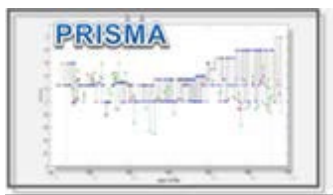# Occasional Paper Series

Erwan Gautier, Peter Karadi, Juergen Amann,
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Price adjustment in the euro area in
the low-inflation period: evidence
from consumer and producer micro
price data

No 319

Price-setting Microdata Analysis Network (PRISMA)

This Occasional Paper contains research conducted within the Price-setting Microdata Analysis Network (PRISMA). PRISMA (2018-22) consisted of economists from the European Central Bank (ECB) and the national central banks (NCBs) of the European System of Central Banks (ESCB). PRISMA was coordinated by a team chaired by Luca Dedola (ECB) and consisting of Chiara Osbat (ECB), Peter Karadi (ECB) and Georg Strasser (ECB). Fernando Alvarez (University of Chicago), Yuriy Gorodnichenko (University of California Berkeley), Raphael Schoenle (Federal Reserve Bank of Cleveland and Brandeis University) and Michael Weber (University of Chicago) acted as external consultants (for further information, see Price-setting Microdata Analysis Network (PRISMA).

This work is part of a set of papers within the ECB's Occasional Paper Series, resulting from the report of the ECB's PRISMA network, which is summarised here.

Set of Occasional Papers related to the ECB's PRISMA network

No 319, "Price adjustment in the euro area in the low-inflation period: evidence from consumer and producer micro price data"

No 320, "E-commerce and price setting: evidence from Europe"

No 321, "Some implications of micro price-setting evidence for inflation dynamics and monetary transmission"

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Contents

Abstract

This paper documents five stylised facts relating to price adjustment in the euro area, using various micro price datasets collected in a period with relatively low and stable inflation. First, price changes are infrequent in the core sectors. On average, 12% of consumer prices change each month, falling to 8.5% when sales prices are excluded. The frequency of producer price adjustment is greater (25%), reflecting that the prices of intermediate goods and energy are more flexible. For both consumer and producer prices, cross-sectoral heterogeneity is more pronounced than cross-country heterogeneity. Second, price changes tend to be large and heterogeneous. For consumer prices, the typical absolute price change is about 10%, and the distribution of price changes shows a broad dispersion. For producer prices, the typical absolute price change is smaller, but nevertheless larger than inflation. Third, price setting is mildly state-dependent: the probability of price adjustment rises with the size of price misalignment, mainly reflecting idiosyncratic shocks, but it does not increase very sharply. Fourth, for both consumer and producer prices, the repricing rate showed no trend in the period 2005-19 but was more volatile in the short run. Fifth, small cyclical variations in frequency did not contribute much to fluctuations in aggregate inflation, which instead mainly reflected shifts in the average size of price changes. Consistent with idiosyncratic shocks as the main driver of price changes, aggregate disturbances affected inflation by shifting the relative number of firms increasing or decreasing their prices, rather than the size of price increases and decreases.

Keywords: price stickiness, consumer prices, producer prices, scanner data.

JEL codes: E3, E5.

1   Introduction

From a theoretical point of view, how often prices adjust is of critical importance for the transmission of monetary policy. In standard macro models, monetary policy shocks affect the marginal cost of firms by shifting aggregate demand. If prices are sticky, firms cannot adjust their prices immediately in reaction to a change in marginal costs, leading to real monetary policy effects. Recent theoretical and empirical studies have emphasised that frequency is not the only relevant statistic when assessing the real effects of monetary policy; they show that the dispersion of the price change distribution may also be crucial for monetary policy transmission. This literature has documented, particularly for the United States, the importance of both small and large price changes (see, for example, Eichenbaum et al., 2013, or Midrigan, 2011).[1]

Documenting simple facts about how firms adjust their prices requires micro price data. The aggregate inflation variables at our disposal cannot provide us with information on the typical time period between two price changes or moments in price change distribution. Analysing micro datasets containing price quotes underlying the consumer price indices (CPIs) or producer price indices (PPIs) is the most direct and representative way to assess the degree of price stickiness in an economy. More recently, very detailed supermarket scanner data have been made available. Although supermarket scanner data cover a more limited set of consumer goods than CPI microdata, scanner data allow direct measurement of which prices are more likely to change, according to their price misalignment (i.e. the gap between the actual price and the price that would have been set without pricing frictions).

All the micro price data analysed in this paper were collected between the early 2000s and 2019 (the most recent). This period was characterised by a rather low and stable inflation rate: the average Harmonised Index of Consumer Prices (HICP) inflation rate in the euro area was 1.7% in the period, and even lower between 2013 and 2019 (close to 1%).[2]

This chapter documents new evidence on the adjustment of consumer and producer prices at the micro level in the euro area. Based on the micro price data underlying the HICP, Section 2 presents stylised facts concerning the average frequency of price changes in the euro area, the distribution of price changes and the time variation of both the frequency and the size of price changes. Section 3 analyses the main features of price setting from the perspective of the PPI. Finally,

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[1]   In a more recent contribution, Alvarez et al. (2022) show, theoretically, that the cumulative real effects of monetary policy not only relate to the frequency of price changes but also to the kurtosis of price changes. See also Dedola et al. (2023) for a detailed discussion of the macroeconomic implications of the results presented in this document.

[2]   Henkel et al. (2023) provide more facts on how the shocks associated with the COVID-19 pandemic may have affected price setting in 2020-21. Dedola et al. (2023) also provide some preliminary evidence on firms' price adjustments when inflation is high.

Section 4 discusses state dependence in price setting by means of supermarket scanner data.

2 Consumer price setting in the euro area

In this section[3]**, we summarise findings from Gautier et al. (2022). Since the early 2000s, several new findings on consumer price adjustment have been documented for many countries worldwide, including by the Inflation Persistence Network (IPN) for the euro area** (see Klenow and Malin, 2010, for a survey). For the United States, Bils and Klenow (2004), followed by Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008), have documented extensive evidence on consumer price adjustment for a very large share of the CPI basket. For the euro area, Dhyne et al. (2006) have provided empirical findings on consumer price rigidity for 50 representative products which are common to several euro area countries but only represent just over 10% of the CPI. Meanwhile, several papers have documented findings at the country level, with more coverage of the CPI, but with a much less harmonised empirical approach, making the results hard to compare across countries and difficult to aggregate at the euro area level. Early studies covering periods between the late 1990s and early 2000s include, for example, Aucremanne and Dhyne (2004) for Belgium, Hoffman and Kurz-Kim (2006) for Germany, Baudry et al. (2007) for France, Fabiani et al. (2005) for Italy, Benkovskis et al. (2012) for Latvia, Lünnemann and Mathä (2005) for Luxembourg, Alvarez and Hernando (2006) for Spain and Rumler et al. (2011) for Austria. More recent studies have included Berardi et al. (2015) for France and Blanas and Zimmer (2020) for Belgium.

We have extended and updated the IPN results of Dhyne et al. (2006) by expanding the product coverage under review and by looking at a more recent period. In particular, we document new evidence on consumer price rigidity for the euro area using about 130 million price quotes underlying the HICP in 11 countries and covering about 60% of euro area HICP in the period from 2010 to 2019 for most countries.

We also document new CPI price adjustment statistics for the euro area: in particular, the effect of sales prices on price rigidity, the distribution of the size of price changes and the development of the frequency and size of price changes over time.

Sales prices have been shown to have strong implications for understanding price rigidity in the United States (see, for example, Nakamura and Steinsson, 2008). Moreover, a recent, growing body of literature examines the determinants of sales in the United States and in the United Kingdom and their aggregate implications (Kehoe and Midrigan, 2010, Guimaraes and Sheedy, 2011, Anderson

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[3]   This section was prepared by Cristina Conflitti (Banca d'Italia), Riemer P. Faber (Nationale Bank van België/Banque Nationale de Belgique), Brian Fabo (Národná banka Slovenska), Ludmila Fadejeva (Latvijas Banka), Erwan Gautier (Banque de France), Valentin Jouvanceau (Lietuvos Bankas), Jan-Oliver Menz (Deutsche Bundesbank), Teresa Messner (Oesterreichische Nationalbank), Pavlos Petroulas (Bank of Greece), Pau Roldan-Blanco (Banco de España), Fabio Rumler (Oesterreichische Nationalbank), Sergio Santoro (European Central Bank), Elisabeth Wieland (Deutsche Bundesbank), Ladislav Wintr (Banque Centrale du Luxembourg) and Hélène Zimmer (Nationale Bank van België/Banque Nationale de Belgique).

et al., 2015, Kryvtsov and Vincent, 2020, and Coibion, Gorodnichenko and Hong, 2015). However, evidence for euro area countries is rare. In the national micro datasets used in Dhyne et al. (2006), price changes due to sales were only imperfectly observed, either because sales flags were not available, or because the methodology of price collection failed to capture all the prices of the products on sale. This complicates cross-country comparisons, as well as the assessment of the frequency of regular price changes for the euro area as a whole. For example, in Dhyne et al. (2006), reported price change frequencies include sales for some countries but not for others, depending on the availability of a reliable sales flag in the country dataset. In contrast, we report results on the frequency of price changes excluding sales.

As mentioned above, recent theoretical and empirical literature has shown that not only the frequency, but also the entire distribution of price changes, is important for monetary policy transmission. The shape of the price change distribution, as well as the share of very small and very large price changes, may provide information on the relevance of macro versus idiosyncratic shocks for price setters (Midrigan, 2011 and Karadi and Reiff, 2019) and on the relevance of price selection effects which might reduce the real effect of monetary policy shocks (Alvarez et al., 2021). We document the full distribution of price changes in the euro area.

Finally, we investigate more deeply how time variation in the size and frequency of price changes shapes aggregate inflation. Inflation results from the aggregation of millions of individual firms' pricing decisions. In a given month, inflation may rise because more prices are increased, or because the size of price changes is larger on average, while the number of price changes remains the same. Looking at the period 2013-19, when inflation was rather low, we can investigate whether this low inflation may be related to less frequent price changes or to a smaller size of price adjustment. This may have several policy implications: a lower frequency of price adjustment would suggest that prices were more rigid than before, which would contribute to the flattening of the Phillips curve, with all other factors being equal. In addition, whether firms adjust to aggregate shocks mainly through the size or the frequency of price adjustment could provide information on the empirical relevance of the theoretical micro foundations of sticky price models, and particularly whether empirical facts are more consistent with predictions of time or state-dependent models of price rigidity.

We first describe the CPI micro price datasets in Section 2.1. In Section 2.2, we document cross-sectional findings on the frequency of price changes. Section 2.3 describes our results for the size of price changes. In Section 2.4, we analyse the time variation of the frequency and size of price changes, while in Section 2.5, we investigate the pricing behaviour of retailers underlying changes in inflation.

2.1   130 million consumer prices from 11 euro area countries

PRISMA began the compilation of micro price data into a single dataset, which contains comparable statistics on price adjustment patterns, i.e. the frequency and size of price changes for euro area countries. This dataset is based on consumer prices at the individual product level that are used by national statistical institutes (NSI) to compute CPIs and HICPs, for 11 countries accounting for about 90% of the euro area HICP (Austria, Belgium, France, Germany, Greece, Italy, Latvia, Lithuania, Luxembourg, Slovakia and Spain), which together amount to about 130 million price observations, during the period 2000-19.[4] One advantage in using CPI/HICP data to analyse price adjustment (compared with more frequent and detailed scanner data) is that the price collection and data compilation process is framed in all countries by the same general recommendations and regulations defined at the European level (Eurostat, 2018). As such, the data can be considered comparable across countries, and reliable, as NSIs carefully sample products according to national breakdowns of household consumption. Furthermore, price data are available for various broad sectors (i.e. processed and unprocessed food products, non-energy industrial goods, energy and services) and are largely collected on site across different outlet types and on a monthly basis. Furthermore, these datasets contain information on imputed (estimated) prices, i.e. for products that are temporarily unavailable, and on product replacements, i.e. if an existing product is exchanged for a similar but different product variety. The datasets also contain flags for sales and promotions as well as information on product quantity and quality.

In order to derive comparable micro price statistics across countries, the dataset is restricted to a common sample of products that includes a product only if it is available for at least three of the four largest euro area countries (Germany, France, Italy and Spain). The statistics are available at the most granular level of the HICP, which is the five-digit level of the European Classification of Individual Consumption According to Purpose (ECOICOP), e.g. "01.1.1.1 – Rice, incl. rice preparation". Our common product sample includes 166 COICOP-5 products. For most of the products in our common sample, we have price information for all or nearly all the 11 countries: for 84% of the COICOP-5 products, price information for at least nine countries is available.

The common sample of 166 COICOP-5 products covers 59% of the euro area HICP and 65% of the euro area HICP, excluding energy. The sample, however, does not contain any energy products and is missing data on approximately half of all services in the HICP: in particular, housing services (rents), communication services and some travel-related services, such as package holidays. Moreover, our common sample does not include some centrally collected prices of non-energy

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[4]   The product coverage and sample period vary across countries. The highest product coverage amounts to 97% of the HICP (Luxembourg), while the lowest is around 43% (Belgium). The longest time periods span almost two decades of micro price observations (Austria (2000-17) and Greece (2002-19)), while the shortest cover three years (Latvia, 2017-19). Note that, due to peculiarities relating to price collection, our sample does not cover the pandemic year of 2020. See Henkel et al. (2023) for an analysis of price setting during 2020 in four euro area countries (Germany, Italy, Latvia and Slovakia).

industrial goods (NEIG), such as new and used cars, pharmaceutical products and ICT products, as well as some administered food products, such as tobacco and alcohol. Centrally collected, administered or regulated prices typically raise serious measurement issues for price dynamics statistics (e.g. unit values, average price and quality adjustment), since they bias the size and frequency of price adjustment (see Eichenbaum et al., 2013, for a discussion). Also, whenever possible, quantity and quality-adjusted price data are used to capture only "true" price changes. While information on quantities is available for most countries, quality-adjusted data at the micro level are only available for Germany, France and Luxembourg.

