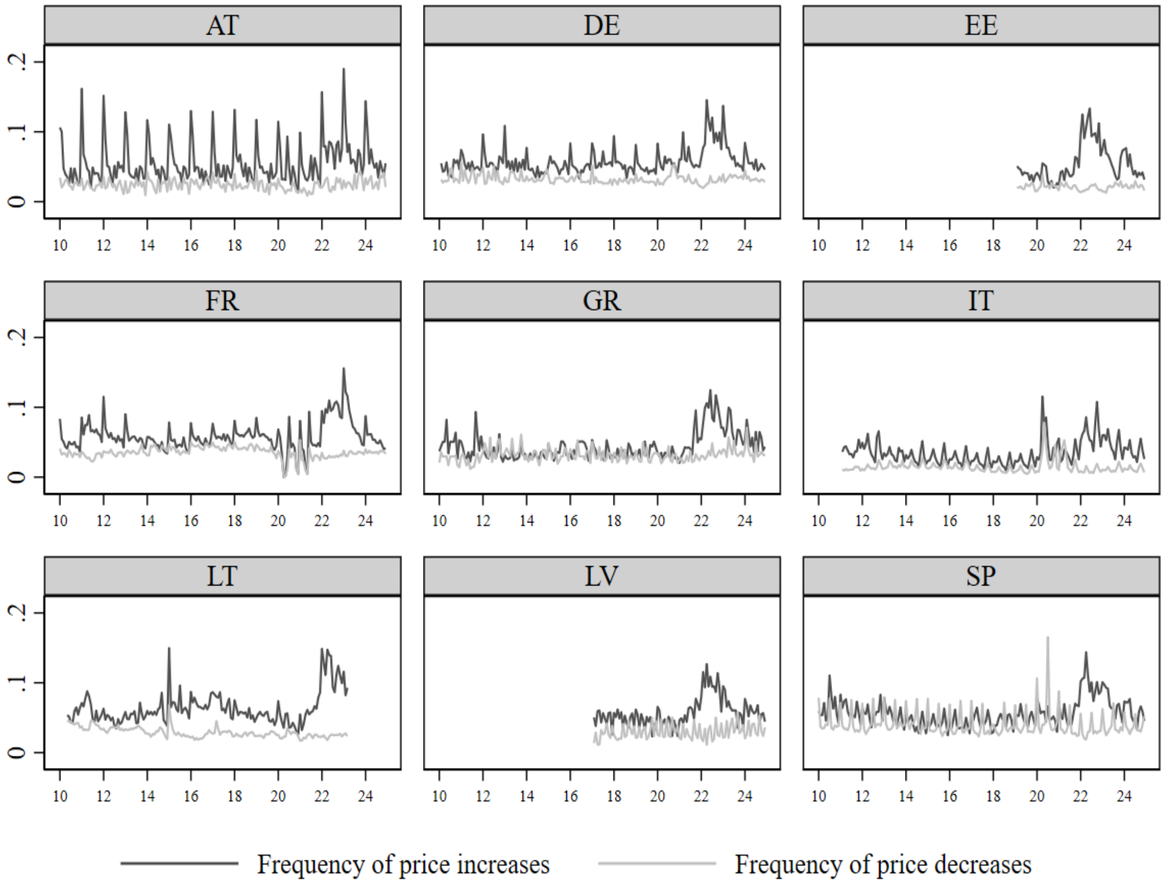
Notes: The graph shows the frequency of price changes, increases and decreases (excluding sales) by sector in the euro area over time. Country-level sectoral statistics are controlled for VAT changes by replacing the sectoral country statistics by their average values during the VAT changes.

Figure C2: Frequency of price increases and decreases in the euro area



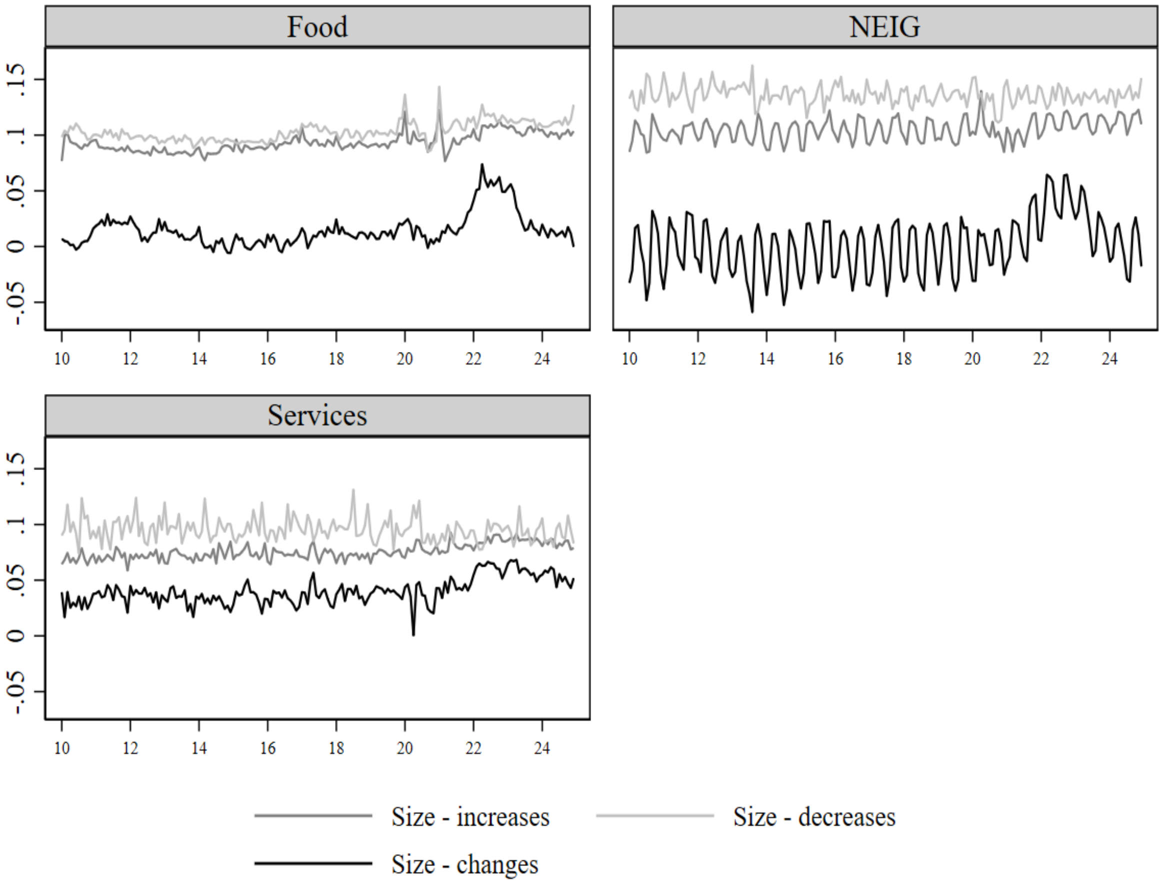
Notes: The graph shows the average frequency of price increases and decreases (excluding sales) in the euro area over time. Trends are obtained by applying a moving average with a +/- 6-period window. Country-level statistics are controlled for VAT changes by replacing the country statistics by their average values during the VAT changes.

