LIETUVOS BANKAS
EUROSISTEMA

Producer and consumer price rigidity: the case of Lithuania

Discussion Paper Series

No 27 / 2022

Discussion Paper Series
No. 27 / 2022

ISSN 2345-0835 (online)

Producer and consumer price rigidity: the case of Lithuania

Valentin Jouvanceau[1]
Bank of Lithuania Email: VJouvanceau@lb.lt

[1]Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the Bank of Lithuania or the Eurosystem. I thank Jose Garcia-Louzao and an anonymous reviewer for their valuable comments. I also express my gratitude to the Lithuanian Statistical Office for providing me with access to these data.

ABSTRACT

I provide the first statistics on producer and consumer price rigidity in Lithuania based on HICP and PPI item-level databases covering about 73% and 99.5% of their respective weights between 2010 and 2018. Producer prices are much more flexible than consumer prices, with an average monthly frequency of price change of 58% versus 18%. Contrariwise, the average size of price increases and decreases is higher in the HICP, reaching about 17-18% in absolute terms, whereas it is 7.5% in the PPI. In both price families, changes in item-level inflation are primarily due to variations in the size of price changes. However, the sources of these size changes are substantially shaped by shifts in the share of the number of price increases in the total.

JEL Classification: D40, E31, E50.

Keywords: Price rigidity, price-setting, producer prices, consumer prices.

Gedimino pr. 6, LT-01103 Vilnius, Lithuania

www.lb.lt

1. INTRODUCTION

Producer and consumer price indices (PPI and HICP/CPI) measure an average of a wide variety of individual price changes. Statistics on the size and frequency of these changes are crucial for the design and estimation of macroeconomic models that assume nominal rigidities. The advent of price data at the disaggregated level has led to a real breakthrough in the accuracy of their estimates. Nominal rigidities are now supported by evidence of the low frequency of price changes, thus undermining the theoretical neutrality of nominal shocks. Among others, Nakamura and Steinsson (2008) was able to study price rigidity in the United States (US) using product-level consumer and producer prices.[2] For the euro area (EA), Vermeulen et al. (2012) studied the price inertia in PPI of 6 countries, while Dhyne et al. (2006) examined CPI/HICP data for 10 countries. Recently, Gautier et al. (2022) has made a collective effort to update and deepen the evidence on consumer price stickiness for 11 countries.[3]

I contribute by providing the first analysis on price rigidity in Lithuania using, in a rare exception, almost the entire universe of micro prices underlying the HICP and PPI between 2010 and 2018. Having such a range of information is valuable because Gautier et al. (2022) show that consumer price rigidity statistics are quite similar in 11 EA countries between 2010-2019 (including Lithuania). The following findings could therefore reasonably be transposed to the EA, subject to the different weights for the price indices in each country, but also because Lithuania stands out as a small open economy highly exposed to external shocks. In fact, consumer and producer prices have grown in a large V-shape, starting with a sharp deceleration from 2010, reinforced by the Russian export and global oil crises of 2014-2015. Subsequently, they rebounded strongly with the entry into the EA in January 2015.[4]

The micro-data in my study go almost all the way down to the product prices and thus can be used to calculate size and frequency statistics at the lowest level where HICP and PPI weights are available, namely ECOICOP4 and NACE Rev. 2 (2 digit). The HICP database has approximately 5 million price records, representing about 73% of average consumer expenditure over the period. The PPI covers an impressive 99.5% of average producer weights, with nearly 125,000 price entries. In addition, they contain information about sales (promotions), replacement and entries of products. These phenomena are of crucial importance for accurately assessing the degree of price rigidity, and thus the transmission of monetary policy (Kehoe and Midrigan (2015)). My micro-level statistics are also interesting for theory. In a standard price problem, one typically develops the choices of a producer, yet the calibrations of the models are commonly done on consumer prices (Midrigan (2011); Alvarez and Lippi (2014); Karadi and Reiff (2019)). Such an approach could be problematic when the main price statistics differ significantly between producer and consumer prices, as we will see is the case in Lithuania. Indeed, Alvarez et al. (2016) prove that the real effects of monetary policy can, under certain conditions, be summarized as the ratio of kurtosis to the frequency of price changes; hence, here their evaluations will diverge.

I find that the average frequency of price changes is much higher for the PPI than for the HICP, 58% versus 18%. In comparison, the average frequency in the EA is 21% in the PPI (Vermeulen et al. (2012)) and about 12% between 2010 and 2019 in the CPI (Gautier et al. (2022)).[5] The main reason for the high frequency in the Lithuanian PPI is the importance of energy-related prices, which averaged about 30% of the index over the period and which change almost monthly. Contrariwise, I observe almost no prices directly linked to energy for the HICP. The composition of the two indices I use is therefore not the same, nor their weights,

[2] See Klenow and Malin (2010) for a survey.

[3] There are also country-specific studies, such as with the CPI in France (Berardi et al. (2015)), or with the PPI in Spain (Álvarez et al. (2010)).

[4] See Figures 1 and 2 for more detail.

[5] The period of coverage of the 6 countries, Belgium, France, Germany, Italy, Portugal and Spain, extends from 1991 to 2005 in Vermeulen et al. (2012).

and the comparison must therefore be taken with a grain of salt. However, this shows the importance of taking into account micro-level heterogeneity, given its important impact on the aggregate statistics. In fact, even within the HICP, there is considerable diversity in price stickiness by category. Price changes for services are rare (about every two years) and quite often upward (73%). In contrast, unprocessed food prices vary approximately every two to three months and symmetrically up and down.