To compute aggregate statistics for the euro area, ECOICOP-5 level statistics are first aggregated at the country level, using euro area HICP weights, averaged over the period 2017-20, such that differences in price adjustment between countries are not driven by differences in national consumption patterns. Subsequently, country-specific results are aggregated using country weights (averaged over 2017-20) to derive aggregate euro area statistics. The same procedure is applied to obtain the statistics by broad sector.

For analyses of price rigidity, it is important to account for price changes due to sales and promotions, as these usually imply large but temporary or very seasonal price changes (Nakamura and Steinsson, 2008). Therefore, all price adjustment statistics are additionally computed excluding any price changes due to sales and promotions. In order to perform this computation, in most countries, temporary promotions are identified by a sales flag reported by the NSI. The price collector assigns a sales flag in the NSI micro price database whenever a collected price is visibly flagged as a sale in the store or when a discount is given to all customers at the check-out desk. However, sales flags are not available for all countries, and the definition of sales and promotions might depend on national practices. Therefore, a sales filter building on Nakamura and Steinsson (2008) has also been used to detect temporary price decreases. Furthermore, as discussed by Berardi et al. (2015), another key concern in constructing measures of price rigidity relates to product replacements or substitutions. Typically, when a product is (temporarily) unavailable or discontinued, the price of a close substitute is used for CPI compilation. For most countries in the sample, a flag for such product replacements is available, but as the definition of product replacements varies across countries due to differences in national statistical practices and product identifiers (e.g. link between old and new product identifiers and qualitative information on the type of replacement, i.e. whether it is a fully new, very similar or different product), price changes due to replacements are excluded from the baseline statistics.

2.2   Typical prices do not change for 12 months in the euro area

Consumer prices in the euro area change infrequently: on average, 12.3% of all prices change in a given month, and only 8.5% change when sales prices are excluded. When we exclude price changes due to sales, which make up more than 4% of the observations, the frequency of price changes decreases to 8.5% (Table 1). This is also the case if we use the sales filter instead of the NSI flag to exclude price changes due to sales. This frequency of price changes excluding sales implies that the typical duration between two price changes is about one year. Looking at price increases as a proportion of price changes, we find that roughly two-thirds of all price changes are price increases, with the proportion increasing slightly when excluding price changes due to sales.[5]

Differences in the frequency of price changes are limited across countries: the frequency ranges from 10.3% in Italy to 18.6% in Latvia, whereas for most countries it is between 11% and 14%. This small cross-country heterogeneity narrows when we exclude sales, as in this case the frequency varies between 7% and 10% for most countries.

In contrast, there is substantial cross-sectoral heterogeneity in the euro area. The highest frequency of price changes is observed for unprocessed food, with 31%, whereas the frequency is 15% for processed food and 13% for NEIG (Table 1). The lowest frequency is found in the services sector (6%). Excluding price changes due to sales has a sizeable impact on the frequency of price changes in the unprocessed food, processed food and NEIG sectors, where the frequency decreases by about 5 to 7 percentage points, but has only a limited impact on services. Specifically, the share of sales and promotions is 8.6% for NEIG and 7.4% for unprocessed food, less than 5% for processed food but only 0.5% for services. Nakamura and Steinsson (2010) find that sectoral heterogeneity in price rigidity may amplify the real effects of monetary policy shocks and argue that a model calibrated using median frequency may generate monetary non-neutrality similar to that observed in a multi-sector model (Gautier and Le Bihan, 2022, find similar results for France).

In the euro area, the median frequency is 9.6% when we include price changes due to sales, and 5.7% when we exclude them. These median frequencies are only a little lower than the average frequency (the gap just under 3 percentage points), whereas in Nakamura and Steinsson (2010) or Gautier and Le Bihan (2022), the difference is greater than 6 percentage points. This is because we have not included energy products. In the other studies, energy products contribute substantially to the difference between the median and mean frequency.

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[5]   These findings are robust to several sensitivity checks. Rather than using data for the entire period available for a country, we can restrict the sample to a common period of seven years (2011-17), in which case the frequency of price changes remains the same. The frequency of price changes is also close to the baseline case when we use alternative product samples (i.e. all products that are available for a country or only products that are available for all 11 countries).

Table 1

Euro area price rigidity: frequency of price changes

(percentages)

	Including sales		Excluding sales		% of sales
	Frequency of price changes	% of price increases	Frequency of price changes	% of price increases	
By sector					
Unprocessed food	31.4	54.5	24.0	57.6	7.4
Processed food	15.4	57.0	10.4	61.8	4.3
NEIG	12.9	48.2	6.4	59.8	8.6
Services	6.0	82.5	5.7	82.4	0.5
By country					
Austria	11.1	64.5	7.2	72.0	5.1
Belgium	14.5	69.0	13.3	69.7	1.1
France	12.7	60.8	9.8	66.9	5.5
Germany	12.7	61.9	9.2	67.2	4.1
Greece	11.3	61.3	7.3	63.9	3.8
Italy	10.3	69.9	4.8	75.6	4.3
Latvia	18.6	60.0	7.9	71.1	10.7
Lithuania	12.8	62.3	9.7	68.4	2.3
Luxembourg	14.1	73.4	8.8	78.4	4.6
Slovakia	14.3	64.8	9.3	66.6	4.9
Spain	13.5	64.0	9.0	65.3	5.1
Euro area	12.3	64.0	8.5	68.8	4.4

Source: Gautier et al. (2022).
Notes: The statistics are based on the country-specific period and on products that are available for at least three of the four largest countries (France, Germany, Italy and Spain). Price changes due to product replacements are excluded beforehand (except for Greece and Slovakia). Results excluding sales are based on the NSI sales flag, except for Greece, Luxembourg, Slovakia and Spain, for which no such flag is available and for which sales are excluded by the sales filter. The percentage of sales is also based on the sales filter for these countries. Seasonal sales are excluded from the Belgian dataset, but temporary promotions are included.

The cost structure of a product matters in explaining cross-sectional differences in the frequency of price changes. In particular, the share of labour costs has a negative impact on frequency, whereas the share of energy and raw material inputs has a positive impact. In their baseline regression, Gautier et al. (2022) find that an increase of 10 percentage points in the share of labour costs decreases the frequency of price adjustment by about 2 percentage points. Keeping the share of all imported inputs constant, an increase of 10 percentage points in the share of imported energy and raw material inputs increases the frequency of price adjustment by about 8 percentage points. The share of all imported inputs, the percentage of online consumers and whether a price is regulated do not have a significant impact. These results are robust to the inclusion of a retail market concentration variable. This evidence is consistent with the volatility of firms' costs affecting the frequency of price changes, as implied by state-dependent pricing models.

The frequency of price changes is larger in the United States than in the euro area, but once we exclude price changes due to sales, the frequency is about the same in the two economic areas. Using the product-level results provided by Nakamura and Steinsson (2008), Gautier et al. (2022) are able to compare quite precisely the degree of price stickiness in the euro area and the United States. The

comparison is restricted to equivalent products to control for possible differences in the composition of consumption baskets. To control for possible differences in product weights, euro area HICP weights are applied to derive aggregate statistics for both economic areas.[6] When all price changes are taken into account, prices are, on average, more frequently updated in the United States than in the euro area. The frequency of price change is 19.3% in the United States, which is 7 percentage points higher than in the euro area (Table 2). When price changes due to sales are excluded, the frequency of price changes falls to 10.0% in the United States, versus 8.5% in the euro area. Hence, the difference between the United States and euro area is mainly caused by sales. The share of price increases is similar in both economic areas. The share of sales is higher in the United States (Nakamura and Steinsson, 2008, report 7.4%, compared with 4.4% in the euro area).

Table 2
Euro area versus US price rigidity: frequency and size of price changes

(percentages)

	Euro area		United States	
	Including sales	**Excluding sales**	**Including sales**	**Excluding sales**
Average frequency of price changes	12.3	8.5	19.3	10.0
% of price increases	64.0	68.8	62.0	71.1
Average size				
Price increases	12.3	8.9	17.8	10.6
Price decreases	16.2	11.6	21.6	13.4
Absolute price changes				
25th percentile	6.0	3.9	7.2	5.2
50th percentile	10.9	7.1	14.2	10.7
75th percentile	18.9	12.5	25.4	20.1

Source: Gautier et al. (2022).
Notes: The US results are based on the detailed product-level results of Nakamura and Steinsson (2008). To make the results for the two economic areas as comparable as possible, the average statistics have been calculated using the same products for both economic areas and euro area product weights.

2.3   The euro area median price change is 10% for increases and 13% for decreases

Typical price increases and decreases in the euro area are much larger than aggregate inflation. This section describes the distribution of the size of (non-zero) price changes in the euro area. Table 3 reports the median increase and decrease of price changes. When price changes due to sales are included, the median price increase equals 9.6%, while the median price decrease is larger (in absolute terms), namely 13%. When sales are excluded, both the median price increase and the median price decrease are smaller in absolute terms: the median increase is 6.7%,

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[6]   An important caveat is that the results for the United States are for the period 1998-2005, whereas most euro area results are more recent. However, to our knowledge, Nakamura and Steinsson (2008) provide the only information available for the United States at this disaggregated product level.

whereas the median decrease is 8.7%.[7] [8] Overall, even when sales (i.e. the largest price changes) are excluded, the typical price increase and decrease are quite large compared with aggregate inflation over the period (average inflation in the euro area over the sample period is closer to 1.5%). As aggregate shocks tend to be small, this would suggest that firm-specific shocks play a more important role in driving the size of price changes than aggregate shocks.

Table 3

Euro area price rigidity: size of price changes

(percentages)

	Including sales		Excluding sales	
	Median price increase	Median price decrease	Median price increase	Median price decrease
By sector				
Unprocessed food	12.6	15.0	10.1	11.0
Processed food	9.2	12.0	5.8	6.5
NEIG	13.9	19.2	7.9	10.7
Services	5.6	8.2	5.5	7.9
By country				
Austria	10.4	14.6	6.9	8.7
Belgium	7.0	8.2	6.6	7.5
France	7.8	11.9	5.1	7.3
Germany	11.6	16.1	8.4	11.0
Greece	9.6	12.8	8.0	11.4
Italy	9.1	11.4	4.4	5.5
Latvia	15.9	14.8	7.9	6.2
Lithuania	13.5	17.2	11.8	12.8
Luxembourg	7.5	10.7	5.5	7.8
Slovakia	10.5	11.1	9.2	8.5
Spain	8.9	11.1	8.1	10.4
Euro area	**9.6**	**13.0**	**6.7**	**8.7**

Source: Gautier et al. (2022).
Notes: The statistics are based on the country-specific period and on products that are available for at least three of the four largest countries (France, Germany, Italy and Spain). Price changes due to product replacements are excluded beforehand (except for Greece and Slovakia). Results excluding sales are based on the NSI sales flag, except for Greece, Luxembourg, Slovakia and Spain, for which no such flag is available, and for which sales are excluded by the sales filter. Seasonal sales are excluded from the Belgian dataset, but temporary promotions are included.

Cross-country heterogeneity is rather limited, but more pronounced than the differences observed for frequencies (Table 3). In France, Italy, Luxembourg and Spain, the median increase is between 7.5% and 9%, whereas in Austria and Germany, as well as in Latvia, Lithuania and Slovakia, the median price increase is more than 10%. A similar difference is observed for price decreases: in the first group of countries, the median decrease is between 11% and 12%, while in the second group, the median is closer to 15%. When we exclude price changes due to

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[7]   The median decrease is 11% when we use the sales filter for all countries to exclude sales (rather than the sales flag), and the median increase is 7.2% in this case.

[8]   These results do not change much when harmonising the sample period across countries or changing the product sample.

sales, country differences are still observable and the ranking of countries remains similar.

As in the case of frequency, sectoral differences are quite considerable, especially when including sales prices. Both NEIG and unprocessed food show relatively large median price increases of 13.9% and 12.6% respectively, while the median price decreases are 19.2% and 15.0% respectively. These figures can be contrasted with the services sector, where the median increase is 5.6% and the median decrease is 8.2%. Excluding price changes due to sales reduces sectoral heterogeneity, as it lowers the median increase and decrease for NEIG as well as for processed and unprocessed food, where the majority of sales are concentrated.

The size of price changes in the euro area is very heterogeneous, with many changes smaller than average inflation, but with thick tails of large increases and decreases. Chart 1 plots the full distribution, including price changes due to sales (black line) and excluding price changes due to sales (grey histogram). For all price changes, the main distribution patterns are as follows: it is asymmetric, with more small positive price changes than negative ones; it shows a modal range of values between +1% and +3%; and it shows several peaks at large values corresponding to price changes due to sales. When price changes due to sales are removed, the peaks at large values are smaller, but still significant, and the asymmetry around zero is more pronounced. Furthermore, both including and excluding sales, large price increases and decreases are quite frequent. For example, excluding sales, 10% of price changes are greater than 15.8%, and 10% are below -13.2%.

The distribution of price changes differs between sectors. The distributions for food and NEIG share similar patterns: a small degree of asymmetry, large peaks corresponding to sales and a quite dispersed distribution of price changes. For services, the distribution is much more asymmetric (i.e. many more positive small price changes than negative small price changes) but also much less dispersed (more than 25% of price changes are between 0 and 3%). This finding for services might reflect the relatively higher relevance of aggregate nominal shocks (the aggregate wage component of production cost, for example) compared with firm-specific shocks as a motive for price changes, and is also consistent with the lower frequency of price changes being driven by less volatile idiosyncratic shocks.