Figure C3: Frequency of price increases and decreases by country



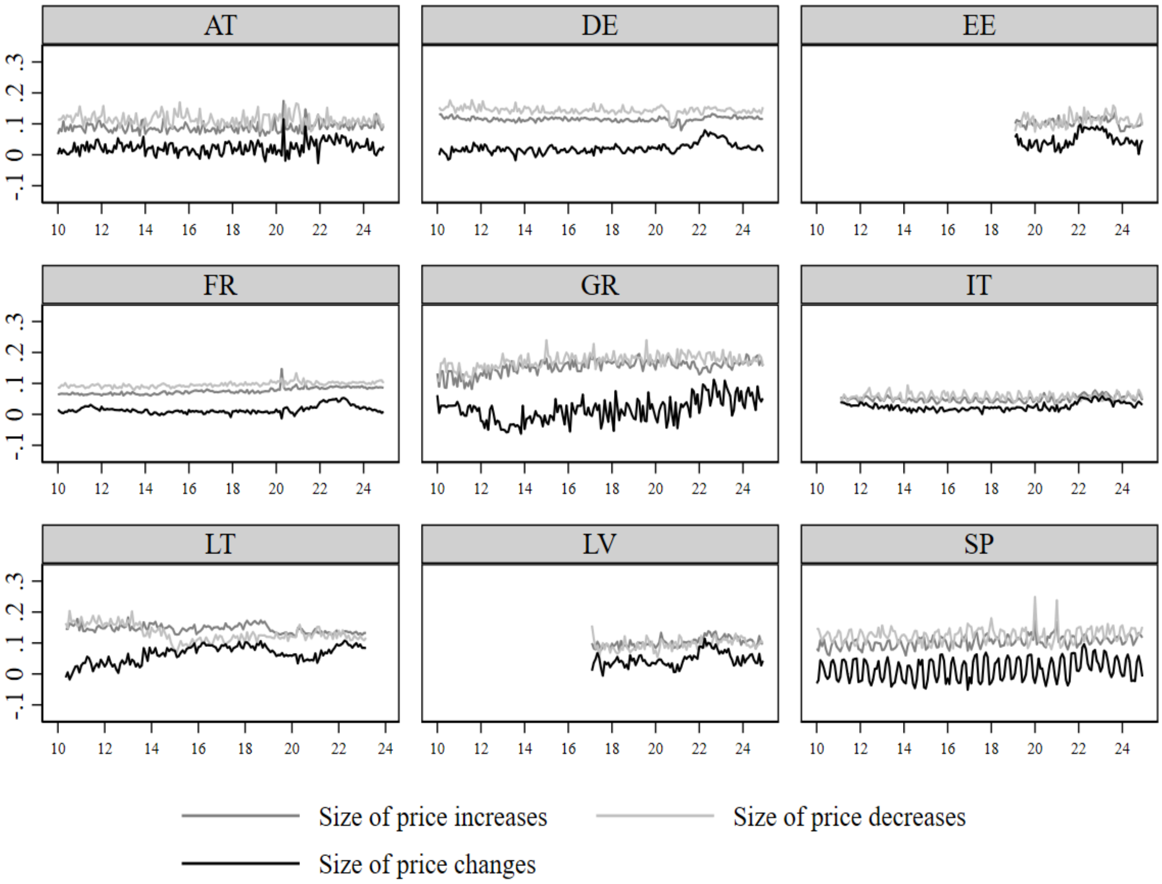
Notes: The graph shows the frequency of price increases and decreases (excluding sales) by country over time. Country-level statistics are controlled for VAT changes by replacing the country statistics by their average values during the VAT changes.

Figure C4: Size of price changes in the euro area by sector



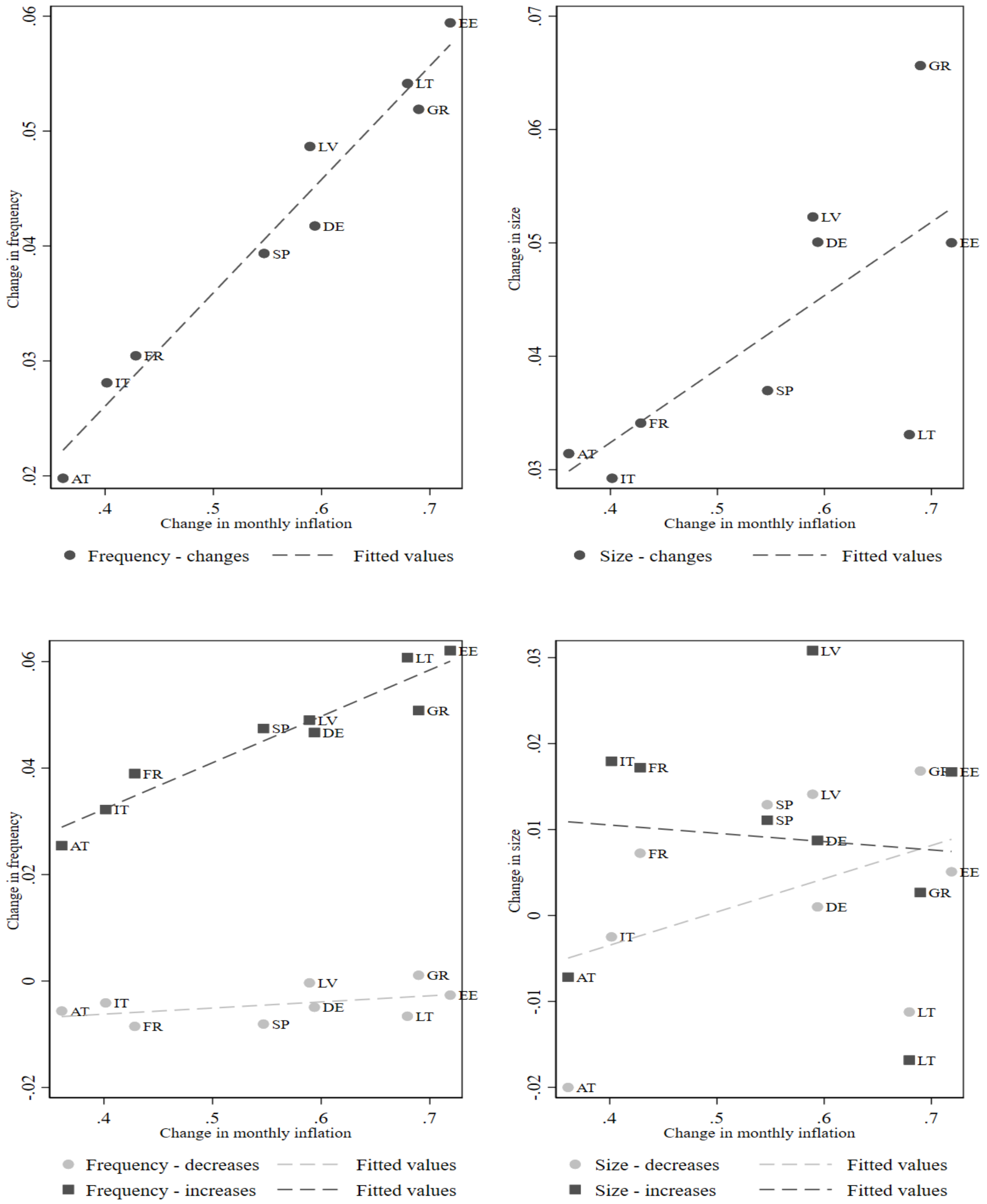
Notes: The graph shows the size of price changes, increases and decreases (excluding sales) by sector in the euro area over time. Country-level statistics are controlled for VAT changes by replacing the country statistics by their average values during the VAT changes.

Figure C5: Size of price changes by country



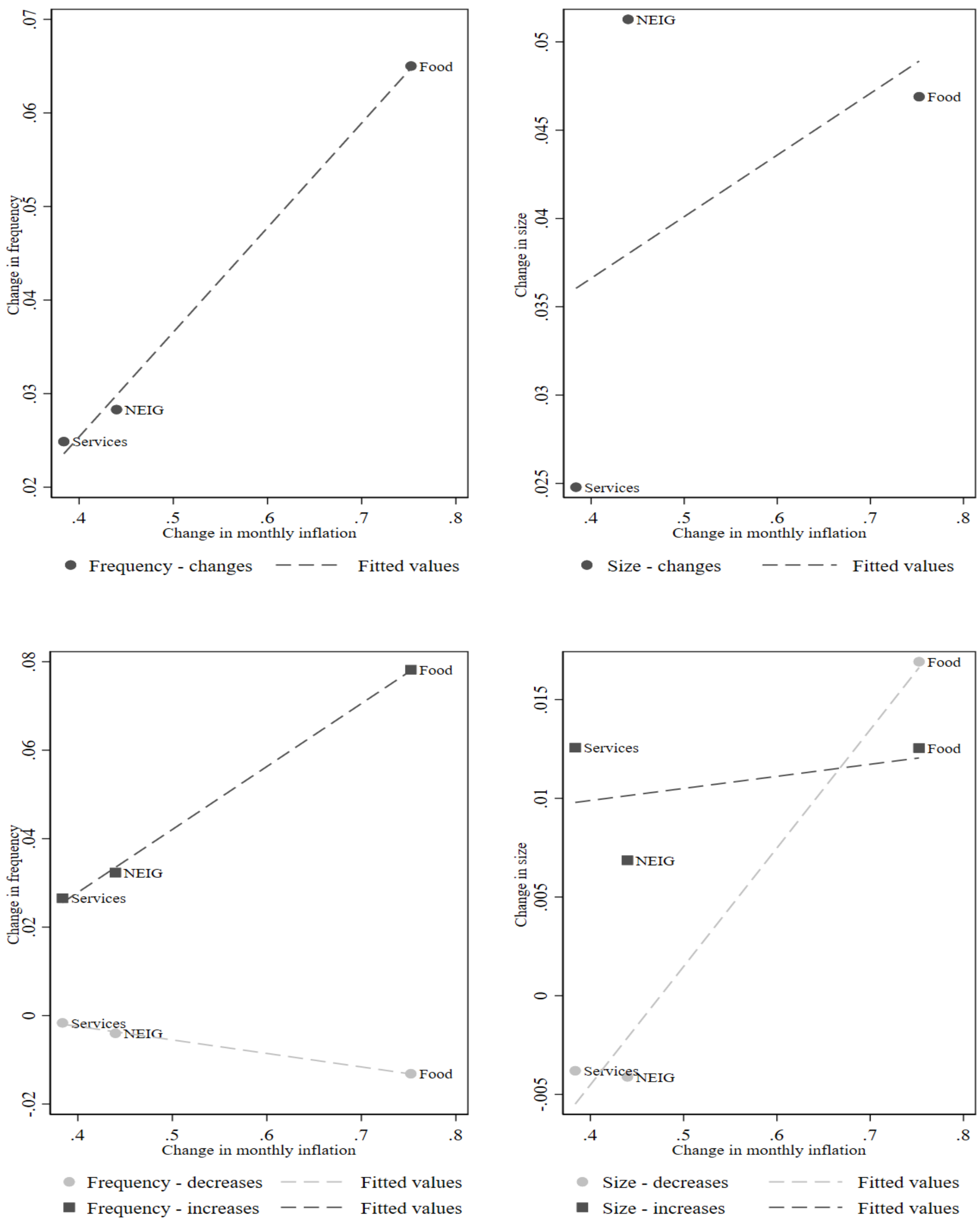
Notes: The graph shows the size of price changes, increases and decreases (excluding sales) by country over time. Country-level statistics are controlled for VAT changes by replacing the country statistics by their average values during the VAT changes.