Moreover, the average size of price increases and decreases is almost similar in absolute value, at about 18% for the HICP and 7.5% for the PPI. In the EA, average sizes are about 12% for price rises and 16% for price falls in the CPI (Gautier et al. (2022)). For the PPI, Vermeulen et al. (2012) report a median size of 3% for upward price changes and 2% for downward price changes. The respective medians are both 6.5% in absolute value for Lithuanian producer prices. I also provide distributions of standardized non-zero price changes. Both the PPI and HICP histograms have a rather leptokurtic shape, i.e. with a high concentration of small price changes. Modeling on these consumer price statistics, the high kurtosis and low average frequency of price changes suggest that the real impact of nominal shocks would be large in Lithuania (Alvarez et al. (2016)). On the other hand, the high flexibility of producer prices indicates that these same shocks should be fairly neutral. This opens up interesting avenues of research.

Furthermore, I reveal by means of fixed-effects regressions that the Lithuanian HICP and PPI inflation rates are mainly related to the fluctuation of the overall size of price changes. Incidentally, the frequency of price changes plays almost no role. Digging deeper, I find that changes in the share of price increases are also determinant. In other words, much of the upward variation in price size is due to higher numbers of price increases. I also show that price setters adjust size rather than frequency in response to a monetary policy and an oil supply shock. Theoretically, a Calvo (1983) type model or a menu cost model in a low inflation environment would yield a similar result (Alvarez and Lippi (2014)). Importantly, PPI inflation responds to these shocks by a factor of about six times that of HICP. This may indicate that producers' menu costs are lower than retailers', and thus that macroeconomic disturbances lead to smaller and more frequent price adjustments.

In this paper, I first describe the micro-price databases. In a second part, I discuss cross-sectional statistics. In a third part, I analyze the time series patterns. Finally, I conclude with some remarks.

2. DATA

Throughout this analysis, I will examine price rigidity using price series at disaggregated levels. To this end, I rely on databases with a substantial span of prices underlying the HICP and PPI in Lithuania. The data come from the Lithuanian Statistical Office (Lietuvos Statistikos Departamentas) and range from January 2010 to December 2018. PPI price observations are monthly and cover about 99.5% of average PPI weights at the NACE Rev. 2 (2-digit) level between 2010 and 2018. HICP price observations are monthly and cover about 73% of consumer expenditures based on average HICP weights at the ECOICOP4 level between 2010 and 2018.[6]

The PPI data series includes price records below the NACE Rev. 2 4-digit level.[7] For example, I can observe the unit price of the production of an apple juice made in Lithuania. There is also a base price as of December of the previous year and an explanation if there is a price change. We will see that this information is valuable in smoothing out the large influence of item entries and replacements. The HICP database contains price

[6]The categories housing, water, electricity, gas and other fuels (ECOICOP 04) and transportation (ECOICOP 07) are underrepresented in the data. Notably, I do not observe prices for electricity (04510), heat energy (04550), diesel (07221), and petrol (07222), which constitute roughly 11% of the average HICP weights between 2010 and 2018. For more details, see Jouvanceau (2021).

[7]Producer price indices are only publicly available at the 2-digit level. More details on the NACE Rev. 2 classification are available on the Eurostat RAMON website.

records at a level below that of the lowest public aggregate, namely ECOICOP4.[8] For example, I can observe the price of 1 kg of rice, and the type of outlet and the region in which it is sold.[9] In addition, the database contains "flags" that can indicate the reason for a price change. These can be due to sales (promotions), product replacements, quality changes, seasonality, etc. From this information, I generate "regular" price series to reveal their effects on price dynamics. Additional information on this procedure, data cleaning, and definitions related to statistics is expanded in Appendices 5 and 5.

3. CROSS-SECTIONAL STATISTICS

To begin, I examine what the two micro-price databases represent in terms of official inflation. PPI inflation rates are compared in Figure 1. Panel A highlights monthly aggregate inflation rates and panel B shows year-over-year variations. The match with official inflation rates is very high. Correlation is 86% for monthly changes and 89% for yearly ones. Figure 2 illustrates the HICP inflation rates. The monthly rates have a lower dispersion than the official ones and the correlation is only 53%. Annual rates are better correlated (about 75%), but the rates are frequently higher. These differences are principally caused by the absence of a large part of the energy prices in the sample.[10] Controlling for their unavailability, I show in Jouvanceau (2021) that the correlation increases to 82% and 95% for the monthly and annual rates respectively.[11,12]

[Figure 1 about here]

[Figure 2 about here]

FREQUENCY OF PRICE CHANGES

For the PPI, the average frequency of price changes is 58% ("B to E" in Table 1). For the HICP, it is 18% ("All-items" in Table 2).[13] For comparison, the average frequency is 21% for PPI and 12% for CPI in the EA (see Vermeulen et al. (2012) and Gautier et al. (2022) respectively).[14] The large difference in frequency in Lithuania (40pp) is therefore striking. This can be explained in part by three "non-economic" reasons. First, new item observations are very high in January in the PPI micro database (see Figure A1 in the appendix 5). Second, prices reported by firms are assumed to represent the same item sold in the same market to the same customer throughout the pricing period, unless a change in item, market and/or customer occurs. However, it is up to the company to report these changes. Therefore, there can be many measurement errors if left unreported. Third, some firms provide an average price for a group of products instead of a single item; this undoubtedly results in many price changes from month to month.[15]

[Table 1 about here]

[Table 2 about here]

[8] For more details on the ECOICOP classification, please refer to the Eurostat RAMON website.