(x-axis: log difference, y-axis: percentages)

■ Euro area - all price changes
■ Euro area - excluding price changes due to sales
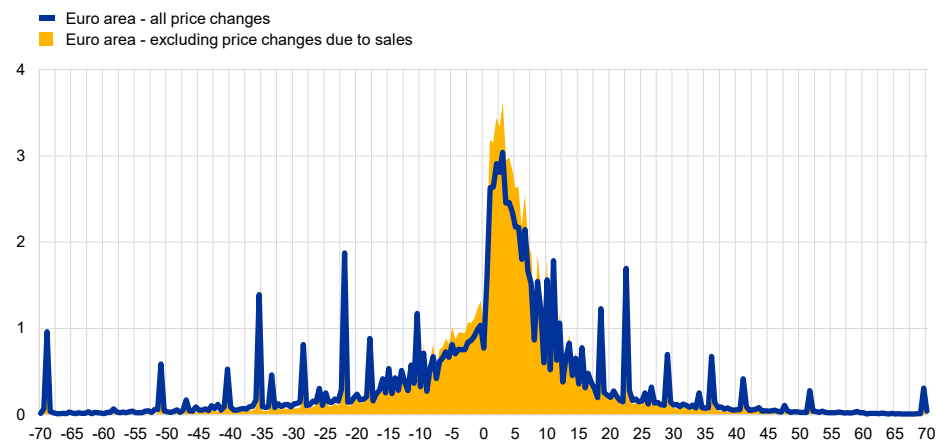
Source: Gautier et al. (2022).
Notes: The chart plots the distribution of price changes (in log difference, in %) calculated first at the product/country level for the common sample of products (bins of 0.5 percentage points), then aggregated at the country level using euro area product weights and then aggregated at the euro area level using HICP country weights. The grey histogram corresponds to the distribution of price changes, excluding price changes due to sales, while the black line corresponds to the distribution of price changes, including price changes due to sales. Results excluding sales are based on the NSI sales flag if available and the sales filter otherwise.

Small price changes are quite common: about 11% of price changes are smaller than 2% in absolute terms and 14% when sales are excluded. This proportion is quite similar across sectors when sales are excluded. Differences are more pronounced across countries, with the share of small price changes being particularly high in France (especially in the food sector), Italy, Latvia, Luxembourg and Spain, but relatively low in Germany, for example.

The average price change is larger in the United States than in the euro area, but this difference is mainly driven by sales. In the same way as for frequency, we compare the size of price changes in the euro area with findings for the United States (Nakamura and Steinsson, 2008). Including sales, price changes are about 5.5 percentage points larger in the United States than in the euro area. As for the frequency results, when excluding price changes due to sales, the difference is much more limited: the average price increase is 10.6% in the United States, versus 8.9% in the euro area. The difference for price decreases is similar (Table 2). On the share of small price changes, Eichenbaum et al. (2013) find that, for the United States, the percentage of price changes below 2.5% in absolute terms is 10.5% including sales and 13.8% excluding sales. Hence, the share of small price changes is larger in the euro area than in the United States, but the difference is quite small.

Box 1

Comparing results on price setting from PRISMA with earlier evidence from the Inflation Persistence Network

The Inflation Persistence Network (IPN) was the first attempt to document the degree of price rigidity based on micro-level consumer price index (CPI) data using an harmonised approach across euro area countries. The results are summarised in the paper by Dhyne et al. (2006), covering the period 1996-2001. A comparison of PRISMA (for the period 2011-17) with the IPN results poses a number of challenges related to coverage in terms of countries and products, as well as methodology. The findings in Dhyne et al. (2006) are derived from ten countries and a harmonised sample of 50 individual products, which cover only about 10% to 14% of the CPI baskets of the respective member countries. In our comparative exercise, we have therefore focused on exactly the same 50 products.[9] Due to limitations on the availability of information at the very disaggregate level in some countries, only a smaller number of countries (Austria, Belgium, Germany, France and Italy) can be included in the comparison. Another challenge for the comparison is the fact that in Dhyne et al. (2006), some countries included price changes due to temporary sales and promotions, and also due to product substitutions, in their calculations of the frequency and size of price changes, while others did not. To be consistent in our comparison, we calculated the frequencies and sizes with respect to the treatment of sales and promotions and substitutions in exactly the same way as in the IPN.

The main result is that, in all the countries considered, prices change more frequently, most strikingly in Germany, Austria and Belgium, and particularly in the non-energy industrial goods (NEIG) sector (Table A). Specifically, the frequency of price changes increased between the IPN and PRISMA period by about 6 percentage points in Austria, followed by more than 4 percentage points in Germany and 2.5 percentage points in Belgium, whereas the increase was only minor in France and Italy (around 1 percentage points). This implies an overall increase for the aggregate of these five countries (euro area-5) of 2.4 percentage points. Looking at the individual sectors, the increase was most pronounced for NEIG and somewhat smaller for food and services.

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[9]   Note that some products are no longer available in some countries in the PRISMA sample.

Table A

Frequency of price changes in % – comparison of PRISMA and IPN results based on 43 products

|	Processed food	NEIG	Services	Total core
IPN 1996-2001: core items (43 products)				
Euro area-5	13.6	9.4	5.0	7.8
Austria*	17.0	8.5	8.8	9.7
Belgium**	18.3	3.5	2.6	5.5
France*	20.2	16.8	6.4	12.0
Germany**	9.7	7.1	4.8	6.2
Italy**	10.6	5.9	3.6	5.4
PRISMA 2011-17: core items of available products				
Euro area-5	15.6	12.8	7.0	10.2
Austria*	21.1	19.7	11.8	15.7
Belgium**	22.1	6.6	4.1	8.0
France*	24.6	18.6	5.3	12.7
Germany**	11.0	12.6	9.1	10.5
Italy**	9.9	6.4	5.5	6.5

Source: Gautier et al. (2022).
Notes: *: Price changes including sales; **: Price changes excluding sales (except for processed food in Germany). Price changes include substitutions (except for Belgium). Euro area-5 refers to Austria, Belgium, Germany, France and Italy. Only products available in both sample periods are included in the comparison and results are aggregated using country-specific product weights to product groups and then product-group weights (average of 2011-17) to the "Total core".

The trend of increased frequency between the IPN and the PRISMA period can also be seen at the product level in Chart A, which plots the frequency of price changes in the PRISMA period (y-axis) against the frequency in the IPN period (x-axis) for all product/country combinations. The plot shows that a majority of products (about 70%) have a higher frequency in the newer PRISMA period, but there is also a non-negligible number of products with a lower frequency in the more recent period. For these products, however, the difference over time is rather small, while there are some products above the 45-degree line that have a much higher frequency in the more recent sample. This demonstrates the main caveat of this analysis: that, given the small number of products analysed, the results could be driven by a few rather extreme changes over time, while for most products the frequency has not changed dramatically.

Chart A

Frequency of price changes: comparison of results of IPN (1996-2001) and PRISMA (2011-17)

(x-axis: percentages IPN period; y-axis: percentages PRISMA period)
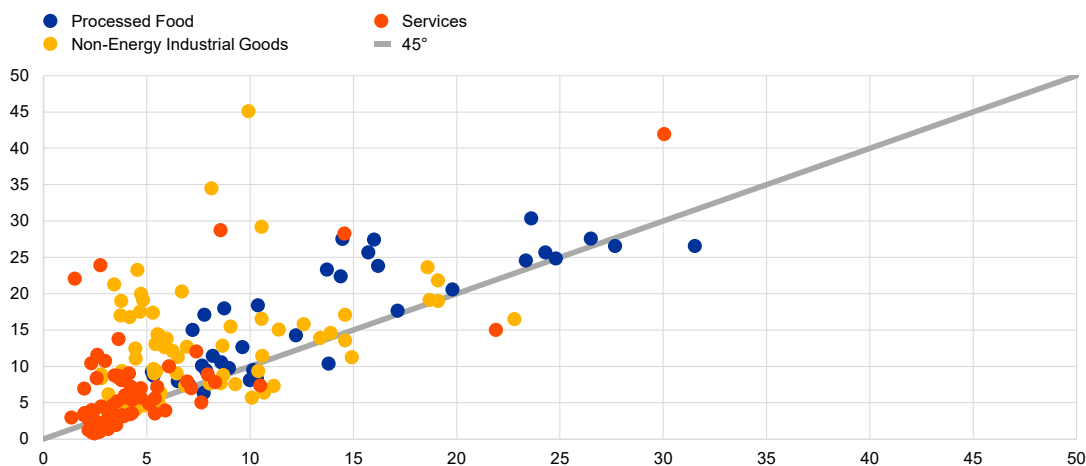
Source: Gautier et al. (2022).
Note: Each dot corresponds to a product-country combination.

For the average size of price changes, in contrast, we do not find major differences between the two periods. At the euro area level, the median size of price increases is very similar for both the IPN and the PRISMA period, while the size of price decreases is somewhat larger in the more recent period. The latter is mainly due to a pronounced increase in the size of price decreases in France, particularly for NEIG.

Overall, we find a higher frequency of price changes in the PRISMA period (2011-17) than in Dhyne et al. (2006) for the period 1996-2001, but no clear trend in the size of price changes, with increases in some countries counterbalanced by decreases in other countries. The increase in frequency is dominated by NEIG in Austria, Belgium and Germany. The product-by-product comparison between PRISMA and IPN results presented here, however, comes at the cost of low coverage, compared with the set of products that would be available in the PRISMA sample, which hampers to some degree the generalisability of these results to the entire basket of goods and services.

## 2.4 How have the frequency and size of price changes evolved over the last 15 years?

This section documents the change in the frequency and average size of price changes in the euro area, both within a given year (seasonality) and in the period 2005-19. We estimate simple-panel ordinary least squares regressions that relate the frequency and size of price changes at the product-country level, including and excluding price changes due to sales and to month and year fixed effects (Chart 2). These regressions yield two main results.

Chart 2

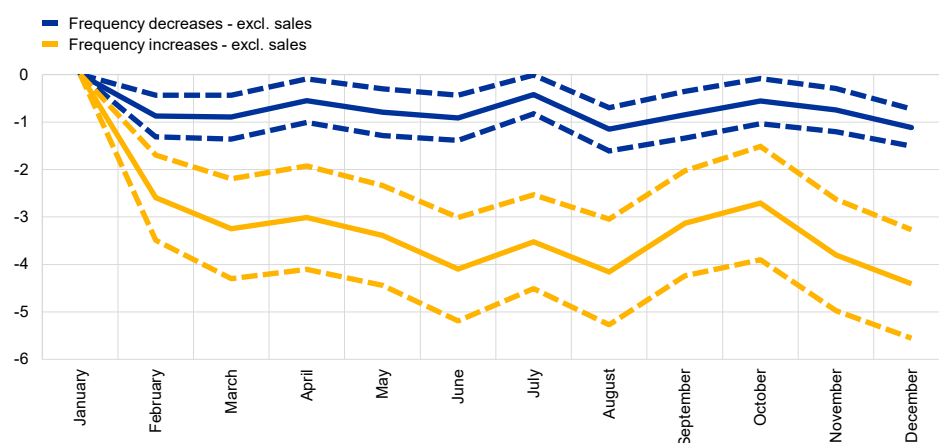### Month effects in the frequency of price adjustment

a) Frequency of price changes
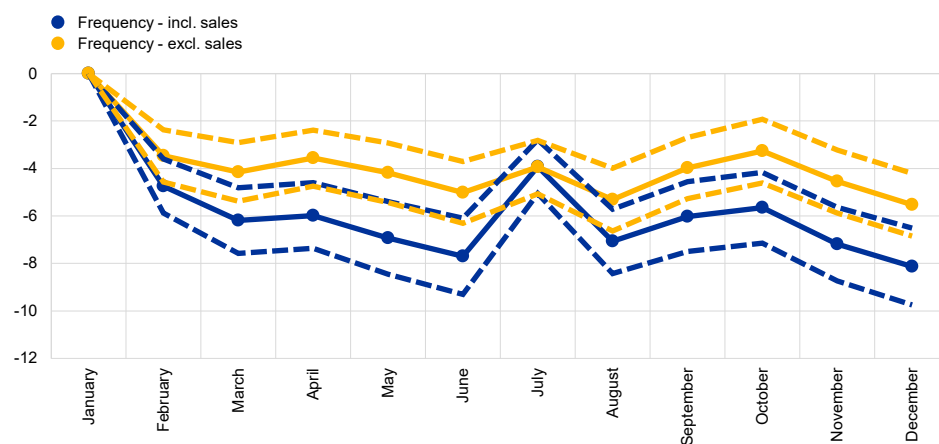
(y-axis: percentage points, reference=January)

- ● Frequency - incl. sales
- ● Frequency - excl. sales

b) Frequency of price increases/decreases

(y-axis: percentage points, reference=January)

- ▬ Frequency decreases - excl. sales
- ▬ Frequency increases - excl. sales

Source: Gautier et al. (2022).
Notes: Coefficient plots from weighted panel regressions with COICOP, country, and time-fixed effects and dummy for VAT changes in France (04/00, 01/12, 01/14), Italy (09/11), Slovakia (01/11), and Spain (09/12, 07-09/10), with country weights in euro area HICP (2017-20 average) and robust standard errors. Dependent variables are the frequency of price adjustment. Regressions are based on the country-specific period and on products that are common to at least three of the four largest countries. The reference month is January. For instance, in March, the frequency of price changes (including sales) (solid blue line) is 6 percentage points lower than the frequency of price changes in January. Price changes due to replacement are excluded beforehand (except for Greece and Slovakia). Results excluding sales are based on 1) NSI sales flag if available or 2) common sales filter. Outliers are adjusted beforehand.

The frequency of price changes shows large seasonal movements. In most months of the year, the frequency of price changes is 6 percentage points lower than in January, whereas in July, the frequency is a little higher than in the remaining months (solid blue line in Chart 2, panel a). These movements are partly explained by seasonal sales. If price changes due to sales are excluded, the main pattern persists and the frequency of price changes is about 4 percentage points higher in January than in other months of the year (solid yellow line in Chart 2, panel a). The findings for the average size of price increases and price decreases are similar (Gautier et al., 2022): sales are associated with much larger variations in January and July. However, when price changes due to sales are excluded, the seasonality in the size of price increases and decreases is much more limited.