Figure C6: Country-level frequency and size of price changes and inflation



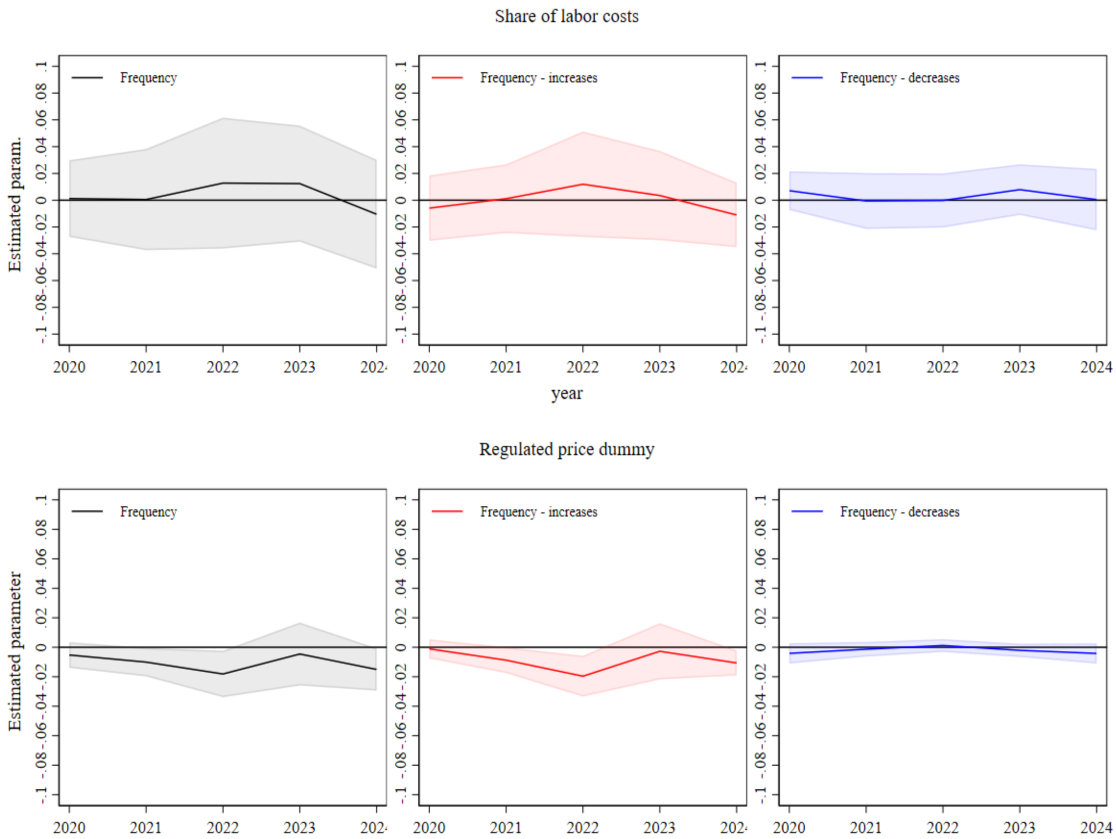
Notes: These graphs link the average change in 2022 from the average for 2010-2019 of the price setting statistics and the corresponding recomposed monthly inflation rate. To do this, we first calculate the average frequency and size of price changes (excluding sales) at the product level for the period 2010-2019 and the year 2022; we also calculate the monthly inflation rate for the same subperiods as the product of the frequency times the average size of price changes excluding sales. Next we calculate the product-level difference in these statistics between the two subperiods and aggregate these differences at the country level using euro area HICP weights (average 2017-2024).

Figure C7: Sector-level frequency and size of price changes and inflation



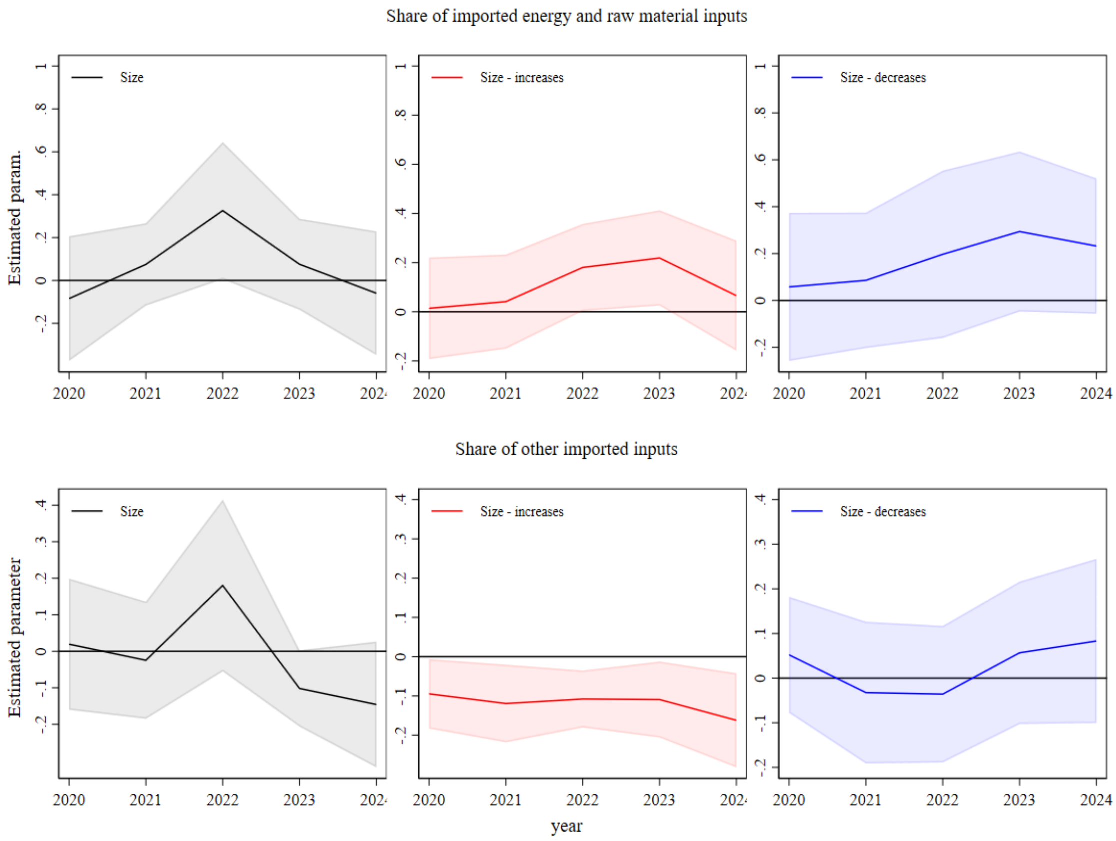
Notes: These graphs link the average change in 2022 from the average for 2010-2019 of the price setting statistics and the corresponding recomposed monthly inflation rate. To do this, we first calculate the average frequency and size of price changes (excluding sales) at the product level for the period 2010-2019 and year 2022; we also calculate the monthly inflation rate for the same subperiods as the product of the frequency times average size of price changes excluding sales. Next we calculate the product-level difference in these statistics between the two subperiods and aggregate these differences at the sector level using euro area HICP weights (average 2017-2024).