[9] There are six geographical locations: Vilnius, Kaunas, Klaipėda, Šiauliai, Panevėžys and "another territory".

[10] I observe 3 out of 10 ECOICOP4 categories related to the special aggregate "energy" after the cleaning procedure (04522, 04530, 04549). They are missing the most important in terms of HICP weights, namely electricity (04510), heat energy (04550), diesel (07221) and gasoline (07222)). These four categories alone account for about 11% of the average HICP weights between 2010 and 2018.

[11] Note that energy prices are generally very volatile and price changes are frequent, thus the aggregate statistics on the size and frequency of price changes are slightly skewed. However, because of these, consumer energy prices are usually not included in the analyses of price rigidity (Gautier et al. (2022)).

[12] My calculation of the PPI and HICP aggregate inflation rates are also different from that of the Lithuanian Statistical Office which uses Laspeyres formulas. A detailed note on the official CPI methodology can be found at: https://osp.stat.gov.lt/documents/10180/250665/VKI_metodika_en.pdf. The PPI methodology can be found at: https://osp.stat.gov.lt/documents/10180/250665/GKI_metodika_EN.pdf

[13] The PPI statistics are broken down by the five NACE Rev. 2 sections (1-digit). I provide in Table A1 of appendix 5 a further breakdown by major industry group (MIG).

[14] In Vermeulen et al. (2012), the statistic is based on a sample of data from 6 countries from 1991 to 2005. In Gautier et al. (2022), it is based on 11 countries from 2010 to 2019.

[15] This does not rule out the possibility that the latter two problems are also present in our consumer price sample and in other studies using micro-level prices. On balance, the excessive number of item turns in January is the problem that generates the greatest bias on Lithuania PPI frequency in my case. In appendix 5, I report a "January" effect in frequency of about 10pp (see Figure A2). This indicates the potential size of this bias, so the difference between the PPI and the HICP frequency would be closer to 30pp.

The statistics calculated on the "regular" series partially smooth out these problems. However, the difference in average frequency is still significant, 48% for the PPI versus 9% for the CPI. This indicates that producer prices are much more flexible than consumer prices in general. The main reason for this will be discussed later. Importantly, the composition of the two indexes I observe is not the same, nor is their weight. The comparison of statistics that I make throughout these sections should be taken with a grain of salt. Nevertheless, this is useful for understanding the importance of micro-level heterogeneity on aggregate statistics. In this sense, the average frequency by category differs significantly in the PPI. Prices in category D related to energy change on average every month (69%), but those in category B, "mining and quarrying", only every 5 months (21%). In the HICP, services prices (6%) are much more rigid than unprocessed food prices (38.5%), with the former adjusting about every two years compared to almost every two to three months for the latter. Gautier et al. (2022) find a somewhat similar spread between services (6%) and unprocessed foods (31%), with the other categories having frequencies of the same order as mine. Note that this heterogeneity remains in the "regular" statistics for both types of prices, and thus is not simply due to sales or replacements.

I address this heterogeneity in more detail with the weighted frequency distributions of price changes in Figures 3 and 4. In the PPI, the distributions are highly distinct by category; the frequency peaks appear at different intervals. It is also clear why the average frequency of price changes is so high in manufacturing (C) and energy-related prices (D). It turns out that these two distributions have a mode in the highest interval, i.e. between 99% and 100% frequency. These extremes indicate that a large portion of the prices in these categories change each month. This is precisely because divisions C19: "Manufacture of coke and refined petroleum products" and D35: "Electricity, gas, steam and air conditioning supply" often have a monthly frequency of 100%.[16] This is perhaps not surprising given the nature of the items in these divisions. I argue that it may also be due to the fact that they are average prices, not individual prices. These categories also matter a great deal in the overall "B to E" frequency, as they have an average weight of about 25% and 12% in the PPI between 2010 and 2018.[17]

In the HICP, it is very rare that more than 10% of service prices change each month. The frequencies in the energy, NEIG (non-energy industrial goods), and processed food categories show fairly similar distributions, with a main mass concentrated around the average frequency of prices for "All-items." In contrast, the frequency distribution of unprocessed food prices is multi-modal around 20% and 65%. The latter is very high because of the large number of rotations and sales (they represent 14% of the total prices, see Table 2). And when adjustments are made, the distribution does indeed shift significantly to the left. At the extreme, only 0.8% of the service prices are adjusted to produce "regular" statistics.

Finally, prices for services show another peculiarity. The majority of price changes are upward (73%, see Table 2). In comparison, the share of increases is between 50% and 60% for all producer and consumer price categories. Moreover, this share increases by 5 to 10pp for each category when HICP prices are adjusted. In contrast, this share increases only slightly after the adjustment of PPI prices. The main reason for this difference is the large number of consumer price promotions/sales.

[Figure 3 about here]

[Figure 4 about here]

I continue by studying the hazard of price changes. The hazard rate at time t indicates the probability that a

[16] These categories may be considered outliers, but their weight in the total index is so high that it is difficult to ignore them. Note again that I lack a lot of information about energy-type consumer prices. This would likely reduce the difference in the frequency of price changes between the HICP and the PPI.