Price increases are more frequent in January than in other months. When price changes due to sales are excluded, the January effect in the frequency of price changes is mainly driven by the frequency of price increases (Chart 2, panel b). In particular, prices in the services sector tend to be updated much more frequently in January than in other months of the year. While this effect is observed in almost all countries and in all sectors, it is more pronounced in Austria, Luxembourg, France, Germany and Spain. This type of seasonal effect, which is unrelated to seasonal sales, is in line with time-dependent price setting, in which some prices are revised at regular time intervals (see Taylor, 1980, where prices are kept constant for a fixed duration). Time dependence resulting in synchronisation of price adjustments in the same month of the year might also matter for monetary policy transmission when many prices may be more responsive to macroeconomic conditions (see Olivei and Tenreyro, 2007, for evidence on how the timing of wage adjustment may matter for responses to monetary policy).

There were no strong trends in price change frequency in the period 2005-19, but some fluctuations over time. Chart 3 plots the time trends of price change frequency (estimated using a standard HP filter), showing it to be quite flat over time. Since the link between inflation and "slack" in a structural Phillips curve depends on the frequency of price changes, *inter alia*, one important implication of frequency stability over time is that any change in the slope of the Phillips curve cannot be attributed to a change in the frequency of price changes. Compared with the base year of 2013, the frequency of price changes was significantly higher (+1 percentage point) during the global financial crisis, when euro area inflation reached a maximum of 4.1% in July 2008, before decreasing to -0.6% in July 2009.[10] It also decreased somewhat after 2013, when the average inflation rate was rather low in the euro area. This variation was mostly driven by changes in the frequency of price increases. By contrast, the frequency of price decreases remained quite flat. Interestingly, the picture does not change if sales prices are excluded. Overall, we find that the lower inflation rates observed after 2013 are associated with slightly less frequent price increases than before 2013. As regards the size of price changes, when including sales, we find a small increasing trend for both increases and decreases (about 1-2 percentage points). Sales are an important driver of this trend, as it largely disappears when sales are excluded (see also Gautier et al., 2022, for details).
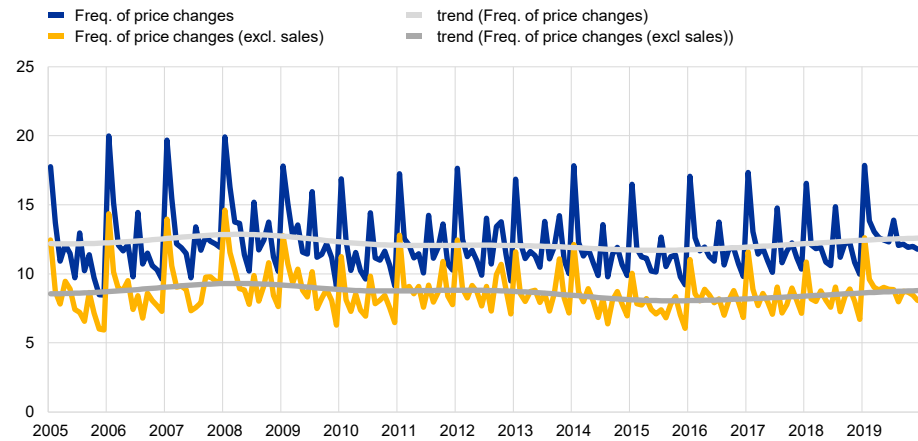
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[10] See Dixon et al. (2022) for more evidence on how the global financial crisis and the euro area sovereign debt crisis have affected price adjustment patterns.

Chart 3

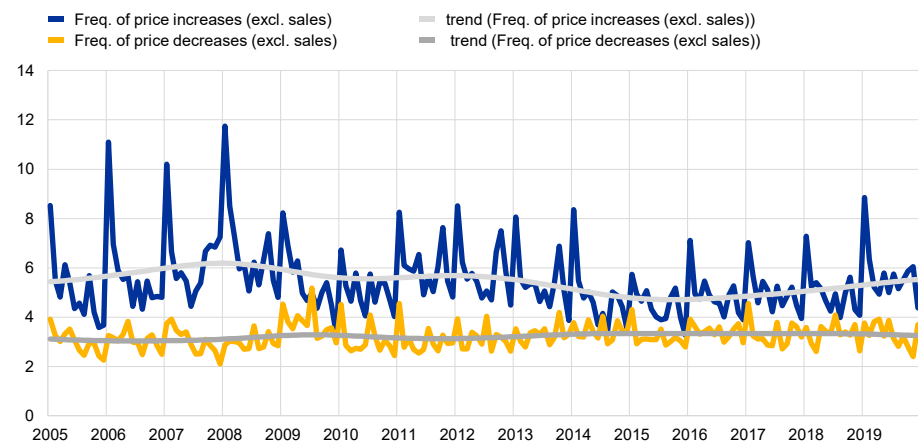**Frequency of price changes in the period 2005-19 in the euro area**

a) Frequency of price changes

(y-axis: percentages)

- ▬ Freq. of price changes
- ▬ Freq. of price changes (excl. sales)
- ▬ trend (Freq. of price changes)
- ▬ trend (Freq. of price changes (excl sales))

b) Frequency of price increases/decreases

(y-axis: percentages)

- ▬ Freq. of price increases (excl. sales)
- ▬ Freq. of price decreases (excl. sales)
- ▬ trend (Freq. of price increases (excl. sales))
- ▬ trend (Freq. of price decreases (excl sales))

Source: Gautier et al. (2022).
Notes: The statistics are based on the country-specific period and on products that are common to at least three of the four largest countries and calculated using euro area product weights at the COICOP-5 level (2017-20 average) and country weights in the euro area HICP (2017-20 average). Price changes due to replacements are excluded beforehand (except for Greece). Results excluding sales are based on 1) NSI sales flag if available or 2) common sales filter. Outliers are adjusted beforehand.

2.5 Which price-setting adjustment is behind inflation?

Aggregate inflation can be broken down into the product of the average frequency and the average size of price changes. For each product at the COICOP-5 level in all countries in the sample, we can calculate the size and frequency of price changes at every date and then aggregate over COICOP-5 groups to approximate the aggregate monthly inflation rate (hereinafter. "recomposed" inflation). These recomposed inflation rates are highly correlated with actual inflation at the product level. In a second step, we compute several counterfactual inflation rates. A first counterfactual inflation rate assumes that changes in inflation over time are solely due to the size of price changes, and that

the frequency is constant. Hence, for a given product, it is computed as the product of the time-average of frequency and the actual size at each point in time. A second alternative counterfactual inflation rate assumes that the size of price changes is fixed and only the frequency of price change can vary over time. We also consider counterfactual inflation rates, assuming that i) only the size of price increases and decreases can vary over time, ii) only the frequencies of price increases and price decreases can vary over time, and iii) only the share of price increases can vary over time (i.e. assuming constant frequency and constant sizes of price increases/decreases).

Inflation variation is mainly due to variation in the size of price changes and not to variation in the frequency of price changes. For each set, we calculate the correlation between the recomposed and counterfactual monthly inflation rates. The main finding of this exercise is that recomposed inflation is highly correlated with counterfactual inflation, assuming constant frequency (the average correlation coefficient is 0.8, irrespective of the inclusion of price changes due to sales (Table 4)). The recomposed inflation has a lower correlation with the counterfactual inflation rate, which assumes a constant size of price changes (correlation coefficient of about 0.4). Thus, most of the short-term changes in inflation are due to variation in the overall size of price changes and not to variation in their overall frequency. This pattern of the data is consistent with the standard predictions of a Calvo model (by construction of our counterfactual inflation) but also with a menu cost model in a relatively stable low-inflation environment (see Alvarez et al., 2019, or Nakamura and Steinsson, 2018). In this latter model, aggregate shocks are relatively small by comparison with firm-specific shocks and are less of a motive for firms to change their prices. It follows from this model that movements in overall frequency over time are very small, whereas inflation varies more with the average size of non-zero price changes.

Table 4

Correlation between recomposed and counterfactual inflation rates

	Constant frequency of price changes	Constant size of price changes	Constant frequency of price increases and decreases	Constant sizes of price increases and decreases	Constant frequency of price changes and sizes of price increases and decreases
By sector					
Unprocessed food	0.94	0.26	0.49	0.92	0.82
Processed food	0.85	0.45	0.40	0.86	0.72
NEIG	0.82	0.19	0.46	0.80	0.63
Services	0.59	0.65	0.38	0.88	0.44
Euro area (including sales)	**0.79**	**0.36**	**0.44**	**0.86**	**0.64**
Euro area (excluding sales)	**0.75**	**0.43**	**0.42**	**0.85**	**0.59**

Source: Gautier et al. (2022).

Variation in the size of price changes over time is mainly due to movements in the share of price increases. When we analyse counterfactual inflation rates considering price increases and decreases separately, we find that the recomposed inflation rate is much more closely correlated with counterfactual inflation, assuming constant sizes of price increases and decreases (correlation coefficient of about 0.85), than with the counterfactual inflation rate, assuming constant frequencies of price increases and decreases (correlation coefficients of less than 0.5, col. 3 and col. 4 of Table 4). Thus, changes in inflation over time are much more likely to be due to time variation in the frequency of price increases and the frequency of price decreases than to variation in the size of price increases and the size of price decreases.

Overall, inflation is mainly driven by movements in the share of price increases and decreases (translating to a change in overall size) and less by changes in overall frequency. This is confirmed by the high correlation between recomposed inflation and counterfactual inflation, assuming that only the share of price increases can vary over time (last column of Table 4). Time variation in inflation is driven, to a great extent, by changes in the share of price increases. This last result is also consistent with the predictions of a standard menu cost model in a low-inflation environment. The average sizes of price increases and decreases mainly depend on idiosyncratic shocks, but an aggregate shock will nevertheless shift the price change distribution, and will have more of an effect on the relative share of price increases and decreases (see Nakamura et al., 2018, for similar evidence for the United States, and Alvarez et al., 2019, for Argentina when inflation is low (generally below 5%)).

3 Producer price setting in the euro area

Most of the evidence on price rigidity relies on consumer micro price data, but documenting patterns of producer prices may be relevant, for several reasons.[11] First, producer prices can help us investigate how productive firms actually set their prices and how they incorporate marginal cost shocks into their prices. In particular, at the firm level, it is often easier to match prices with observed changes in marginal costs (labour or input costs) than in the retail sector.[12] In addition, producer prices often cover sectors ranging from raw material production to the manufacturing of consumer goods, giving us the opportunity to examine how patterns of price adjustment differ at the various stages of production. Indeed, price rigidities in these various production stages are a key factor in the propagation of nominal shocks into final prices. Finally, having data on producer price changes could help us calibrate more complete macro models, usually incorporating both a productive sector and a retail sector. More generally, standard macro models generally represent firms' decisions in the productive sector, and calibrating the model using producer price data might be more consistent.

In the euro area, the existing literature on producer price rigidity dates back to the IPN. Using individual prices collected to build official PPIs, Vermeulen et al. (2012) document, in particular, that price changes are infrequent for producer prices: the typical monthly frequency of price changes is 21%, with little country heterogeneity but considerable differences across sectors.[13] Compared with the CPI, there have been fewer papers documenting facts on producer prices for euro area countries. More recently, Dedola et al. (forthcoming) have also investigated producer price rigidity in Denmark, relating producer prices to measures of costs.[14]

Information on producer price adjustment can be obtained from data sources other than micro prices underlying PPIs. First, several studies have used Prodcom surveys, which collect values and quantities sold by individual firm and industrial product. From these data, it is possible to calculate unit values that can be used as a proxy for prices. Recent examples include papers investigating how domestic producer prices in Belgium respond to different shocks, such as marginal costs, suppliers' costs and competitors' costs (Amiti, Itskhoki and Konings, 2019, and Duprez and Magerman, 2018) or differentiate according to export status (Fuss, 2020). Using Swedish data, Carlsson and Nordstrom-Skans (2012) and Carlsson (2017) have investigated the relevance of price rigidity models. However, since these

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[11] This section was prepared by Catherine Fuss (Nationale Bank van België/Banque Nationale de Belgique), Erwan Gautier (Banque de France), Theodora Kosma (Bank of Greece), Valentin Jouvanceau (Lietuvos Bankas), Fernando Martins (Banco de Portugal), Pavlos Petroulas (Bank of Greece), Domingos Seward (Banco de Portugal), Irina Stanga (De Nederlandsche Bank) and Emmanuel de Veirman (De Nederlandsche Bank).

[12] Fabiani et al. (2006) provide survey evidence that mark-up pricing over costs is the predominant price-setting approach among European firms.

[13] National papers include Alvarez et al. (2010) for Spain, Cornille and Dossche (2008) for Belgium, Dias et al. (2008) for Portugal, Gautier (2008) for France, Stahl (2006) for Germany and Sabattini et al. (2005) for Italy.

[14] Zhou and Dixon (2019) recently investigated producer and consumer price rigidity in the UK, focusing on duration analysis.

data are collected annually or are close to average prices, they usually do not allow for the computation of statistics related to individual price changes, such as the monthly frequency of adjustment or the duration of price spells. Another source of information on firms' price-setting behaviour are monthly business surveys, which usually collect qualitative variables on price changes and expected price changes on a monthly basis. Several studies have used this type of data to document new findings on how producer prices adjust to shock (Loupias and Sevestre, 2013, for France) or to document patterns of price stickiness (Andrade et al., 2022, and Harris et al., 2020, for France, Bachmann et al., 2019, for Germany and Lein, 2010, for Switzerland). One difficulty with this type of survey data is that they usually contain no quantitative information, so it is not straightforward to obtain information from them on individual price changes, which is useful for theoretical models.

In this section, we present preliminary findings on producer price rigidity using microdata underlying official PPIs in Belgium, France, Greece, Lithuania, the Netherlands and Portugal.[15] In Section 3.1, we present the PPI microdata and discuss measurement issues related to the collection of these price data. In Section 3.2, we document cross-sectional findings on the frequency of producer price changes. Section 3.3 describes our results on the size of price changes. In Section 3.4, we analyse the time variation of the frequency and size of producer price changes.