Figure C8: Cross-sectoral frequency of price changes in 2020-2024 and labour cost share/regulated prices



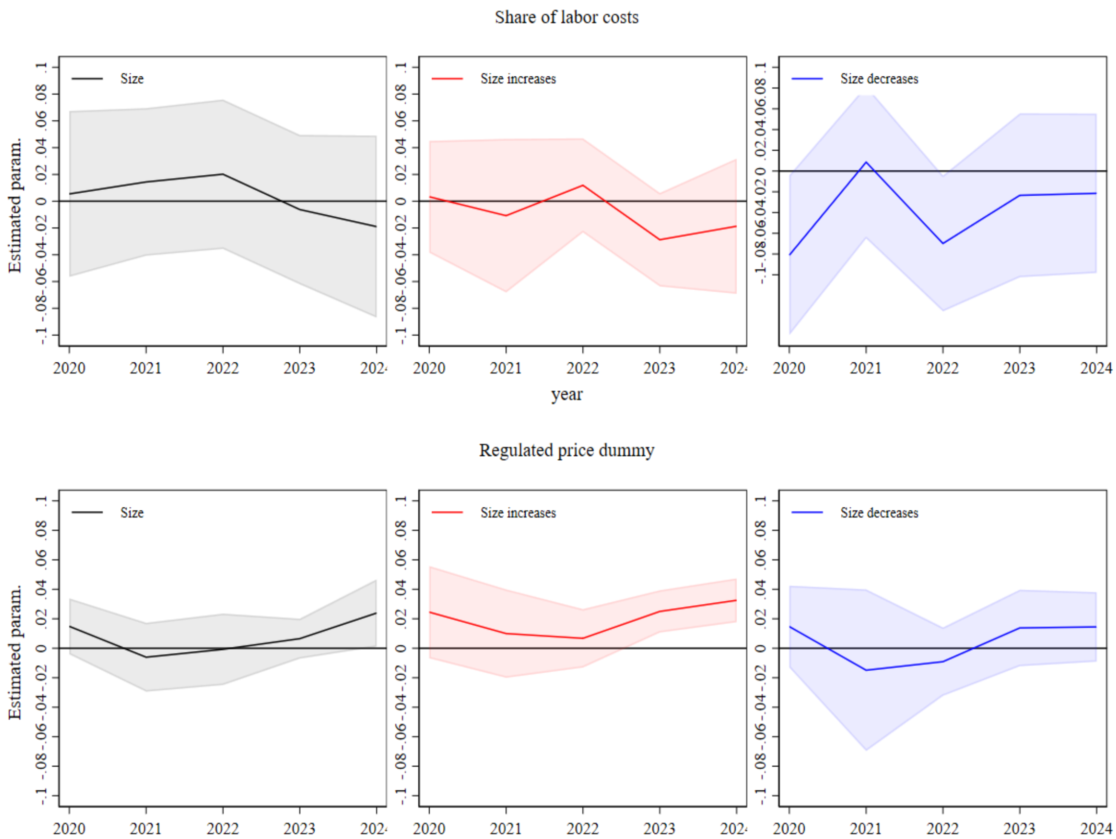
Notes: The figure shows the estimates of an OLS regression relating the year fixed effects estimated in equation (1) the product level β_j^y (capturing how the frequency is different in year t to that in 2019) to the product-level cost structure constructed from EA input-output matrices (equation (2)). This OLS equation is estimated for each set of year fixed effects (2020, 2021, 2022, 2023 and 2024) and for each variable (total frequency, frequency of price increases/decreases) taken separately. The top panel shows the results using a dummy variable for regulated prices as exogenous variable, whereas the lower panel reports the results for the labour cost share in total costs.

Figure C9: Cross-sectoral size of price changes in 2020-2024 and product-level cost structure



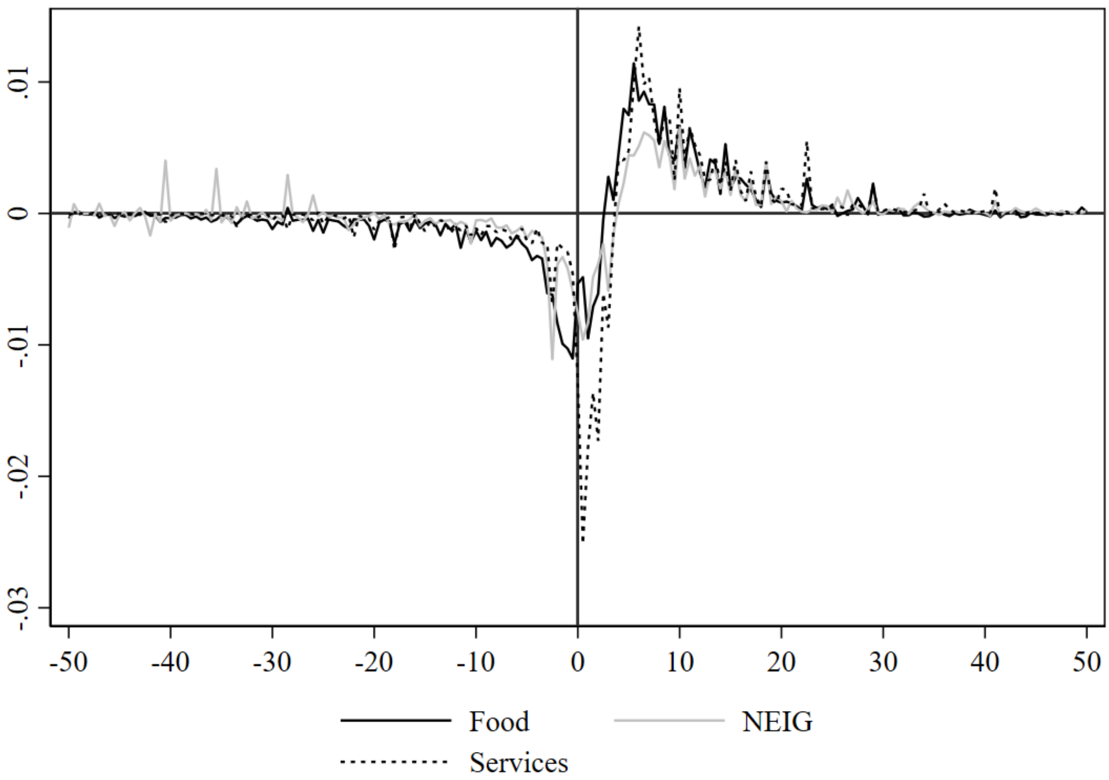
Notes: The figure shows the estimates of an OLS regression relating the year fixed effects estimated in equation (1) at the product level β_j^y (capturing how the size of price changes is different in year t to that in 2019) to the product-level cost structure constructed from EA input-output matrices (equation (2)). This OLS equation is estimated for each set of year fixed effects (2020, 2021, 2022, 2023 and 2024) and for each variable (total average size, size of price increases/decreases) taken separately. The top panel shows the results using the share of energy inputs as exogenous variable whereas the lower panel reports the results for the share of other imported inputs in the total costs.