[17] When considering "regular" prices, frequencies tend to decrease significantly, except for energy prices where only 1.5% of the price is adjusted (see Table 1).

price will change after t periods if it has remained fixed until then. I estimate the hazard functions for "regular" price changes assuming discrete time proportional hazard models.[18] As a benchmark, the estimates are initially based on pooled data. This approach can lead to downward bias due to item heterogeneity (Nakamura and Steinsson (2008)). To address this potential problem, I split the estimates by categories and subsequently assume Gaussian frailty at the item level. Figures 5 and 6 illustrate the shape of the hazard functions for PPI and HICP price changes, respectively. First, neither function is upward sloping, meaning that the probability of a price change does not increase as it remains unchanged.

[Figure 5 about here]

[Figure 6 about here]

For pooled data ("B to E", "All-items"), the hazard has a steep downward slope in the first few months and is fairly flat thereafter. In other words, prices are very likely to change again right after they change. There is also a 12-month peak, which is particularly pronounced in PPI categories B "mining and quarrying" and D energy-related prices, and in HICP categories NEIG, services and processed foods. This behavior suggests that some firms set prices for a fixed duration, as theoretically modeled by Taylor (1980). Importantly, this form of decreasing hazard cannot be emulated by a model with a constant hazard rate as in Calvo (1983) or a state-dependent model with persistent shocks as in Golosov and Lucas (2007) in which the hazard is increasing.

In addition, the estimates by category show significant differences in hazard. For example, hazard is considerably more constant in services than in food-related prices (Figure 6). In addition, the hazard is also strongly influenced by item heterogeneity. In the HICP, hazard is steeper when unobserved heterogeneity is considered.[19] These shapes help diagnose which structural pricing model would be most appropriate here. To fit them, it would be preferable to consider mixed models with heterogeneous constant-time-dependent hazard as in Carvalho (2006), or a combination of time and state dependence as proposed in Nakamura and Steinsson (2008). In sum, unobserved heterogeneity is essential to explain the slope in the hazard in our data, as otherwise demonstrated theoretically and on US data in Alvarez et al. (2021).

SIZE OF PRICE CHANGES

Beyond the frequency, the size of price changes is also crucial for understanding price dynamics. Tables 1 and 2 indicate that, on average, the overall size of changes is close to zero in the PPI ("B to E") and slightly positive, 1.7%, for the HICP ("All-items").[20] In the PPI, the average size of price increases and decreases is about 7.5% in absolute value, and the respective median sizes are both 6.5% in absolute value. In the HICP, the average size of price decreases is on average slightly larger than that of price increases (17%) and reaches 18%. In comparison to EA evidence, the average size of price increases is about 12% and that of price decreases 16% in the CPI (Gautier et al. (2022)). In the PPI, the median upward price size is 3% and that of downward prices is 2% (Vermeulen et al. (2012)).

In theory, the large size changes in the Lithuania HICP would be related to the importance of idiosyncratic shocks in a model of menu costs in a low inflation environment (Midrigan (2011); Alvarez and Lippi (2014)). Smaller price changes in the PPI may reflect lower menu costs, making it likely that prices change more often and that selection effects may occur (i.e., spikes in the number of price adjustments, see Karadi and Reiff (2019)).

[18] I control for the official CPI and PPI indices in the respective models so that the estimated probability is independent of inflation indexing responses. I truncate price periods to 24 months in the model when possible, otherwise to 12 months when few price changes occur between 12 and 24 months. Survival time is modeled by monthly dummies.

[19] Note that heterogeneity is probably poorly identified in the PPI data due to the small number of observations at the item level.

[20] The average size is calculated only from non-zero price changes, see appendix 5 for more details on the inflation decomposition.

In "regular" series, the average size remains close to zero for the PPI, while it increases significantly for the HICP (4.5%).[21] This reflects the strong importance of sales in consumer prices. Among the PPI categories, E "Water supply [...]" has the highest average size of price change (2%), with a decrease and increase of 11%.[22] It should be noted that the other categories have average sizes below 10% in absolute value. In comparison, all HICP categories show average sizes of at least 14% in both directions, with a peak of -21% for average price declines in NEIG.

The weighted distribution of the average size of the non-zero price changes in Figures 7 and 8 completes this picture. For the PPI, the distributions are fairly symmetric in all cases. In the aggregate ("B to E"), the distribution is quite narrow and most of the price variations are between -40% and 40%. The distribution in category E, "Water supply [...]", is wider than the others and slightly skewed (right modal, about 3%). Contrariwise, the consumer price distributions show several density peaks. These are, as the "regular" distributions indicate, primarily caused by sales. Interestingly, two modes emerge in most of these distributions due to the few occurrences of tiny price changes. Moreover, all are skewed, marking the overrepresentation of positive price changes. This is particularly significant for service prices.

[Figure 7 about here]

[Figure 8 about here]

As an additional inspection, I calculate kurtosis statistics. Since these are heavily influenced by outliers, I first normalize the price changes to the ECOICOP4 or NACE Rev. 2 division level, as appropriate. I also trim the data by removing very small and very large price changes and dropping divisions with less than 10 observations per month. Figures 9 and 10 show the histograms of the two price families. Following Alvarez et al. (2016), I compare the distribution of the data to the standardized Gaussian and Laplacian distributions which have a kurtosis of 3 and 6, respectively. The histograms of the PPI "benchmark" and "regular" series are clearly more peaked than the Gaussian. Their respective kurtosis is 4.8 and 4.7. The distribution of "benchmark" HICP price changes is much less leptokurtic, with a kurtosis of 2.8 and two distinct masses around one standard deviation. This shape is largely explained by sales. In fact, the kurtosis is 4.4 in the adjusted series. These measures of kurtosis are interesting because the greater the kurtosis, the greater the real effects of monetary policy (Alvarez et al. (2021)). Note, however, that the frequency of variation must be small for this to hold true.[23] Thus, our HICP statistics would point to significant real effects of monetary policy in Lithuania. However, given the high frequency of the PPI, the effects would be strongly absorbed by producer prices.