3.1 Micro datasets underlying PPI in the euro area

Producer prices are not directly observed in outlets but are collected through surveys of firms. These surveys are conducted by NSI. The data collection follows EU legislation and Eurostat recommendations (Eurostat methodological handbook, 2012). Although actual practices may differ from one country to another (see below), these recommendations provide guidelines on how producer prices should be collected in principle. For a given product in the index and in each country, the NSI builds a representative sample of firms producing this product using annual firm surveys. Then, for each of the sampled firms, the most representative transactions are selected and the price for a specific product to a specific customer is collected every month. Prices refer to ex-factory basic prices that include all duties and taxes, including subsidies on products received, but exclude VAT, other similar deductible taxes directly linked to turnover and subsidies on products received, as well as transport costs (if not otherwise mentioned). In theory, individual price quotes underlying the PPI are specific, not only to a product and a firm (as for consumer prices), but also to a customer. In principle, the price also refers to an actual transaction price, and not a list price. Furthermore, it should refer to orders booked during the relevant period and not at the moment the products leave the factory gates.

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[15]   See Jouvanceau (2022) for detailed PPI results for Lithuania.

However, in practice, the collection of prices through surveys raises several measurement issues. Gautier (2008), using information on the type of price collected in the French survey, reports that many price quotes were not individual prices but average prices over different customers or several transactions, or sometimes even unit values (i.e. values of sales divided by quantities). This might be less of an issue for the construction of a price index than for the assessment of price rigidity. In the latter case, we need to track individual prices in order to calculate a precise duration between two price changes. An average of prices changes approximately every time one of the underlying individual prices changes. Therefore, when using price averages, one tends to overstate the actual frequency with which individual prices are adjusted. Different countries have different ways of dealing with average prices. For example, for the Netherlands, we were able to exclude prices averaged across customers or across time by using a flag that identifies such price averages.

Another example is the recent methodological change in Belgium in 2015. Until 2015, industrial production prices were collected through a monthly telephone survey. Since 2015, they have been collected on paper (Self-administered Paper Questionnaire) and online (Self-administered Web Questionnaire). As discussed within a Eurostat taskforce on the PPI, *"[…] investigations concluded that the different price developments partly arose from methodological differences from country to country,"* (Eurostat, 2012). In particular, it was pointed out that some collection methods may be biased towards reporting no price change. This may be the case with automatic telephone surveys (used in the United Kingdom, for example), and surveys where information on the last price level is provided to the respondent. Chart 4 reports the frequency of producer price changes over time in Belgium. The change in collection method clearly coincides with a steep rise in the frequency of price changes: the average frequency of price changes increases from about 20% in 2001-14 to more than double in 2015-17 (45%). In addition, the "January effect" (estimated at around 2 percentage points before 2015), which is clearly evident from the spikes in the frequency of price changes before 2015 and is also present in CPI microdata, despite the differences in collection methods discussed in the previous section, becomes insignificant following the implementation of the new collection system.

Chart 4

Unweighted frequency of monthly price changes in the period 2001-17 in Belgium

(y-axis: percentages)
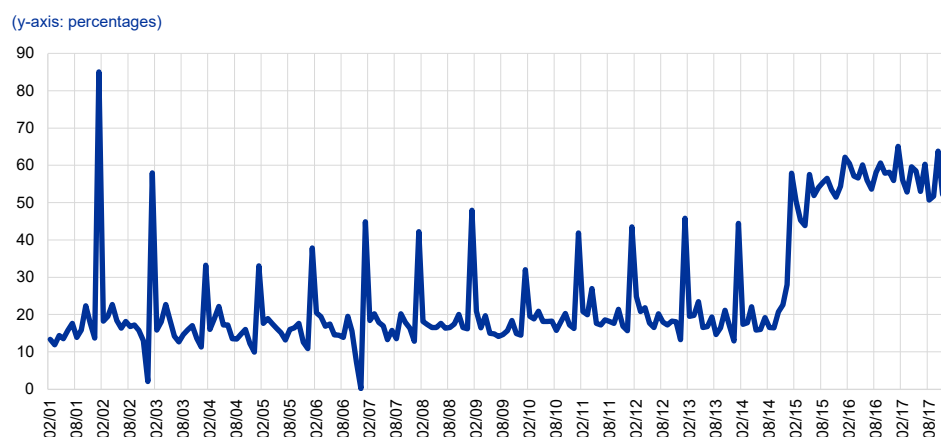
Source: PPI micro data set for Belgium; NBB calculations.
Notes: The figure plots the share of producer price changes in Belgium over the period 2001-2017.

Other measurement issues include replacements and the frequency of price collection. In the Netherlands, only some prices are collected monthly. Most are collected once a quarter (about 60%), while some are collected only once or twice a year. For all other countries in our sample, most producer prices are collected monthly. This difference in the frequency of price collection raises a number of statistical issues, including the fact that for prices that are not collected monthly, we have to decide how to express the price adjustment frequency as the share of price changes per month. We do so in two ways, with the first implying a low estimate of adjustment frequency and the second implying a high estimate. In the first approach, we assume that prices do not change between survey dates. For example, for prices that are surveyed once a quarter, this is equivalent to dividing the quarterly frequency of price adjustment by three in order to express it as a monthly rate. In the second approach, when we observe a price change, we assume that the price also changed in all the months between that survey date and the previous one. For prices that are surveyed quarterly, this is equivalent to using the quarterly adjustment frequency as such, assuming that it is equal to the adjustment frequency at a monthly rate.[16]

Product substitution is another important empirical issue. Statistical offices register a product change directly on the basis of information provided by the firm. Sometimes this information is translated into a specific flag in the price dataset; sometimes it is not. In Lithuania, where information on product replacement is available, the share of product replacement is highly seasonal, and in January, it is close to 30% (versus 4% on average between 2010 and 2018).

Finally, in contrast to consumer prices, there is no sales flag. However, this issue might be much less relevant for the PPI than for the CPI (see Vermeulen et al., 2012, for a discussion).

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[16]   See Dias-Costa et al. (2008) for a similar approach applied to Portuguese CPI quarterly data.

The survey collecting producer prices covers different prices for products sold on different markets: domestic, foreign (in the euro area or outside the euro area) and imports. Statistical agencies use these prices to construct the price indices corresponding to the different markets. Here, for most countries, we focus on prices for products sold on the domestic market and in the manufacturing sector (exceptions include Greece, Lithuania and Portugal, for which we consider prices for products sold on the domestic market and exports).

PPIs at the four-digit level are chain-linked indices, with product weights that are revised every year. However, for the euro area as a whole, the annual weights are not publicly available on national statistical websites or on Eurostat, unlike the HICP. However, in order to avoid country differences that could be due to different production structures, we have used French PPI weights to provide weighted statistics. France is a large euro area country, and we assume that French weights may be a good proxy for euro area weights. Table 5 summarises the main characteristics of the national PPI datasets to which we have access.

Table 5
PPI dataset characteristics

	Period	Collection frequency	Number of observations in the sample	Destination markets
Belgium	2001-14	Monthly	~150,000	Domestic market
France	2013-19	Monthly	~750,000	Domestic market
Greece	2008-20	Monthly	~420,000	Domestic and external markets
Lithuania	2010-18	Monthly	~130,000	Domestic and external markets
The Netherlands	2000-19	Monthly, quarterly, semi-annually, annually	1,600,000	Domestic market
Portugal	2010-20	Monthly	~900,000	Domestic market only (before 2015)
				Domestic and external markets (after 2015)

Sources: PPI micro data sets for Belgium, France, Greece, Lithuania, the Netherlands, and Portugal; authors' calculations.

3.2 Frequency of price changes

Producer prices change much more frequently than consumer prices. The frequency of price changes is 21% to 27% for Belgium, France, Greece and the Netherlands, but is much higher in Portugal and Lithuania (34% and 41% respectively), while the average frequency of price changes for CPI in the euro area is about 12.3% on average when including sales, as shown in the previous section (although sales are not as common in producer prices).[17] As a comparison, Vermeulen et al. (2012) find an average frequency of 21% for the euro area as a whole, covering a period from the late 1990s to the early 2000s.[18] In most countries, we find that there are rather more price increases than decreases: between 52% and

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[17] The sample of products in the HICP and PPI and the weighting structure differ substantially and might explain some of the marked difference.

[18] Another difference is that Vermeulen et al. (2012) cover a different sub-set of countries, including Germany, France, Italy, Spain, Belgium and Portugal.

63% of price changes are price increases. This country heterogeneity is not related to the different goods covered by the national PPI.

Table 6

Monthly frequency of price changes in the period 2001-17

(percentages)	Freq. of price changes	Freq. of price increases	Freq. of price decreases	Share of price increases
Belgium*	22.5	12.5	10.0	61.7
France	26.6	14.0	12.6	54.4
Greece	20.6	11.3	9.3	60.0
Lithuania	40.6	20.7	20.0	52.7
The Netherlands – option 1	13.7	8.1	5.6	62.0
The Netherlands – option 2	26.6	16.5	10.0	62.9
Portugal	33.8	17.0	16.9	52.2

Sources: PPI micro data sets for Belgium, France, Greece, Lithuania, the Netherlands, and Portugal; authors' calculations.
Notes: The statistics are first calculated at the disaggregate product level (NACE 4-digit), then weighted using the same weighting structure (French PPI as a proxy for euro area PPI weights). For the Netherlands, in option 1, we divide the frequencies calculated using quarterly data by three, whereas in option 2, we use frequencies calculated based on quarterly data as such (only monthly and quarterly data have been used to compute statistics).
* Belgian sample defined over 2001-14 and prices that are five times higher or five times lower than their previous month value, and excluding price changes that are less than 1/100,000.

Sectoral heterogeneity is pervasive. The frequency of price changes is highest in the energy sector, for all countries (Chart 5). Intermediate goods is the sector with the second-highest frequency in all countries. In many countries, the adjustment frequency for consumer non-durable goods is close to that for intermediate goods. Price changes are less frequent in the durable goods and capital goods sectors. This sectoral heterogeneity is close to what Vermeulen et al. (2012) documented earlier in the IPN results (Chart 5).

Chart 5

Monthly frequency of price changes across broad sectors (MIG)
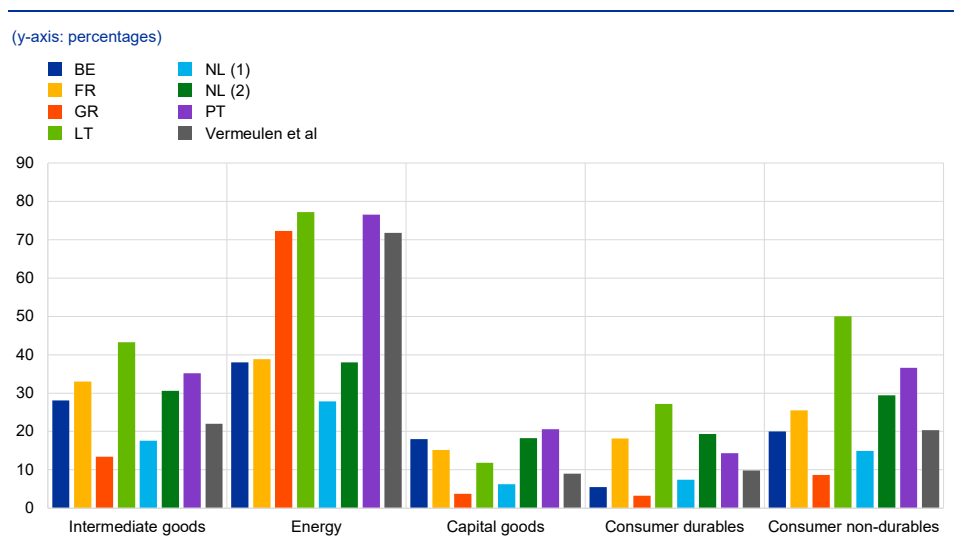
Sources: PPI micro data sets in Belgium, France, Greece, Lithuania, the Netherlands, and Portugal; authors' calculations.
Notes: The statistics are first calculated at the disaggregate product level (NACE 4-digit), then weighted using the same weighting structure (French PPI as a proxy for euro area PPI weights). For the Netherlands, in option 1, we divide the frequencies calculated using quarterly data by three, whereas in option 2, we use frequencies calculated based on quarterly data as such (only monthly and quarterly data have been used to compute statistics).

3.3 Size of price changes

The typical size of producer price changes is smaller in absolute terms than the size of consumer prices. The average size of price increases ranges from 2.5% in France to 9% in Lithuania, while median price increases range from 1.5% to 5.3% (Table 7).[19] For the CPI, the median size of price increases is 9.6% when price changes due to sales are included, and 6.7% when they are excluded. If we restrict consumer prices to manufacturing goods, the respective median sizes are 14% and 8%. Overall, producer price changes are much smaller than consumer price changes. However, the median size we find is somewhat higher than that reported in Vermeulen et al. (2012), which is closer to 2% to 3%. The smaller size of the price changes associated with a higher frequency of price adjustments is consistent with lower price-setting frictions (for a given volatility of idiosyncratic shocks). Another finding is that the average sizes of price increases and of price decreases are fairly similar in absolute terms, suggesting a more symmetric distribution of price changes than for consumer prices and a lower inflation trend.

Table 7
Median and average size of price increases and decreases

(percentages)

	Average size		Median size	
	Increase	**Decrease**	**Increase**	**Decrease**
Belgium	5.8	5.4	3.9	3.8
France	2.3	2.8	1.5	1.4
Greece	4.6	5.3	3.1	3.5
Lithuania	9.0	9.6	5.3	5.9
The Netherlands	4.9	5.3	3.5	3.0
Portugal	7.8	5.4	2.6	2.5

Sources: PPI micro data sets for Belgium, France, Greece, Lithuania, the Netherlands, Portugal; authors' calculations.
Note: The statistics are first calculated at the disaggregate product level (NACE 4-digit), then weighted using the same weighting structure (French PPI as a proxy for euro area PPI weights).