Figure C10: Cross-sectoral size of price changes in 2020-2024 and product-level labour cost share/regulated prices



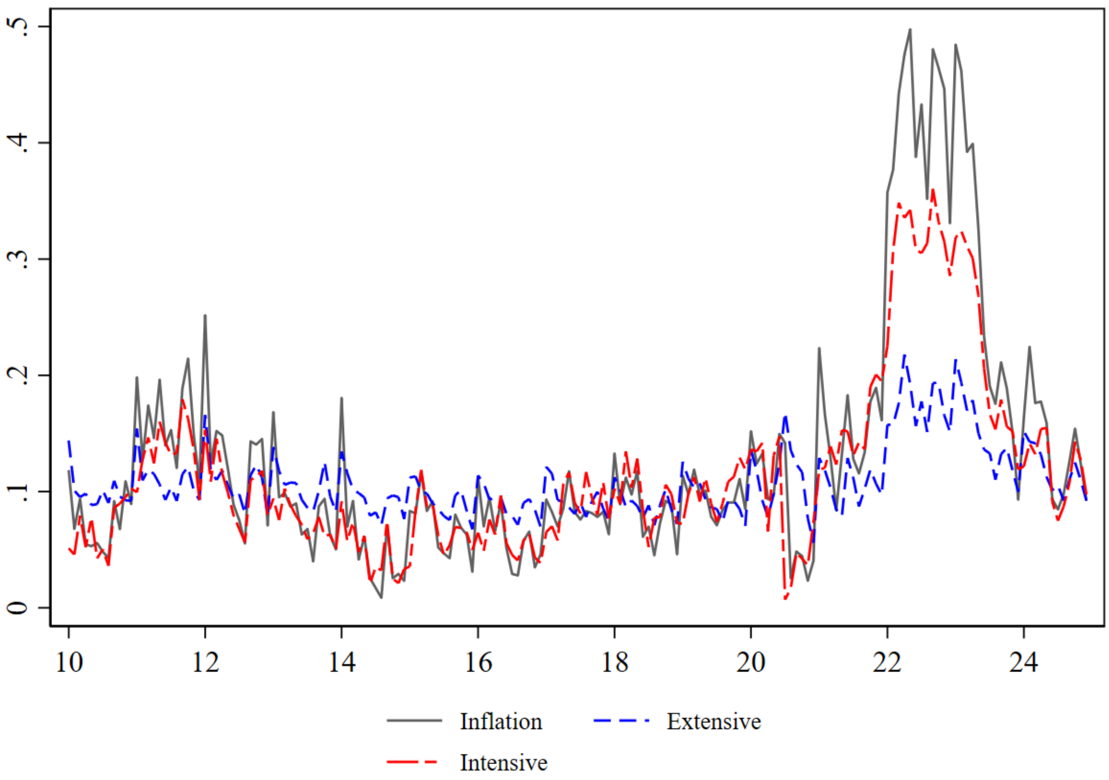
Notes: The figure shows the estimates of an OLS regression relating the year fixed effects estimated in equation (1) at the product level β_j^y (capturing how the size of price changes is different in year t to that in 2019) to product-level cost structure constructed from EA input-output matrices (equation (2)). This OLS equation is estimated for each set of year fixed effects (2020, 2021, 2022, 2023 and 2024) and for each variable (total average size, size of price increases/decreases) taken separately. The top panel shows the results using a dummy variable for regulated prices as exogenous variable whereas the lower panel reports the results for the labour cost share in total costs.

Figure C11: Change in the distribution of price adjustment size by sector before and after 2022



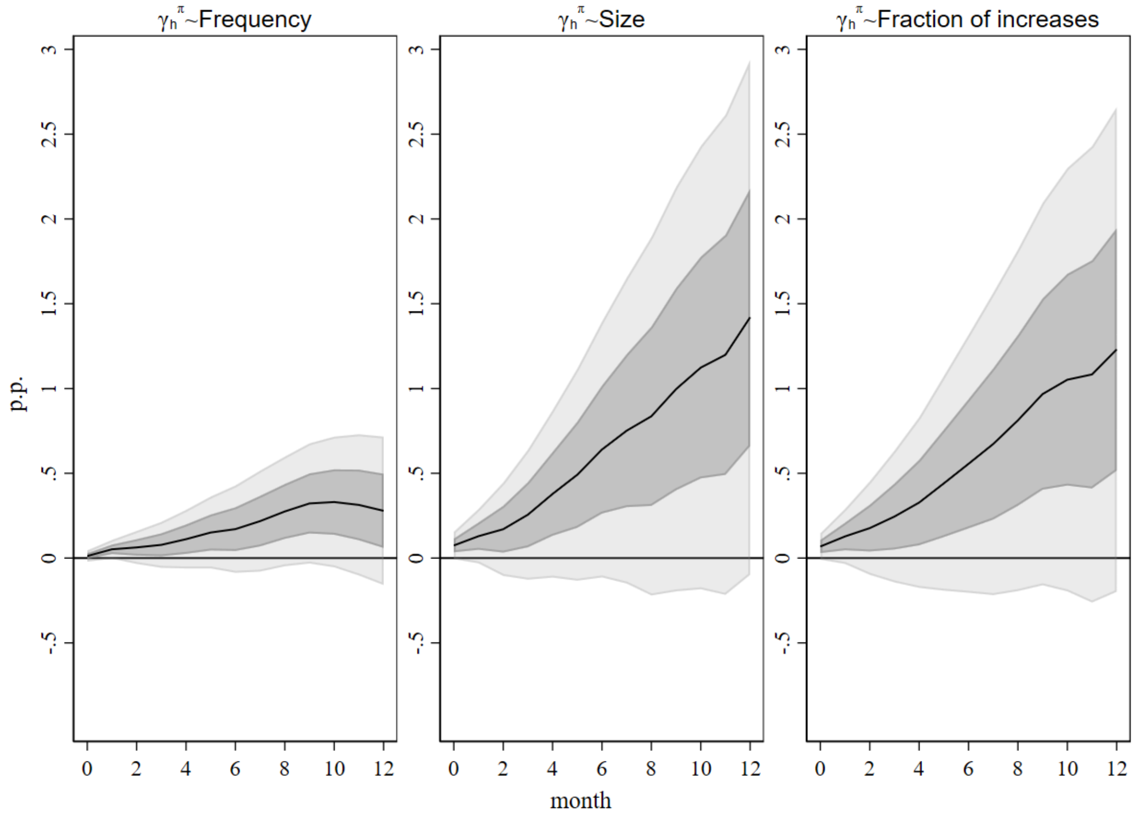
Notes: The graph shows the change in the distribution of the size of price changes (excluding sales) by sector between 2022/2023 and before 2022 estimated by histogram bins.

Figure C12: Counterfactual inflation rates: extensive and intensive margins



Notes: The graph shows the monthly inflation rate calculated as a weighted average of the recomposed inflation rates from our price setting statistics (excluding sales) (solid black line), the counterfactual inflation rate assuming that the size of price changes does not vary (extensive margin, blue dashed line) and the counterfactual inflation rate assuming that the frequency of price changes does not vary over time (intensive margin, red dashed line).

Figure C13: Counterfactual inflation rate responses to a negative oil supply shock: periods of high and low inflation



Notes: This graph plots the estimated response of product-specific counterfactual inflation rates (excluding sales) to a negative oil supply shock (Baumeister and Hamilton, 2019) in the high inflation period from January 2022 to June 2023 in comparison to the period before 2020. The left panel plots the response of the counterfactual inflation rate assuming a constant size of price changes (extensive margin), the centre panel the response of the counterfactual inflation rate assuming a constant frequency (intensive margin), and the right panel the response of the counterfactual inflation rate assuming that only the fraction of price increases varies.

D Details on the Measurement of the Price Gap

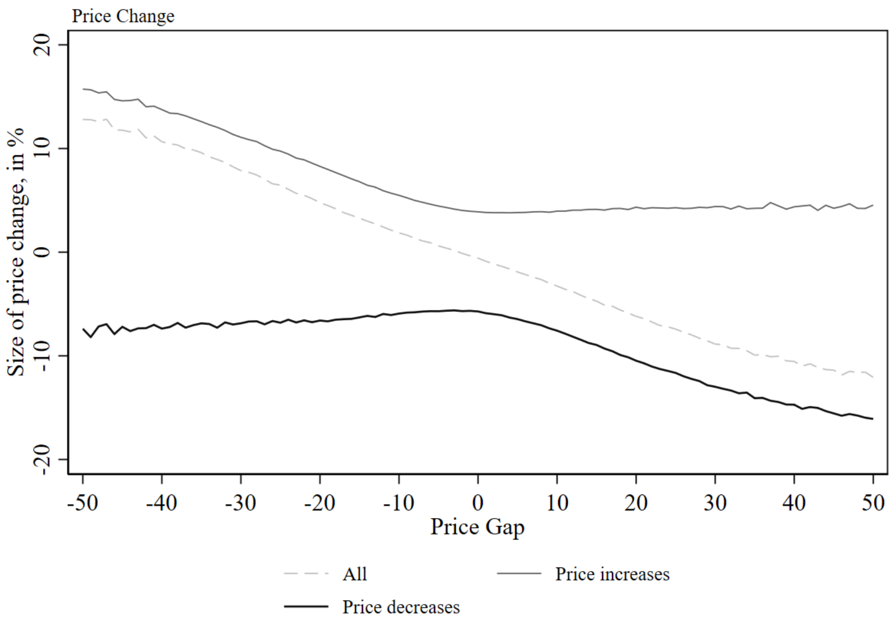
The hazard rate of price adjustments measures the probability of a price change occurring as a function of the price gap between the observed price and the frictionless price. Estimating this price gap presents an empirical challenge, as the frictionless price is unobservable. We use the average price of competitors as a proxy for this frictionless price and measure the price gap as follows:

1. We take the logarithm of the reference prices of each outlet o selling a product of COICOP-5 category j at time t, denoted p_{jot}.
2. We calculate the unadjusted gap as $x^*_{jot} = p_{jot} - p_{jt}$, where p_{jt} is the average reference reset price of the same product across outlets that changed the price of the same product category in month t.
3. To deal with persistent heterogeneity across outlets, we subtract the average outlet price gap α_{js}, and we reformulate the price gap as $x_{jot} = x^*_{jot} - \alpha_{js}$.
4. We remove unobserved heterogeneity across items and the common impact of aggregate fluctuations by estimating product and time fixed effects: $x_{jot} = \alpha_j + \beta_t + \epsilon_{jot}$. The price gap is measured as: $g_{jot} = x_{jot} - \hat{\alpha}_j - \hat{\beta}_t$.

The challenge is to measure accurately the reference price of competitors that have changed prices, and this requires detailed information at the product level. This information is available for 166 products at the COICOP-5 level for all countries. We also exploit more detailed product-level data for Germany, Austria, France and Spain. Information is available for Germany for instance for around 770 products at the COICOP-10 level, and the COICOP-5 component "cheese and curd" is decomposed into the five groups of "hard cheese", "sliced cheese", "soft cheese", "curd", and "cream cheese". Information is available for Austria for 1,140 products with detailed information for COICOP-6 codes. Data for France are available for 4,500 products at the variety level, with around 22 varieties per COICOP-6 code. Information for Spain is available for 211 products with detailed information for some COICOP-5 codes.

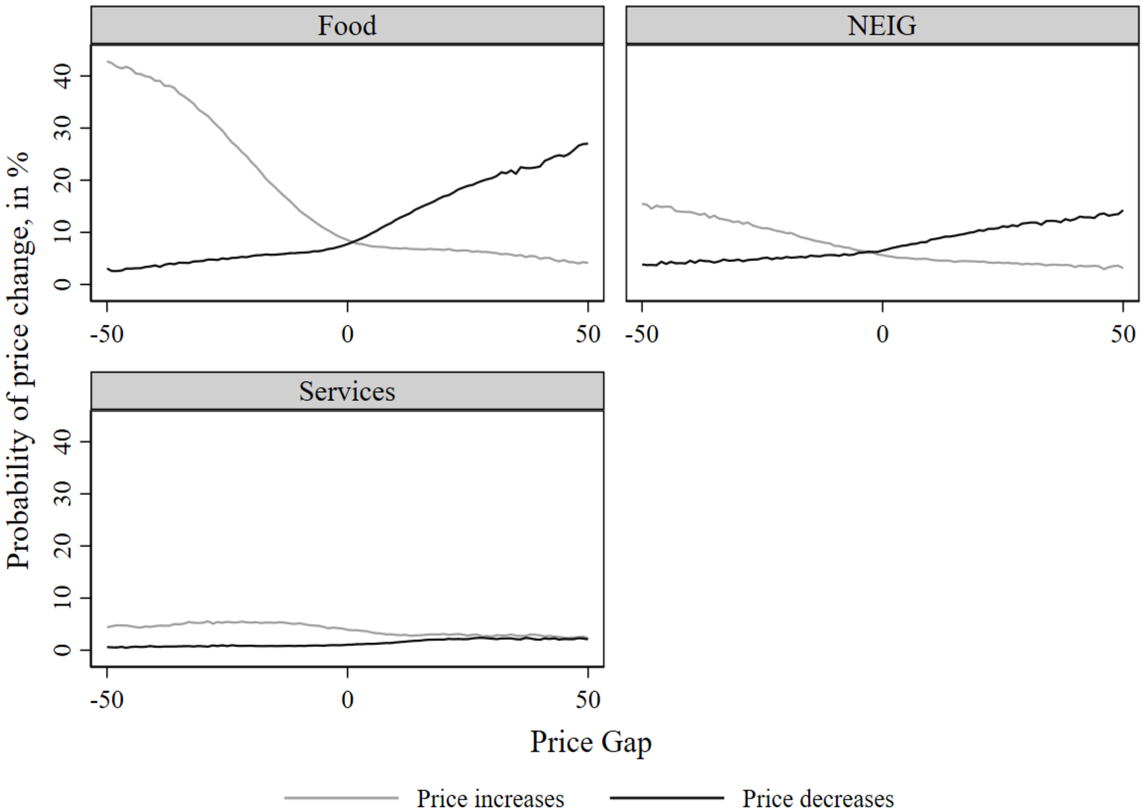
As a robustness check, we have calculated the price gap using the COICOP-5 product category for Austria, France, Germany and Spain, which together account for around 75% of our country sample in terms of HICP weights. This implies that, in contrast with the results of section 5, the product definition is less detailed and the number of countries available is lower. Figure D4 plots the average frequency of price changes as a function of the estimated price gap for the baseline product disaggregation (solid lines) and the common COICOP-5 product disaggregation (dashed lines). The probability of price increases is plotted in grey and the probability of price decreases in black. Our results using products at the COICOP-5 level depict a lower state dependency for price gaps below 20%, meaning the slope of the hazard rate is less steep for values between -20 and 0 for price increases and between 0 and 20 for price decreases. This would be consistent with larger measurement errors when we define the reference price at a less disaggregated level of products. We observe a larger difference in hazard rates for larger price gaps, but this is because only a very small share of price gaps are larger than 20% in absolute values. Overall, the differences in hazard rates are quite limited, as the probability of prices being adjusted when they are 10% below the optimal for instance is 10.6% in our baseline case, while it reaches 10.0% when the COICOP-5 disaggregation is used. For the same positive gap, the probability of a downward adjustment is 9.8% in the baseline and 9.1% with the COICOP-5 disaggregation.

Figure D1: Average size of price changes by price gap in the euro area



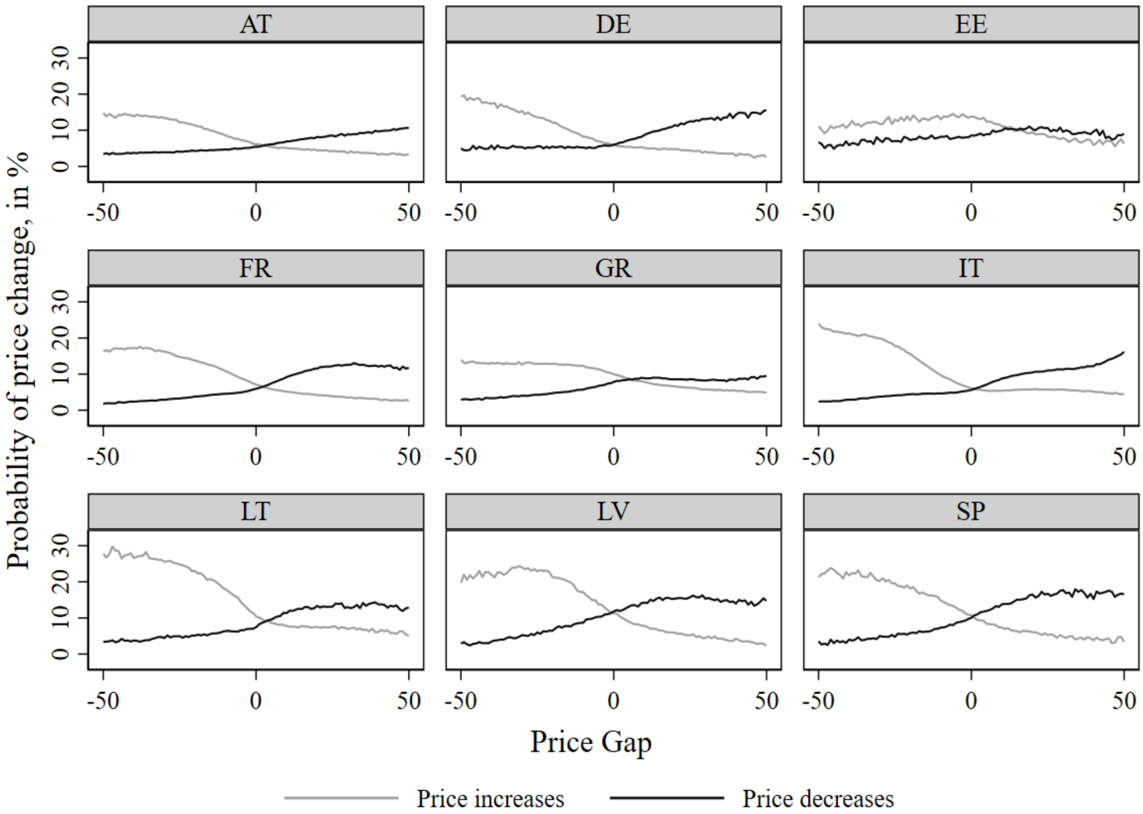
Notes: For each country, we calculated the average of (non-zero) price changes/increases/decreases for each bin (width=1%) of the price gaps ($x_{jt} = p_{jt} - p^*_{jt}$) between -50% and +50%. The euro area figure is obtained by averaging the country results using average HICP country-level weights over the period 2017-2024.