[Figure 9 about here]

[Figure 10 about here]

4. TIME SERIES PATTERNS

I now analyze how the frequency and size of price changes evolve and contribute to PPI and HICP inflation over time. Formally, item-level inflation can be decomposed as follows (Klenow and Kryvtsov (2008)):[24]

$$\pi_{jt} = f_{jt} \times \Delta p_{jt} \tag{1}$$

[21]Note that this average for HICP is underestimated because the flags to capture sales prior to August 2013 are missing.

[22]The category E contains: "Water supply; sewerage, waste management and remediation activities".

[23]More precisely, in a large class of sticky price models, the non-neutrality of nominal shocks can be reduced to a simple statistic that is the ratio of the kurtosis of the size distribution of price changes to the frequency of price changes.

[24]See Appendix B for more details on the inflation decomposition.

where j is ECOICOP4 or NACE Rev 2. (2-digit) division, as appropriate. Figures 11 and 12 show the time variation in the weighted average frequency of price increases and decreases by different aggregates in the "regular" series.[25] In the "B to E" PPI, the two statistics are clearly negatively correlated. During periods of positive/negative inflation, the frequency of price increases/decreases dominates that of price decreases/increases. Within the different categories of the PPI, the picture is fairly similar. In the "All-items" HICP, the frequency of price increases is greater than that of price decreases. A somewhat comparable pattern can be seen in NEIG, processed food, and services.[26] I provide additional insight in the appendix 5 on seasonality and series trends. In summary, a small "January" effect is noticeable in both types of prices.[27] On the other hand, no clear annual trend is apparent.

[Figure 11 about here]

[Figure 12 about here]

Now consider the evolution of the weighted average size of price increases and decreases. In the PPI, the two series are fairly synchronized and show a jump in 2015 (Figure 13). Contrariwise, the average size of price increases is generally larger than that of price decreases in the HICP. Note that this difference is only apparent from about 2014 because I do not observe the flags to properly account for sales beforehand (Figure 14). Further analysis in the appendix 5 shows that the average size has trended downward in the PPI, but upward in the HICP. In addition, size changes tends to be higher in January in producer prices, and in January, March and September in the consumer prices.

[Figure 13 about here]

[Figure 14 about here]

I dig deeper to understand how the interplays between the size and frequency influence PPI and HICP inflation rates at the micro level. To do this, I follow Gautier et al. (2022) and define counterfactual inflation rates at the ECOICOP4/NACE Rev. 2 level. First, I assume that inflation is driven solely by variations in the size of price changes:

$$\tilde{\pi}_{jt}^{\bar{f}} \triangleq \bar{f}_j \times \Delta p_{jt}. \tag{2}$$

where inflation has its frequency component fixed to its average value in each ECOICOP4/NACE Rev. 2 over the period. Equivalently, I assume that movements in the frequency of price changes are the only driver of inflation with:

$$\tilde{\pi}_{jt}^{\Delta\bar{p}} \triangleq f_{jt} \times \Delta\bar{p}_j. \tag{3}$$

I then regress the inflation rates on each of these two counterfactuals with monthly dummy variables and ECOICOP4/NACE Rev. 2 fixed effects, where appropriate. The first two columns of Tables 3 and 4 show the results of these regressions.

[Table 3 about here]

[Table 4 about here]

For the PPI, inflation is driven entirely by movements in the size of price changes (column 1, Table 3). Indeed, only a tiny fraction of the intra-item variations are explained by changes in the overall frequency. The same

[25] Time series of the average frequency of price increases are calculated in two steps: 1) $f_{jt}^{+} = \frac{1}{N_{jt}} \sum_{n}^{N_{jt}} I_{njt}^{+}$ for n items and j ECOICOP4 or NACE Rev. 2 (2-digit) division as appropriate. I_{njt}^{+} are price increase indicators; i.e. $I_{njt}^{+} = 1$ if $p_{njt} > p_{njt-1}$, and 0 otherwise. 2) $\bar{f}_t^{+} = \sum_j^J \omega_{jt} f_{jt}^{+}$. The aggregation is equivalent for the average frequency of downward price changes and the size statistics that follow.

[26] Note the large spike in 2015 due to the changeover to the euro (Jouvanceau (2021)).