Differences in the median size of price changes across sectors are much more limited than for frequencies. The median size of price increases and decreases is quite similar in all broad sectors (Chart 6). The average size of price changes is a little lower in sectors with higher frequencies of price changes, such as energy and intermediate goods, whereas the average price change is larger in consumer non-durable goods. Vermeulen et al. (2012) found very few differences in the size of price adjustment across sectors.
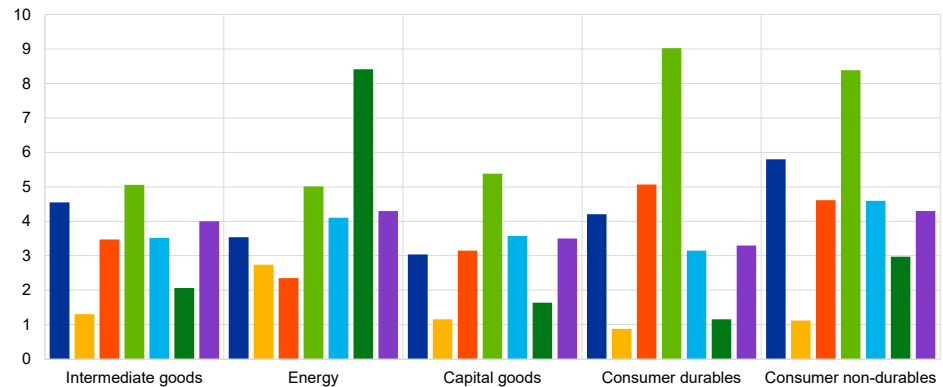
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[19]   For France, we find a lower size of price adjustments compared with Gautier (2008) in a different period. This might reflect certain methodological changes in price reporting in the available research dataset.

Chart 6

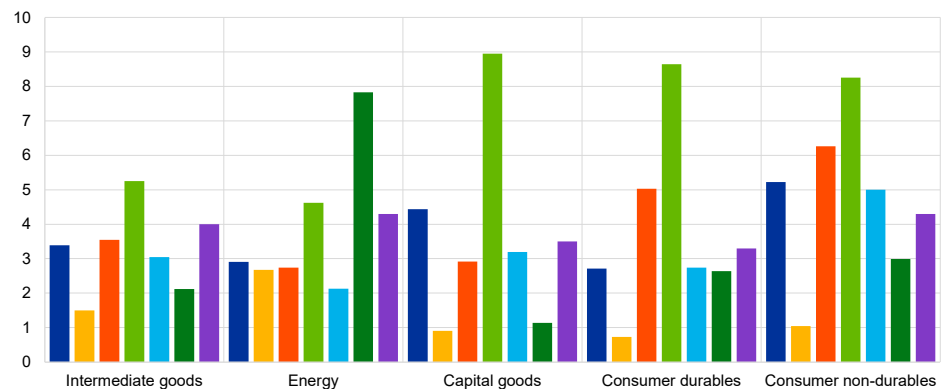**Median size of price increases/decreases across broad sectors (MIG)**

a) Median increase

(y-axis: percentages)

- BE
- FR
- GR
- LT
- NL (1)
- PT
- Vermeulen et al.

b) Median decrease

(y-axis: percentages)

- BE
- FR
- GR
- LT
- NL (1)
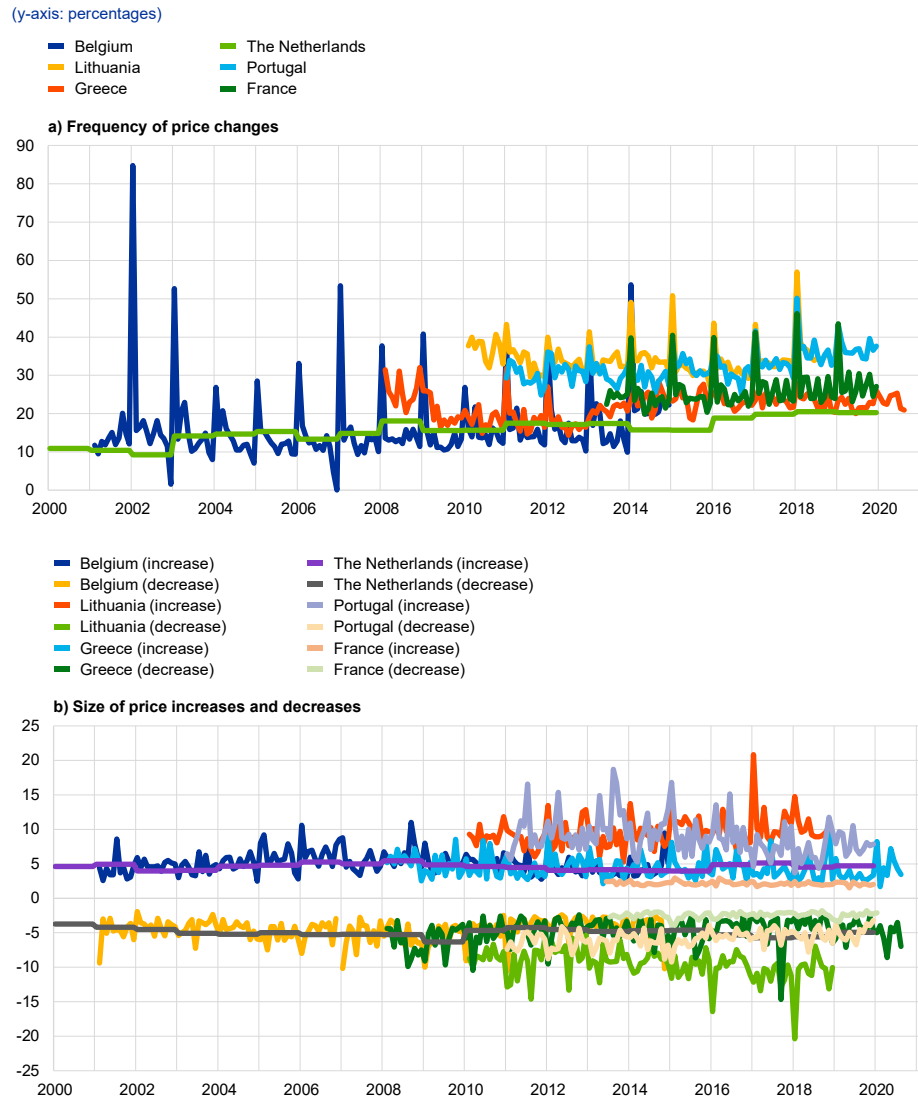- PT
- Vermeulen et al.

Sources: PPI micro data sets in Belgium, France, Greece, Lithuania, the Netherlands, and Portugal; authors' calculations.
Note: The statistics are first calculated at the disaggregate product level (NACE 4-digit), then weighted using the same weighting structure (French PPI as a proxy for euro area PPI weights).

3.4   Time series evidence

This section documents the variation of the frequency and the average size of producer price changes over the last 15 to 20 years. In Belgium, France, Greece and Lithuania, there is basically no positive or negative trend in the frequency of price adjustment. In the Netherlands, the frequency of price changes is computed annually and seems to indicate a higher frequency of price adjustment in the recent period. In Belgium, France and Lithuania, and to some extent in Portugal, the price adjustment is quite seasonal, with large peaks in January. Similarly, the time

variation in the average sizes of price increases and decreases is very limited for all countries.

Chart 7

Monthly frequency and size of producer price changes

(y-axis: percentages)

- Belgium
- Lithuania
- Greece
- The Netherlands
- Portugal
- France

a) Frequency of price changes

- Belgium (increase)
- Belgium (decrease)
- Lithuania (increase)
- Lithuania (decrease)
- Greece (increase)
- Greece (decrease)
- The Netherlands (increase)
- The Netherlands (decrease)
- Portugal (increase)
- Portugal (decrease)
- France (increase)
- France (decrease)

b) Size of price increases and decreases

Sources: PPI micro data sets in Belgium, France, Greece, Lithuania, the Netherlands, and Portugal; authors' calculations.
Notes: Aggregate frequencies and sizes of price adjustments have been weighted at the MIG level by a common weighting structure based on the French PPI weights (as a proxy for euro area PPI weights). For the Netherlands (NL), we have computed average annual numbers to keep all price observations with the different frequencies of price observations.

As for consumer prices, the time variation of producer price inflation is mainly driven by movements in the size of price adjustments, which are driven by variation in the share of price increases. Table 8 reports the correlations calculated over time between the main statistics for price adjustments at the country/broad sector (MIG) levels and the monthly euro area PPI inflation for broad sector levels. The correlation between inflation and the frequency of price changes is quite small and close to zero for most countries and sectors together, reflecting the

fact that the frequency does not move much over time.[20] The correlation between the frequency of price increases is positive, larger and significant at a 1% level for almost all countries and all sectors, whereas the same correlation with the frequency of price decreases is negative and also significant for almost all countries (the exceptions are Belgium and Lithuania).[21] Overall, when inflation is higher, producer prices are more frequently increased and to some extent less frequently decreased. This translates into a positive correlation with the overall size of price changes, while the correlation between inflation and the average negative and positive sizes of price changes taken separately is small, often close to zero, and not statistically significant. Overall, the largest correlation coefficients are observed for the frequency of price increases and the size of price changes, which both move closely in line with inflation.

Table 8
Correlation between recomposed and counterfactual inflation rates

	Frequency of price changes	Frequency of price increases	Frequency of price decreases	Size of price changes	Size of price increases	Size of price decreases
By country						
Belgium	0.17*	0.32*	-0.08	0.35*	0.12*	0.000
France	0.09	0.28*	-0.19*	0.38*	0.02	0.00
Greece	-0.03	0.16*	-0. 25*	0.18*	0.06	-0.01
Lithuania	0.18*	0.25*	0.05	0.10	0.08	0.09
The Netherlands	0.03	0.19*	-0.13*	0.27*	0.11*	-0.07
Portugal	0.02	0.20*	-0.17*	0.13*	-0.05	-0.00
By sector						
Intermediate goods	0.03	0.30*	-0.27*	0.50*	0.08	-0.02
Capital goods	0.20*	0.25*	0.09	0.08	0.05	0.05
Consumer goods – Durables	0.24*	0.32*	0.09	0.12*	0.10*	0.06
Consumer goods – Non-durables	-0.01	0.06	-0.07	0.20*	0.01	-0.01
All countries and all sectors	**0.05***	**0.18***	**-0.10***	**0.21***	**0.04***	**0.01**

Sources: PPI micro data sets for Belgium, France, Greece, Lithuania, the Netherlands, and Portugal; authors' calculations.
Notes: For each country and sector, statistics for the frequency and size of price changes have been calculated at the MIG level (five sectors) and have been matched with MIG PPI monthly inflation for the euro area. Simple time series calculations have been run, * indicates that the correlation is statistically significant at a 1% level. Energy has been excluded.

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[20] The small, positive but significant, correlation between inflation and the frequency of price changes mostly reflects the fact that inflation correlates slightly more with the frequency of price increases than the frequency of price decreases.

[21] The rather low level of correlation coefficients might result from the fact that country-specific PPI inflation is less correlated with euro area inflation. Robustness calculations have been run using aggregate euro area inflation, country-specific PPI inflation or a recomposed inflation based on the frequencies and sizes of price changes at the MIG level for each country, and the main conclusions hold.

4 State dependence in price setting – evidence from supermarket scanner data

This section[22] uses supermarket scanner data in four euro area countries (Germany, France, Italy and the Netherlands) and in the United States to assess the extent of state dependence in price setting. The previous sections have shown that price setting at the firm level is mainly driven by idiosyncratic factors. Therefore, the question arises of how firms decide to change prices, and in particular whether this decision depends on how large idiosyncratic price pressures are. This state dependence in price setting influences which prices adjust. It is a feature of price setting over and above infrequent price adjustment (how often prices adjust), and it can be as important. The reason is that the price level could remain flexible and fully responsive to aggregate shocks even if only a few prices change, if these changes are disproportionately large. This is the case if the adjusting prices are those for which extant, posted prices are most misaligned, even for purely idiosyncratic reasons, which tends to happen in frameworks where the price adjustment frictions are micro-founded by "menu" costs (Golosov and Lucas, 2007). The measurement of state dependence is challenging, because price misalignment is unobservable. The section overcomes these challenges by relying on the unparalleled granularity of scanner data, which allow for the construction of an empirical measure of price misalignment, i.e. the price gap.[23]

Two sets of data-driven moments provide direct information about the extent of state dependence: the price-gap hazard and the price-age hazard. The price-gap hazard function expresses the probability of price adjustment as a function of the size of the price misalignments, or price gaps. The slope of the hazard function provides direct information about the extent of state dependence: the higher the slope, the more sensitive the probability of adjustment to the price misalignment. A key challenge in measuring the price-gap hazard is obtaining a valid proxy for the unobserved price gap. Although supermarket scanner data cover only a limited set of consumer goods, they are crucial in identifying the optimal price from the behaviour of close substitutes, as we explain below. The price-age hazard function expresses the probability of price adjustment as a function of the time elapsed since the last price adjustment. In models with high state dependence, the age hazard function is upward sloping: the probability of price adjustment increases with the age of the price. This is because, as time elapses, the optimal price tends to drift away from the posted price, giving more and more compelling reasons for a price adjustment. A key empirical challenge in measuring the age hazard is controlling for cross-sectional heterogeneity, which biases the slope estimate downward. The granularity of the

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[22] This section was prepared by Peter Karadi, Juergen Amann, Javier Sánchez Bachiller and Jesse Wursten (European Central Bank, DG-Research), with comments from Luca Dedola (ECB).

[23] Scanner data enable the tracking of exactly the same good ("barcode") across many outlets; this is not usually possible with CPI or PPI microdata.

scanner data allows us to control for this at the lowest, product-store level. We first describe the supermarket scanner data in Section 4.1. In Section 4.2, we describe the price gap and the price-age hazard functions. In Section 4.3, we use moments to quantify the extent of state dependence in price setting and its contribution to the flexibility of the supermarket price level. Section 4.4 concludes.