Figure D2: Adjustment hazard rates in the euro area by sector



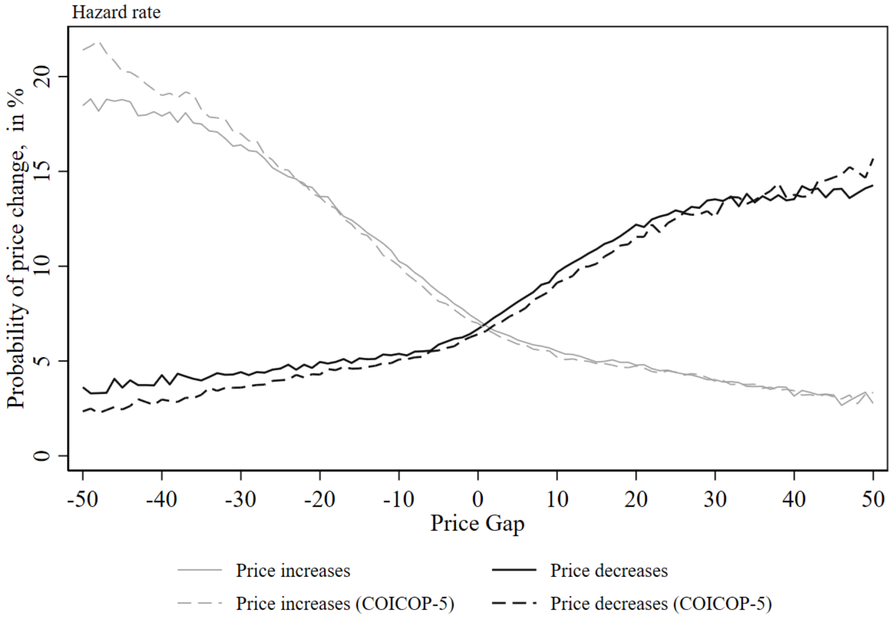
Notes: The graph plots the probability of price increases/decreases as a function of price gaps for a given sector. The euro area figure is calculated as the weighted average of country sector-specific results (average HICP country weights over the period 2017-2024).

Figure D3: Adjustment hazard rates by country



Notes: The graph plots the probability of price increases/decreases as a function of the price gap.

Figure D4: Adjustment hazard rates - Austria, Germany, France and Spain



Notes: This graph plots the hazard rates for the country aggregate of Austria, Germany, France and Spain. It depicts the probability of price increases/decreases as a function of the price gap for the baseline product disaggregation (solid lines) and for the common COICOP-5 products (dashed lines). Country weights of the euro area HICP (2017-2024 average) are used to aggregate country-specific results.

E Details on the Macro Model

The model used in section 5.4 is a standard off-the-shelf model from Gasteiger and Grimaud (2023). In this model, the asymmetry in the firm's profit function in terms of present values generates a strong incentive to avoid being locked into a low relative price. This asymmetry arises because a low relative price can lead to suboptimal profit per unit, and as a result, firms are more likely to update their prices frequently during inflationary shocks to maintain profitability. Conversely, the difference between the resetting and holding prices decreases in terms of present value during disinflationary periods, and so updates are less frequent. This dynamic underpins the state-dependent behaviour observed in the model, where the price-setting frequency is higher in response to inflationary shocks than to disinflationary ones. This model is simpler than the standard state-dependent pricing frameworks and more straightforward to incorporate into a general equilibrium model because it abstracts from selection effects at the idiosyncratic level. By doing so, it provides a reduced-form approximation of the aggregate dynamics of price-setting frequency. This approach aligns with the aggregate implications of state-dependent pricing models featuring random menu costs (Costain and Nakov, 2019; Nakamura and Steinsson, 2010) or information constraints (Woodford, 2009).

The dynamic equations of the model are summarised there:

- Household side:

$$\psi L_t^{\varphi} = C_t^{-\sigma}(1-\varepsilon_{w,t})w_t \tag{E1}$$

$$1 = (1-\varepsilon_t^b)R_t \mathbb{E}_t \Lambda_{t,t+1}\pi_{t+1}^{-1} \tag{E2}$$

$$\Lambda_{t,t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\sigma} \tag{E3}$$

- Linear monetary authority:

$$R_t = (1-\rho)\overline{R} + \rho R_{t-1} + \phi_\pi(\pi_t - \overline{\pi}) + \phi_y\left(\frac{Y_t}{\overline{Y}} - 1\right) + \varepsilon_{r,t} \tag{E4}$$

- Optimal reset price with time-varying Calvo share:

$$\pi_t^{\#} = \frac{\epsilon_p}{\epsilon_p - 1}\frac{x_{1,t}}{x_{2,t}} \tag{E5}$$

$$x_{1,t} = p_{w,t}Y_t + \mathbb{E}_t\theta_{t+1}\Lambda_{t,t+1}\pi_{t+1}^{\epsilon_p}x_{1,t+1} \tag{E6}$$

$$x_{2,t} = Y_t + \mathbb{E}_t\theta_{t+1}\Lambda_{t,t+1}\pi_{t+1}^{\epsilon_p-1}x_{2,t+1} \tag{E7}$$

- Price dynamics:

$$1 = (1 - \theta_t) \left(\pi_t^{\#}\right)^{1-\epsilon_p} + \theta_t \pi^{\epsilon_p - 1} \tag{E8}$$

- Marginal cost:

$$p_{w,t} = w_t \tag{E9}$$

- Price dispersion:

$$v_t^p = (1 - \theta_t) \left(\pi_t^{\#}\right)^{-\epsilon_p} + \theta_t \pi_t^{\epsilon_p} v_{t-1}^p \tag{E10}$$

- Share of fixed prices:

$$\theta_t = \frac{\exp\left(\gamma V_t^f\right)}{\exp\left(\gamma V_t^f\right) + \exp\left(\gamma \left(V_t^{\#} - \tau_p\right)\right)}, \tag{E11}$$

- Present-value for the old price:

$$V_t^f = \left({p_t^f}^{1-\epsilon_p} x_{2,t} - {p_t^f}^{-\epsilon_p} x_{1,t}\right), \tag{E12}$$

- Present-value for the reset price:

$$V_t^{\#} = \left({p_t^{\#}}^{1-\epsilon_p} x_{2,t} - {p_t^{\#}}^{-\epsilon_p} x_{1,t}\right), \tag{E13}$$

- Definition of old price:

$$p^f = \frac{1}{\pi_t} \tag{E14}$$

- Aggregation:

$$Y_t v_t^p = L_t \tag{E15}$$

- Demand shock:

$$\epsilon_t^d = \rho_d \epsilon_{t-1}^d + u_{\epsilon^d,t}, \qquad \text{with} \qquad u_{\epsilon^d} \sim \text{iid } \mathcal{N}(0, \sigma_d^2) \tag{E16}$$

- Supply shock:

$$\epsilon_t^w = \rho_w \epsilon_{t-1}^w + u_{\epsilon^w,t}, \qquad \text{with} \qquad u_{\epsilon^w} \sim \text{iid } \mathcal{N}(0, \sigma_w^2) \tag{E17}$$

- Monetary policy shock:

$$\epsilon_t^r = u_{\epsilon^r,t}, \qquad \text{with} \qquad u_{\epsilon^r} \sim \text{iid } \mathcal{N}(0, \sigma_r^2) \tag{E18}$$

- Observation equations:[11]

$$\text{detrended euro area GDP growth } = 100 \times \left(\frac{Y_t}{Y_{t-1}} - 1\right) \tag{E19}$$

$$\text{Euro area HICP inflation} = 100 \times (\pi_t - 1) \tag{E20}$$

$$\text{Krippner shadow rate} = 100 \times (R_t - 1) + \overline{r} \tag{E21}$$

$$\text{Quarterly share of unchanged prices (excluding sales)} = \theta_t + u_{\epsilon^\theta,t}, \qquad \text{with} \qquad u_{\epsilon^\theta} \sim \text{iid}\mathcal{N}(0, \sigma_\theta^2) \tag{E22}$$

To estimate the model, we follow the methodology of Ascari et al. (2025) and use an inversion filter (Cuba-Borda et al., 2019) combined with a nonlinear solution method (Fair and Taylor, 1983) to recover sequences of observation errors, demand, supply, and monetary policy shocks that replicate observed dynamics of the euro area. The inversion filter yields the log marginal density, which we maximise before sampling parameters 400,000 times with a standard Markov Chains Monte Carlo algorithm (An and Schorfheide, 2007).