[27] Note that this January effect in PPI frequencies may also be related to the very high entry of items into the data in that month (see Figure A1 in appendix 5).

is true for the HICP, where the majority of inflation variations are explained by changes in the size (column 1, Table 4). However, these results do not provide a complete picture. They are insufficient to determine whether the frequencies of price increases and decreases play a role. To learn more, I compute two other counterfactual inflation series. The first one assumes that not only the overall frequency is constant but also that the frequency of price increases and decreases are constant:

$$\tilde{\pi}_{jt}^{\bar{\alpha},\bar{f}} \triangleq \bar{\alpha}_j \times \bar{f}_j \times \Delta p_{jt}^{+} - (1-\bar{\alpha}_j) \times \bar{f}_j \times \Delta p_{jt}^{-}. \tag{4}$$

where $\alpha_{jt} = \frac{f_{jt}^{+}}{f_{jt}}$ is the share of price increases in total price changes. In the second one, the size of the price increases and decreases is constant:

$$\tilde{\pi}_{jt}^{\Delta\bar{p}^{+},\Delta\bar{p}^{-}} \triangleq f_{jt}^{+} \times \Delta\bar{p}_{j}^{+} - f_{jt}^{-} \times \Delta\bar{p}_{j}^{-}. \tag{5}$$

Columns 3 and 4 of Tables 3 and 4 give evidence of how these counterfactuals explain inflation. In addition to the effects of size changes, PPI inflation varies strongly with the frequency of price increases and decreases. In the HICP, these frequency movements are very important in explaining inflation. This implies that changes in size are also due to changes in frequency. To better understand this, consider the following. Suppose that the frequencies of upward and downward price changes are identical in period t. In $t+1$, the frequency of upward price changes increases by 1pp and that of downward price changes decreases by 1pp. Therefore, the overall frequency will remain unchanged. However, as there will be more upward price changes, the average size of the price changes will increase. Therefore, we should find that changes in the share of price increases vary positively with inflation. The following counterfactual illustrates this possibility:

$$\tilde{\pi}_{jt}^{\bar{f},\Delta\bar{p}^{+},\Delta\bar{p}^{-}} \triangleq \alpha_{jt} \times \bar{f}_j \times \Delta\bar{p}_{j}^{+} - (1-\alpha_{jt}) \times \bar{f}_j \times \Delta\bar{p}_{j}^{-}. \tag{6}$$

Columns 5 of Tables 3 and 4 strongly support the implication of the share of price increases in the fluctuations of PPI and CPI inflation. I finally inspect how these counterfactual inflation rates respond to aggregate shocks. I follow Gautier et al. (2022) and use local linear projections (Jordà (2005)). The latter allow for a finer identification of the role of each margin in inflation variations. The following regression is estimated separately for the PPI and HICP:

$$\hat{\pi}_{jt-1,t+h} = \alpha_j + \gamma_m + \beta_h Z_t + \phi_h X_t + \varepsilon_{j,t}. \tag{7}$$

where $\hat{\pi}_{jt-1,t+h}$ is one of the cumulative counterfactual inflation rates described in equations (2) to (6) for each j ECOICOP4 or NACE Rev 2. (2-digit) division, as appropriate.[28] α_j stands for division fixed-effects and γ_m for monthly dummies. X_t are control variables comprising 12 lags of the unemployment rate, of the rate of change of the HICP, and of the 1-year AAA-rated EA government bond yield. Z_t are either series of EA monetary policy shocks (Jarociński and Karadi (2020)) or global oil supply shocks (Baumeister and Hamilton (2019)). The shocks are rescaled to produce a cumulative 1pp increase/decrease in unemployment rate in Lithuania after 18 months, i.e., monetary policy tightening and positive oil supply, respectively. The β_h coefficients related to the impact of the shock for each h horizon are plotted in Figure 15.

The first column describes the response of plain vanilla inflation, which is persistently falling as expected. It is important to note that after 18 months, PPI inflation decreases by a factor of about six times that of the HICP in response to the two shocks. The real impact of the monetary policy shock is therefore much smaller for producer prices, as the effects are mostly absorbed by price changes. The second and third columns

[28] For example, the dependent variable could be the sum of the monthly rate of the counterfactual inflation rate with a constant overall frequency, such that: $\hat{\pi}_{jt-1,t+h} = \sum_{t=0}^{h} \tilde{\pi}_{jt+\tau,t+\tau+h}^{\bar{f}}$. More details on the method can be found in the appendix of Gautier et al. (2022).

show that this decline in inflation is almost entirely explained by changes in the size of price changes, not by variations in frequency. The third and fourth columns reveal that this variation in size is strongly determined by variations in the frequency of price increases and decreases. Finally, the fifth column provides evidence that the share of price increases responds strongly to these shocks.

5. CONCLUSION

In this paper, I provide exclusive statistics about the frequency and size of consumer and producer price changes in Lithuania. For this purpose, I take advantage of a wide range of product price records underlying the HICP and PPI between 2010 and 2018. The PPI data cover about 99.5% of the average producer weights at the NACE Rev. 2 (2-digit) level over the period. HICP price records cover about 73% of average consumer weights at the ECOICOP4 level over the period.

I find the following facts. Producer prices are much more flexible than consumer prices, with an overall frequency of 58% versus 18%. This large difference is mainly due to production prices related to energy, where the average duration of a price change is 1 month. In comparison, the average duration is about 6 months in the HICP. When prices are adjusted for sales, replacements, and entries, the frequency falls by 10pp for both indices. In addition, a high degree of heterogeneity is observed in the statistics by category. For example, the average frequency for NEIG is three times higher than for services (6%). The prevalence of product substitution and promotions in certain categories such as unprocessed foods plays an important role in this phenomenon.

In terms of the size of price changes, these are more salient in the HICP, where the average size of price increases and decreases is about 17-18% in absolute value. This compares with about 7.5% in both cases for the PPI. This difference is partly erased when prices are adjusted for the presence of product replacements and sales.