4.1 Supermarket scanner data

The data cover four European countries: Germany, the Netherlands, France and Italy between 2013-17, and the United States between 2001-12 (Table 9). [24] The datasets are weekly panels of total revenues (TR_{psw}) and units sold (Q_{psw}) for each product p in store s in week w. We refer to a product in a store as an item. The unit-value prices of each item are calculated as revenues over units sold ($P_{psw}^{uv} = TR_{psw}/Q_{psw}$). The products are identified by their unique and unmasked barcodes (European Article Numbers (EANs) in Europe and Unique Product Codes (UPCs) in the United States).[25] The store IDs are masked to protect the identity of the supermarkets, but they are unique over time, allowing us to follow the price spells of each item over time.

The datasets represent the bricks-and-mortar sales of participating supermarket chains. The participating chains include regular and discounter supermarkets and drugstores.[26] In the European countries, our dataset includes 75% of IRi stores.[27]

The European datasets are spatially representative in each country. The datasets include the location of stores up to the first two digits of their postal code. The two-digit postal areas divide the countries into around 100 regions (Table 9). To obtain euro area (EA4) moments, we calculate a weighted average of country-level moments using country-level expenditures as weights. Even though the US sample is not spatially representative, it covers the most populous areas, providing a relevant sample of supermarkets across urban areas.[28]

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[24] Even though the US and euro area datasets do not overlap, this does not prevent us from comparing across countries those features that are stable over time (for example, the frequency of reference price changes.)

[25] The EANs of *private-label* products are masked to protect the identity of the supermarket chain.

[26] The datasets exclude "hard" discounters, such as Lidl, Aldi and Walmart.

[27] In some countries (Germany and Italy), some supermarket chains only share a representative sample of their stores with IRi (i.e. not the census of stores, which IRi obtains for all participating supermarket chains in France and the Netherlands). The impact of this sampling can be remedied using information on whether a store is present in our sample as a census or sample store, and information about the population of stores by geographic unit and store type (e.g. large supermarket, small supermarket, discounter or drugstore), which are also part of the dataset. We use this information to appropriately modify the weights of sample stores to obtain representative moments.

[28] The US dataset covers 50 urban markets across the US. These markets approximately correspond to 50 Metropolitan Statistical Areas (MSA) out of the 384 MSAs in the mainland US in 2010 and cover 73% of the US population.

Table 9

Data coverage (IRi supermarket scanner data)

Time series	DE	FR	IT	NL	US
	2013-17				2001-12
# two-digit postal codes	97	93	93	94	51
# stores	10,335	5,851	14,325	6,559	3,280
# store types	5	4	5	2	2
# chains	17	43	435	29	147
% in HICP/CPI	18.5	23.3	23.4	20.7	19.6
# products	369,907	423,175	697,875	391,673	204,519
Av. ann. exp. (EUR/USD billion)	32.8	56.19	42.16	15.22	6.2
# observations (billion)	13.79	10.02	10.96	7.67	2.7

Some data cleaning is necessary beforehand. In our analysis, we focus on monthly, sales-filtered reference prices.[29] We run a state-of-the-art sales filter. Specifically, we create weekly reference prices as a 13-week running modal price (Kehoe-Midrigan, 2015).[30] A key advantage of the reference price filter over a more conventional regular price filter that controls for V-shaped temporary price cuts (Nakamura-Steinsson, 2008) is that it also controls for temporary increases (spikes) in price spells. Such increases can be rationalised, for example, by inventory management: higher prices temporarily reduce demand and ensure that the store does not run out of the product until a new delivery arrives. Spikes can account for as much as one-third of high-frequency price changes (Kehoe-Midrigan, 2015). We transform weekly prices into monthly prices by choosing the mode over the weeks in the calendar month.

4.2 Moments of state dependence

4.2.1 Price-gap hazard

The price-gap (or generalised) hazard expresses the probability of price adjustment as a function of the price gap. The price gap is the distance between the posted price and the optimal "reset" price the store would set in the event that all price adjustment frictions were temporarily absent. The gap, therefore, influences the strength of the product-level price adjustment impetus: the larger it is, the further the price is from its optimal level, causing a potentially greater loss of profit due to either

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[29]   We first transform the weekly average unit-value prices into posted prices in two steps. In the first step, we filter out same-direction consecutive price changes to reduce the impact of mid-week price changes. In the second step, we round prices upwards to the nearest cent to mitigate the impact of buyer-specific discounts.

[30]   Like Kehoe and Midrigan (2015), we iteratively update the modal price to align the reference price change with the actual price change. As an additional step, we control for clearance and introductory sales in the first and last five weeks of the price spell.

sub-optimal demand (if the price is too high) or sub-optimal mark-up (if the price is too low).

A key empirical challenge is that the optimal reset price is unobservable. As a proxy, we calculate the competitors' reset price (Karadi et al., 2020). It is the average reference price of the same products in those competing stores that also changed the price of the same product in the same month. The measure also controls for permanent store-and-category-level price differences caused by heterogeneity in amenities, geography or market power. The proxy relies on the following assumptions: (i) the price of the same good among price-changing competitors effectively tracks the evolution of the product's wholesale price and aggregate demand conditions, which are the primary drivers of the optimal reset price; (ii) differences in amenities and market power between stores cause permanent store-and-category-level differences between prices; and (iii) chains follow national price-setting strategies (DellaVigna and Gentzkow, 2019), so local demand conditions have an insignificant impact on the optimal reset prices. We validate our proxy by showing that the size of the price change has a very tight, almost exactly one-to-one negative relationship with the price gap.[31]

The price gaps are wide and dispersed in both the euro area and the United States, as panel b) in Chart 8 shows. To arrive at the densities, we control for unobserved heterogeneity across items and the common impact of aggregate fluctuations.[32] The average absolute size of gaps is wide in both regions and narrower in the euro area than in the United States. In particular, it is **10% in EA4** and **14% in the United States**. At the same time, the gaps are dispersed in both regions, with a large mass of narrow gaps and a fat tail of wide gaps. This is true, even though we control for sales-related price changes as well as permanent differences between the store-specific prices. The dispersion of price gaps is also smaller in EA4 than in the United States: 90% of price gaps are between -13% and 14% in EA4 and between -20% and 19% in the United States.

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[31] Formally, we formulate the competitor-reset-price gap x_{pst} for product p in store s in month t in three steps. First, we take the (logarithm of) the sales-filtered reference prices p_{pst}^f. Second, we calculate an unadjusted gap as $\tilde{x}_{pst} = p_{pst}^f - \bar{p}_{p-st}^f$, where $\bar{p}_{p-st}^f$ is the average reference reset price of the same product across those alternative stores that changed the price of the same product in month t. Third, we deal with the persistent heterogeneity across stores (i.e. chains, locations) by subtracting the average store-and-category-level gap α_{cs}, and reformulate the price gap as $x_{pst} = \tilde{x}_{pst} - \alpha_{cs}$, where product p belongs to category c.

[32] We do this by estimating item and time-fixed effects in a panel regression of the form
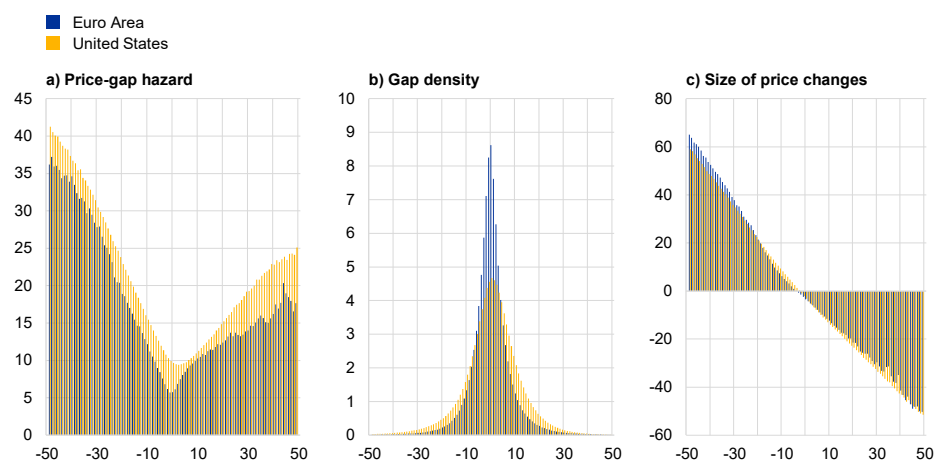
$$x_{pst} = \alpha_{ps} + \alpha_t + \varepsilon_{pst} \tag{1}$$

and calculating the share of normalised gaps $(x_{pst} - \hat{\alpha}_{ps} - \hat{\alpha}_t)$ in the 101 unit-percentage-point ranges between -50.5% and 50.5%. We censor the normalised gaps at -50.5% and 50.5%.

Chart 8

Price-age hazard, price-gap density and size of non-zero price changes as a function of the price gap

(price misalignment, percentages)

■ Euro Area
■ United States

Notes: The chart shows the frequency of reference price changes (price-gap hazard, panel a), the average size of non-zero reference price changes (panel c) as a function of the price gap, and the density of the price gap (panel b) in EA4 and the United States. The V-shaped hazard indicates the presence of state dependence in price setting, albeit at a moderate level in both regions. The density indicates the wide dispersion of price gaps, higher on average in the United States. The size chart validates the price-gap measures, showing a tight relationship between the gap and the eventual price change size.

The price-gap measure is valid, because there is a tight, negative, almost exactly one-to-one relationship between the gap and the average non-zero price changes in the subsequent month (Chart 8, panel c). This shows that the price gap is a relevant measure of price misalignment because stores choose to close the gap, on average, when they adjust the price. We estimated the relationship with a minimal set of structural assumptions.[33]

The empirical price-age hazard functions show clear evidence of state dependence in price setting (Chart 8, panel a).[34] The probability of price adjustment clearly increases with the price gap in both the euro area and the United

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[33]   First, we allocate price gaps into 101 bins, each covering a unit percentage-point range between -50.5% and 50.5%. The indicator function $I_{pst-1}^{[x_{j-1},x_j)}$ for bin j takes the value 1 in the event of gap $x_{pst} \in [x_{j-1}, x_j)$, and 0 otherwise. Second, we estimate a relationship coefficient (β_y^j) between the gap x and a variable of interest $y_{pst,t+1}$(frequency or size) for each bin j using the following panel specification:

$$y_{pst,t+1} = \sum_{j=1}^{J} \beta_y^j I_{pst-1}^{[x_{j-1},x_j)} + \alpha_{ps} + \alpha_t + \varepsilon_{pst} \qquad (2)$$

where α_{ps} are product-store and α_t are time-fixed effects. The fixed effects help us control for unobserved heterogeneity across items and common co-movement caused by aggregate fluctuations. Third, we obtain the estimated relationship as a sum of two components. The first component is the β_y^j coefficients for $j = [1,101]$. The second component is the average of the estimated fixed effects $mean_{ps}\hat{\alpha}_{ps} + mean_t\hat{\alpha}_t$ added to each bin j. Adding the second component ensures that the weighted average across bins approximates the sample average of the variable of interest y. The relationship between the average size and the gap is estimated following the above described steps, when the dependent variable is the non-zero reference price changes $y_{pst,t+1} = \Delta p_{pst+1}^f|_{\Delta p^f \neq 0}$.

[34]   These are estimated for each region following the steps outlined above, when the dependent variable is an indicator function that takes the value 1 if the reference price of product p in store s changed in period t+1, and 0 otherwise $y_{pst,t+1} = I_{pst+1}^f$

States, as illustrated by the V-shaped hazard functions.[35] The (weighted) average slope of the hazard functions is 0.51 in EA4 and 0.38 in the United States, implying that a 1% increase in the absolute size of the price gap increases the probability of changing the price by 0.51 percentage points and by 0.38 percentage points in the EA and the United States, respectively. This suggests that the state dependence is moderate in both regions (see Section 1.3.3 for further discussion). The difference between the regions is caused by the larger slope at the narrower gaps, where the biggest mass of price gaps is concentrated. The height of the hazard function is larger in the United States, in line with the higher frequency of price changes there.

4.2.2 Price-age hazard

An alternative way of looking at state dependence is the price-age hazard, which expresses the probability of price adjustment as a function of the months elapsed since the last price adjustment. In the presence of state dependence, the price-age hazard is upward sloping as the optimal price drifts further and further away from the posted price. The advantage of using granular scanner data to estimate the hazard function is that we can control for cross-item heterogeneity, which can bias the slope estimate downward.[36]

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[35] The hazard functions are mildly asymmetric, indicating that firms react more sensitively when their price is below its optimum than when it is above it. Such behaviour is expected in an environment with positive-trend inflation.

[36] We estimate the following panel regression

$$I_{pst,t+1} = \sum_{j=1}^{48} \beta^j I_{pst-1}^j + \alpha_{ps} + \alpha_t + \varepsilon_{pst}, \tag{3}$$

where the indicator function I_{pst-1}^j takes a value 1 if the reference price of product p in store s in month $t-1$ is j months old, and 0 otherwise. As with the price-gap hazards, we add the average of the estimated item and time-fixed effects to the β^j coefficients in order to make the weighted average of the coefficients approximate the frequency of reference price changes.

Chart 9

Price-age hazard function

(price age (in months, lagged), percentages)

■ Euro Area
■ United States
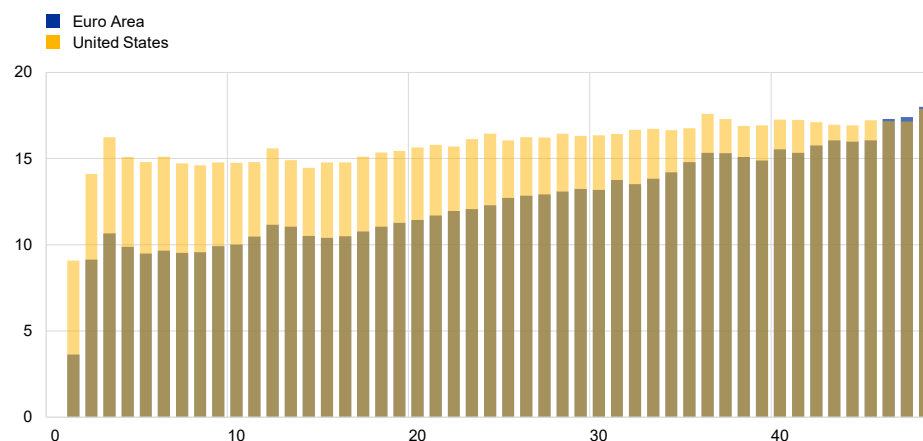
Notes: The chart shows the probability of the reference price change as a function of the price gap (price-gap hazard) in EA4 and US. The chart indicates the presence of state dependence in price setting, which is somewhat stronger in the EA4 than in the United States.