We target the euro area HICP, the detrended GDP growth (euro area GDP), and the Krippner (2013) shadow rate. To reconcile discrepancies between the model's endogenous quarterly aggregate share of fixed prices and the observed data, we also filter a sequence of measurement errors. These observation errors can be attributed to both model-side inaccuracies and data-side limitations, such as the incomplete coverage of the consumption basket underlying the euro area HICP for our measure of frequency of price changes.

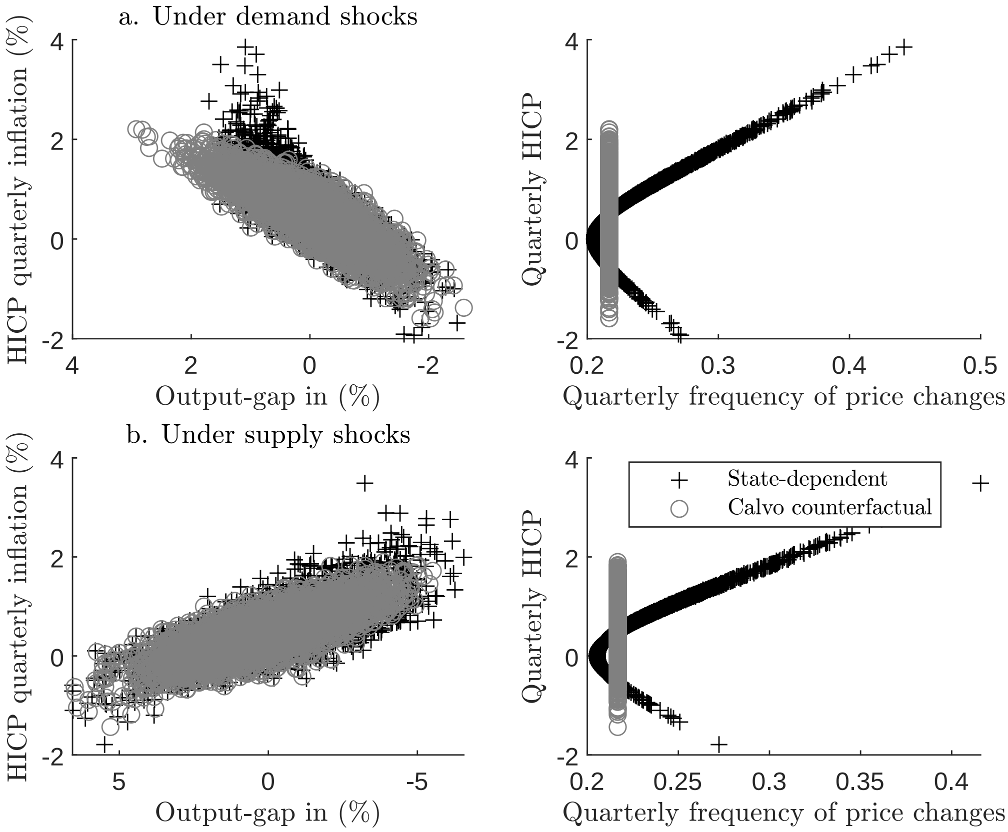
We calibrate two parameters that are difficult to identify, the discount factor $\beta = 0.995$ and the elasticity of substitution $\epsilon = 6$. All other priors are standard in the literature, and results are robust to prior sensitivity. The two key estimated parameters are the steady-state resetting share $\overline{\phi} = 0.783$ and the elasticity of price-resetting frequency $\gamma = 9.4$, broadly in line with Ascari et al. (2025), who identify γ using only macroeconomic moments.

Looking at Figure 7, the main discrepancy between the data and the latent state variable in the resetting frequency arises during periods of sharp increases in the price-resetting frequency, where the model predicts changes one quarter earlier than the observed data. This misalignment may be

[11] It might be argued that the HICP is not the most appropriate time series to use in conjunction with our dataset, particularly given the exclusion of energy prices from the resetting frequency. However we contend that, within a general equilibrium framework and the context of a highly simplified model, the HICP remains the most relevant index from the perspective of both the household and the central bank. This relevance justifies the introduction of measurement errors to connect the model's endogenous dynamics of resetting frequencies with our dataset. To address this concern, we conducted the same analysis using the HICP excluding energy. The results showed no strong differences from those obtained using the overall HICP.

attributed to the exclusion of energy prices from our micro price datasets, which capture only the second-order effects of energy shocks, such as those triggered by Russia's invasion of Ukraine. A second explanation in the timing issue might be the limitation of this model regarding the selection effect. By assuming that the trade-off is based on the average old price and not idiosyncratic hold prices, the model might understate the effect of the extensive margin adjustments on the offset of the shock, meaning the price changes might be too small, and overstate it later during the propagation of the shock, meaning the price changes might be too big.

Figure E1: Counterfactual simulation with and without state dependency under random shocks



Notes: This graph shows the counterfactual simulations for the quarterly frequency of price changes based on the model by Gasteiger and Grimaud (2023). The variance of the shocks are the historical ones. No adjustment has been made to handle the excess volatility during the COVID-19 pandemic. The variance of the demand shock is therefore highly likely to be overstated.

Table E1: Estimated parameters for dynamic simulations (quarterly basis)

		Prior Distribution			Posterior Distribution		
		Shape	Mean	Std	Mode	Mean	[5%:95%]
Panel A: Shock processes							
Demand shock std	σ_d	$\mathcal{IG}_2$	0.001	1	0.0011	0.0012	*[0.0009:0.0016]*
Cost-push shock std	σ_s	$\mathcal{IG}_2$	0.001	1	0.0168	0.018	*[0.0142:0.0223]*
Monetary policy shock std	σ_f	$\mathcal{IG}_2$	0.001	1	0.0012	0.0012	*[0.001:0.0014]*
AR(1) of the demand shock	ρ_d	$\mathcal{B}$	0.5	0.2	0.9805	0.9772	*[0.9622:0.988]*
AR(1) of the cost-push shock	ρ_s	$\mathcal{B}$	0.5	0.2	0.9473	0.9418	*[0.9085:0.9676]*
Panel B: Structural parameters							
Relative risk aversion	σ	$\mathcal{G}$	2	1	2.0653	2.1578	*[1.676:2.6929]*
Inverse Frish elasticity	φ	$\mathcal{G}$	2	1	0.1636	0.2203	*[0.0726:0.4376]*
Inflation stance	ϕ_π	$\mathcal{N}$	2	0.05	1.9494	1.9489	*[1.864:2.0331]*
Output stance	ϕ_y	$\mathcal{N}$	0.125	0.01	0.124	0.1221	*[0.1057:0.1386]*
MPR smoothing	$\rho_\imath$	$\mathcal{B}$	0.5	0.1	0.9279	0.9262	*[0.9087:0.9422]*
Panel C: Pricing parameters							
Steady-state non-resetting share	$\overline{\theta}$	$\mathcal{B}$	0.7	0.1	0.7833	0.7837	*[0.7766:0.7909]*
Elasticity of price resetting frequency	γ	$\mathcal{N}$	10	0.5	9.4421	9.4001	*[8.588:10.2177]*
Observation error std	σ_θ	$\mathcal{IG}_2$	0.001	1	0.0278	0.0291	*[0.0245:0.0346]*
Log marginal data density						-299.71	

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