At the micro level, I reveal that HICP and PPI inflation rates are driven primarily by variations in the size of price changes. Going further, I find that a great part of these size changes are caused by shifts in the share of price increases. This result is comparable to those obtained from EA micro data (Gautier et al. (2022)) and is consistent with the predictions of standard Calvo-type models or the latest generation of menu cost models in a low inflation environment (Alvarez and Lippi (2014)). Moreover, evidence of the importance of unobserved heterogeneity in the hazard of price changes favors hybrid-type models, such as a mixture of time and state dependence as in Nakamura and Steinsson (2008) or menu cost models with multiproduct firms (Midrigan (2011); Alvarez and Lippi (2014)).

Finally, the study of histograms of non-zero standardized price changes shows that the kurtosis is higher than that of a typical Gaussian for both price families. Using HICP statistics, the low frequency and high kurtosis would imply a large impact of nominal shocks in Lithuania (Alvarez et al. (2021)). Conversely, the high frequency and kurtosis of the PPI would generate near neutrality. This contradiction opens an interesting avenue for empirical and theoretical research.

REFERENCES

Alvarez, F., H. Le Bihan, and F. Lippi (2016). The real effects of monetary shocks in sticky price models: A sufficient statistic approach. *American Economic Review 106*(10), 2817–51.

Alvarez, F. and F. Lippi (2014). Price setting with menu cost for multiproduct firms. *Econometrica 82*(1), 89–135.

Alvarez, F. E., K. Borovičková, and R. Shimer (2021). Consistent evidence on duration dependence of price changes. Technical report, National Bureau of Economic Research.

Alvarez, F. E., A. Ferrara, E. Gautier, H. Le Bihan, and F. Lippi (2021). Empirical investigation of a sufficient statistic for monetary shocks. Technical report, National Bureau of Economic Research.

Álvarez, L. J., P. Burriel, and I. Hernando (2010). Price-setting behaviour in spain: evidence from micro ppi data. *Managerial and Decision Economics 31*(2-3), 105–121.

Baumeister, C. and J. D. Hamilton (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review 109*(5), 1873–1910.

Berardi, N., E. Gautier, and H. L. Bihan (2015). More facts about prices: France before and during the great recession. *Journal of Money, Credit and Banking 47*(8), 1465–1502.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of monetary Economics 12*(3), 383–398.

Carvalho, C. (2006). Heterogeneity in price stickiness and the real effects of monetary shocks. *Frontiers in Macroeconomics 2*(1).

Dhyne, E., L. J. Alvarez, H. Le Bihan, G. Veronese, D. Dias, J. Hoffmann, N. Jonker, P. Lunnemann, F. Rumler, and J. Vilmunen (2006). Price changes in the euro area and the united states: Some facts from individual consumer price data. *Journal of Economic Perspectives 20*(2), 171–192.

Gautier, E., C. Conflitti, R. P. Faber, B. Fabo, L. Fadejeva, V. Jouvanceau, J.-O. Menz, T. Messner, P. Petroulas, P. Roldan-Blanco, F. Rumler, S. Santoro, E. Wieland, and H. Zimmer (2022). New facts on consumer price rigidity in the euro area. *ECB Working paper (forthcoming)*.

Golosov, M. and J. R. E. Lucas (2007). Menu costs and phillips curves. *Journal of Political Economy 115*(2), 171–199.

Jarociński, M. and P. Karadi (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics 12*(2), 1–43.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review 95*(1), 161–182.

Jouvanceau, V. (2021). The Effect of the Euro Changeover on Prices: Evidence from Lithuania. *Bank of Lithuania Working Paper Series* (93).

Karadi, P. and A. Reiff (2019). Menu costs, aggregate fluctuations, and large shocks. *American Economic Journal: Macroeconomics 11*(3), 111–46.

Kehoe, P. and V. Midrigan (2015). Prices are sticky after all. *Journal of Monetary Economics 75*, 35–53.

Klenow, P. J. and O. Kryvtsov (2008). State-dependent or time-dependent pricing: Does it matter for recent us inflation? *The Quarterly Journal of Economics 123*(3), 863–904.

Klenow, P. J. and B. A. Malin (2010). Microeconomic evidence on price-setting. In *Handbook of monetary economics*, Volume 3, pp. 231–284. Elsevier.

Midrigan, V. (2011). Menu costs, multiproduct firms, and aggregate fluctuations. *Econometrica 79*(4), 1139–1180.

Nakamura, E. and J. Steinsson (2008). Five facts about prices: A reevaluation of menu cost models. *The Quarterly Journal of Economics 123*(4), 1415–1464.

Taylor, J. B. (1980). Aggregate dynamics and staggered contracts. *Journal of political economy 88*(1), 1–23.

Vermeulen, P., D. A. Dias, M. Dossche, E. Gautier, I. Hernando, R. Sabbatini, and H. Stahl (2012). Price setting in the euro area: Some stylized facts from individual producer price data. *Journal of Money, Credit and Banking 44*(8).