The price-age hazard is upward sloping in both the euro area and the United States, in line with state dependence (Chart 9). The probability of adjustment increases with the age of the product. The slope of the adjustment hazard is higher in EA4 than in the United States. Notably, the hazard function is approximately linear. This is especially true if we disregard the low estimated adjustment frequencies of recently adjusted prices, where sales filtering might introduce uncertainty and a potential downward bias into the estimation by mechanically identifying high-frequency price fluctuations as sales.[37]

4.3   State dependence and price-level flexibility

This section shows how to quantify the implications of this state dependence for price flexibility, using the moments above estimated from microdata. A natural measure of state dependence is how much it contributes to price flexibility, specifically to the inflationary impact of a permanent money shock. To measure this, we follow the framework of Caballero and Engel (2007), who showed that under mild conditions, the price-gap hazard function and the density provide sufficient information to quantify the contributions of the intensive and extensive margins of adjustment. Box 2 describes the analytical framework and explains how the relevant objects in the model relate to our empirical moments, before we go on to use it to decompose an aggregate money shock to adjustment margins.

[37]   Controlling for both cross-item heterogeneity as well as sales-related price changes is important for the results. Without it, we would erroneously conclude that the hazard function is downward sloping.

Box 2
Analytical framework

Caballero and Engel (2007) present a general price-setting framework which encompasses a wide class of sticky price models. There is a continuum of firms, each producing a single product i. The firms set the (log nominal) prices of their product (p_{it}) subject to a price adjustment friction. If these frictions were temporarily absent, the optimal price in period t would be p^*_{it}. The optimal price is driven by both aggregate and idiosyncratic factors $p^*_{it} = m_t + v_{it}$. For simplicity, we assume that shocks to both m_t and v_{it} are permanent. The aggregate shock m_t shifts the optimal nominal price of all firms, whereas the idiosyncratic shock v_{it} affects only firm i. The gap between the price and its optimal value $x_{it} = p_{it} - p^*_{it}$ is the relevant state variable and is sufficient to characterise each firms' price-setting choice. Assuming that the product i is sold in a continuum of stores, the average price set by price-changing stores shows the optimal price p^*_{it}, in line with our empirical application.

The firms' price adjustment decision can be described by a price-gap hazard function $\Lambda(x)$. The function takes values between 0 and 1, and its value expresses the probability of price adjustment for a firm with a price gap x. The hazard function is constant in the time-dependent Calvo (1983) model: there, the probability of adjustment is independent of the price gap. At the other extreme, in the fixed menu cost model (Caplin and Spulber, 1987; Golosov and Lucas, 2007), the hazard function is a step function, which takes the value 0 when the gap is within the inaction band, and 1 otherwise. Caballero and Engel (2007) show that a continuum of intermediate hazard functions can arise when the menu cost is an independent and identical distributed random variable (Dotsey et al., 1999), and when the firm is subject to rational inattention friction, as in Woodford (2009) (see also Alvarez et al., 2022).

In this economy, inflation can be expressed as a function of the price gap size, density and hazard. Formally, it is

$$\pi = \int -x\Lambda(x)f(x)dx \tag{4}$$

where $f(x)$ is the density of price gaps across firms, and suppressing subscripts for notational convenience. The expression is intuitive: the inverse price gap $(-x)$ is the size of the price adjustment, when it takes place, and the hazard is the probability of a price adjustment taking place. Their product, summed across the gap distribution and weighted by the density of the gap is, therefore, equal to the inflation rate.

The response to a money shock can be expressed as the sum of an intensive-margin and an extensive-margin effect. Caballero and Engel (2007) point out that the aggregate shock increases the optimal price of all firms, so it reduces the price gaps of each firm uniformly. The response to the aggregate shock can be therefore expressed as a derivative of the expression on the right-hand side of equation (4) with respect to x, which implies

$$\frac{\partial \pi}{\partial m} = \underbrace{\int \Lambda(x)f(x)dx}_{\text{intensive}} + \underbrace{\int x\Lambda'(x)f(x)dx}_{\text{extensive}} \tag{5}$$

where $\Lambda'(x)$ is the slope of the hazard function. The expression has two terms. The first term, which Caballero and Engel (2007) dub the intensive margin, results from each adjusting firm changing its prices marginally more to incorporate the impact of the aggregate shock. Notably, it is exactly equal to the frequency of price adjustment, and this is the only margin that is active in the

time-dependent Calvo (1983) model, which has a constant hazard. The second term is the extensive-margin effect, which takes into account any shifts in the identity of price-adjusting firms. The slope of the hazard function appears in this expression, because it measures the mass of new price adjusters as the aggregate shock shifts the price-gap density. The extensive margin is powerful if the new adjusters are primarily those with large price gaps. This tends to be the case with strongly state-dependent (S,s)-type menu cost models (Golosov and Lucas, 2007), where it is optimal to adjust prices with the largest gaps in the presence of fixed menu costs of price adjustment. We can compute the two margins using microdata and thus provide a back-of-the-envelope computation of how inflation would react to a monetary shock increasing optimal prices by 1% across all firms.

We quantify the intensive and extensive-margin effects using empirical estimates of the price-gap hazard function and the density. The intensive-margin effect is the average frequency, which is also the average of the hazard function, weighted by the density at each bin. To obtain the extensive-margin effect, we first calculate the slope of the hazard function at each bin as the centred finite difference between subsequent bins. Second, we multiply the slope by the size of the misalignment and, third, we calculate a weighted average using the density weight of each bin.

Accounting for state dependence raises price-level flexibility by around 33% in both the euro area and in the United States relative to a state-dependent benchmark (Calvo, 1983). The second and third rows of Table 10 show the contributions of each adjustment margin relative to the overall effects. Table 10 shows the relative contributions of the intensive and extensive margins to the overall impact effect. It is 25% in both the euro area and the United States, meaning that accounting for state dependence raises price-level flexibility by around 33%=25%/(1-25%) relative to a time-dependent benchmark. This is a meaningful increase, but it is small compared with an (S,s)-type menu cost model, where the price-level flexibility with the same frequency is predicted to be six times that of a time-dependent benchmark (Golosov and Lucas, 2007).

As Table 10 also shows, there is a sizeable heterogeneity among euro area countries in the extent of the contribution of state dependence to aggregate price-level flexibility. It is lowest in France, where it only raises aggregate price flexibility by around 15% relative to the time-dependent benchmark, and highest in Germany, where it raises aggregate price flexibility by 70%.

Table 10

Relative contributions of the adjustment margins

Margins	EA4	US	DE	FR	IT	NL
Intensive	76.4%	75.4%	61.8%	85.4%	73.1%	76.3%
Extensive	23.6%	24.5%	38.2%	14.6%	26.9%	23.7%

Notes: The table presents the relative contributions of the intensive and extensive-margin effects to a unit money shock (Caballero and Engel, 2007). The table shows that state dependence (extensive margin) raises aggregate price flexibility by around 33% in both the euro area and the United States relative to a time-dependent benchmark (intensive margin). There is notable heterogeneity between the contribution of state dependence across euro area countries, with the lowest level of state dependence in France and the highest in Germany.

5 Conclusions and policy implications

This chapter has provided a set of important stylised facts, based on euro area consumer and producer micro prices in a period of low and stable inflation.

Price changes are infrequent in core sectors. On average, 12% of consumer prices (excluding energy) change each month, falling to 8.5% when sales prices are excluded (close to the 10% US frequency). The frequency of producer price adjustment is larger (close to 25%) and reflects the fact that intermediate goods and energy have more flexible prices. For both consumer and producer prices, there is substantial cross-sectoral heterogeneity, but cross-country heterogeneity is much more limited.

Price changes tend to be large and heterogeneous, with both small and large hikes and cuts. Typical (non-zero) consumer price changes are much larger than inflation (even excluding sales): the median increase and decrease stand at around 9% and 12%, respectively. In addition, the distribution of consumer price changes shows a broad dispersion. For producer prices, the typical absolute price change is smaller, but still greater than inflation. Firm-specific cost and demand shocks appear more relevant than aggregate shocks in terms of when and by how much firms reset their prices.

Price setting is mildly state-dependent, mainly driven by firm-specific shocks. Microdata enable direct measurement of which prices are more likely to change depending on their misalignment (although these scanner microdata are limited to supermarkets). The probability of price adjustment rises with the size of the misalignment, mainly reflecting idiosyncratic shocks, but it does not increase very sharply. This direct evidence of a moderate degree of state dependence may still influence monetary transmission, particularly by eliciting non-linearities in response to variations in trend inflation or major cost shocks. In the current volatile environment, more frequent and larger price changes than suggested by historical regularities may occur (see more details in Dedola et al., 2023, using simulation results from a calibrated sticky price model).

For both consumer and producer prices, the repricing rate showed no trend over the period 2005-19 but was volatile in the short run. Despite several possible structural influences, the repricing rate shows little sign of a downward or upward trend during the low-inflation period. However, it does vary over time. In particular, for both producer and consumer prices, it is seasonal, as price increases are more frequent in January.

Cyclical inflation variation was due to fluctuations in the average size of price changes. Small cyclical variations in frequency did not contribute much to fluctuations in aggregate inflation, which instead mainly reflected shifts in the average size of price changes. Consistent with idiosyncratic shocks as the main driver of price changes, aggregate disturbances affected inflation by shifting the relative number of firms increasing or decreasing their prices, rather than the size of

price increases and decreases, or the repricing rate. This "linear" behaviour of aggregate inflation could change, however, when aggregate shocks are greater than in historical experience, because of the aforementioned non-linearities in firm-level decisions. Evidence from the United States confirms that in the 1978-82 "Great Inflation" period. the repricing rate rose to over 15%. In most euro area countries, microdata on prices underlying the HICP or PPI are not available in real time, and we are not able to investigate how the recent surge in inflation has modified price setting in the euro area. However, Henkel et al. (2023) provide more facts on how the shocks associated with the coronavirus (COVID-19) pandemic may have affected price setting in 2020-21. Relying on various data sources collected over the most recent period and previous findings from the literature documenting pricing patterns in high and more volatile inflation periods, Dedola et al. (2023) also provide evidence that the frequency of price changes correlates more closely with inflation when inflation is high.

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Erwan Gautier
Banque de France, Paris, France; email: erwan.gautier@banque-france.fr

Peter Karadi
European Central Bank, Frankfurt am Main, Germany; email: peter.karadi@ecb.europa.eu

Juergen Amann
European Central Bank, Frankfurt am Main, Germany; email: juergen.amann@ecb.europa.eu

Cristina Conflitti
Banca d'Italia, Rome, Italy; email: cristina.conflitti@bancaditalia.it

Riemer Faber
Nationale Bank van België/Banque Nationale de Belgique, Brussels, Belgium; email: riemer.faber@nbb.be

Brian Fabo
Národná banka Slovenska, Bratislava, Slovakia; email: brian.fabo@nbs.sk

Ludmila Fadejeva
Latvijas Banka, Riga, Latvia; email: ludmila.fadejeva@bank.lv

Catherine Fuss
Nationale Bank van België/Banque Nationale de Belgique, Brussels, Belgium; email: catherine.fuss@nbb.be

Theodora Kosma
Bank of Greece, Athens, Greece; email: tkosma@bankofgreece.gr

Valentin Jouvanceau
Lietuvos Bankas, Vilnius, Lithuania; email: vjouvanceau@lb.it

Fernando Martins
Banco de Portugal, Lisbon, Portugal; email: fmartins@bportugal.pt

Jan-Oliver Menz
Deutsche Bundesbank, Frankfurt am Main, Germany; email: jan-oliver.menz@bundesbank.de

Teresa Messner
Oesterreichische Nationalbank, Vienna, Austria; email: teresa.messner@oenb.at

Pavlos Petroulas
Bank of Greece, Athens, Greece; email: ppetroulas@bankofgreece.gr

Pau Roldan-Blanco
Banco de España, Madrid, Spain; email: pau.roldan@bde.es

Fabio Rumler
Oesterreichische Nationalbank, Vienna, Austria; email: fabio.rumler@oenb.at

Javier Sánchez Bachiller
European Central Bank, Frankfurt am Main, Germany; email: javier.sanchez-bachiller@ecb.europa.eu

Sergio Santoro
European Central Bank, Frankfurt am Main, Germany; email: sergio.santoro@ecb.europa.eu

Domingos Seward
Banco de Portugal, Lisbon, Portugal; email: dseward@bportugal.pt

Irina Stanga
De Nederlandsche Bank, Amsterdam, The Netherlands; email: i.m.stanga@dnb.nl

Emmanuel de Veirman
De Nederlandsche Bank, Amsterdam, The Netherlands; email: manu.veirman@dnb.nl

Elisabeth Wieland
Deutsche Bundesbank, Frankfurt am Main, Germany; email: elisabeth.wieland@bundesbank.de

Ladislav Wintr
Banque centrale du Luxembourg, Luxembourg, Luxembourg; email: ladislav.wintr@bcl.lu

Jesse Wursten
European Central Bank, Frankfurt am Main, Germany; email: jesse.wursten@ecb.europa.eu

Hélène Zimmer
Nationale Bank van België/Banque Nationale de Belgique, Brussels, Belgium; email: helene.zimmer@nbb.be