TABLES AND FIGURES

TABLES

Table 1: Aggregate weighted statistics, PPI

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	$\%inc.$	$\bar{\omega}$	$\%Adj.$	$obs.$
Benchmark	%	%	%	$m.$	%	%	%	%	%	%	
B to E	58	29.7	28.3	1.2	0.3	7.4	-7.6	51.8	-	-	126815
B: Mining and quarrying	20.7	11.5	9.2	4.6	0.6	7.5	-7.4	53.1	0.6	-	3200
C: Manufacturing	56.8	29.3	27.5	1.3	0.2	7.8	-7.9	51.7	86.4	-	112039
D: Electricity, gas, steam*	68.9	33.4	35.5	0.9	0.5	4.7	-4.6	52.1	11.9	-	2194
E: Water supply*	44	24.1	19.9	1.2	2	11.2	-11.3	56.5	1	-	9382
Regular	%	%	%	$m.$	%	%	%	%	%	%	
B to E	48.6	25.2	23.4	2.3	0.4	6.1	-6.2	53.1	-	14.3	126815
B: Mining and quarrying	13.4	7.5	5.9	8.5	1	7.1	-8	56.6	0.6	7.8	3200
C: Manufacturing	46.4	24.4	22	2.4	0.4	6.2	-6.4	53.4	86.4	15.8	112039
D: Electricity, gas, steam*	67.9	32.5	35.4	0.9	0.3	4.8	-4.6	51.1	11.9	1.4	2194
E: Water supply*	30.6	16.7	13.9	2.5	2	8.7	-7.8	57.4	1	2	9382

Notes: The aggregate weighted average frequency of price changes is calculated as: 1) $f_{jt} = \frac{1}{N_{jt}} \sum_{n}^{N_{jt}} I_{njt}$. 2) $\bar{f} = \sum_{t}^{T} \sum_{j}^{J} \omega_{jt} f_{jt}$. The other statistics in this table are aggregated in the same way (see appendix 5 for further details). "$\%inc.$" refers the share of price increases in the total price changes. "$\%Adj.$" refers to the share of prices adjusted to produce the "regular" statistics in each category. "$m.$" refers to a month. "$dur.$" gives the implied average duration using: $dur = -1/ln(1-f)$ where f is the weighted median frequency at each category level. *The category D contains: "Electricity, gas, steam and air conditioning supply". The category E contains: "Water supply; sewerage, waste management and remediation activities". The sample covers an average of 99.5% of the PPI NACE Rev. 2 (2-digit) weights between 2010 and 2018; the weights for each category are normalized. "Benchmark" refers to raw price changes, "Regular" refers to series adjusted for the phenomena described in section 2.

Table 2: Aggregate weighted statistics, HICP

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	%$inc.$	$\bar{\omega}$	%$Adj.$	$obs.$
Benchmark	%	%	%	$m.$	%	%	%	%	%	%	
All-items	18.1	10.1	8	5.7	1.7	17.3	-18.7	58.4	-	-	5207152
Energy	19.4	11.2	8.2	6.1	1.6	13.8	-15.3	57.4	2	-	21574
NEIG	17.8	9.3	8.5	5.5	0.6	20	-21.2	53	35	-	2040974
Proc. food	20.9	12.1	8.7	4.8	0.9	16.4	-17.9	58	36	-	2349538
Services	6.2	4.2	2	27.4	6.3	14.6	-15.9	72.7	20	-	433958
Unproc. food	38.5	20.1	18.4	2.5	0	15.9	-16.7	51.5	7	-	361108
Regular	%	%	%	$m.$	%	%	%	%	%	%	
All-items	8.9	5.8	3.1	16	4.5	12.9	-11.6	66.8	-	11.6	5207152
Energy	15.1	9.1	6	10.3	2.8	10.8	-10.3	62	2	4.2	21574
NEIG	6	3.8	2.2	18.7	4.3	13.7	-11.9	64	35	12.8	2040974
Proc. food	10.1	7	3.1	12.7	4.1	12	-10.7	67.4	36	12.3	2349538
Services	5.3	3.7	1.6	31	7	13.6	-13.4	75.8	20	0.8	433958
Unproc. food	25.4	14.3	11.2	4.3	1.7	12.9	-12	56.1	7	14	361108

Notes: The aggregate weighted average frequency of price changes is calculated as: 1) $f_{jt} = \frac{1}{N_{jt}} \sum_{n}^{N_{jt}} I_{njt}$. 2) $\bar{f} = \sum_{t}^{T} \sum_{j}^{J} \omega_{jt} f_{jt}$. The other statistics in this table are aggregated in the same way (see appendix 5 for further details). "%$inc.$" refers the share of price increases in the total price changes. "%$Adj.$" refers to the share of prices adjusted to produce the "regular" statistics in each category. "$m.$" refers to a month. "$dur.$" gives the implied average duration using: $dur = -1/ln(1-f)$ where f is the weighted median frequency at each category level. The sample covers an average of 73% of the HICP ECOICOP4 weights between 2010 and 2018; the weights for each category are normalized. "Benchmark" refers to raw price changes, "Regular" refers to series adjusted for the phenomena described in section 2. NEIG refers to "non-energy industrial goods".

Table 3: PPI item-level regressions, counterfactual inflation rates

	$\tilde{\pi}^{\bar{f}}_{jt}$	$\tilde{\pi}^{\Delta\bar{p}}_{jt}$	$\tilde{\pi}^{\bar{\alpha},\bar{f}}_{jt}$	$\tilde{\pi}^{\Delta\bar{p}^+,\Delta\bar{p}^-}_{jt}$	$\tilde{\pi}^{\bar{f},\Delta\bar{p}^+,\Delta\bar{p}^-}_{jt}$
Benchmark, $\tilde{\pi}_{jt}$					
	0.967***	-1.568	1.379***	1.402***	1.405***
	(0.025)	(1.032)	(0.217)	(0.191)	(0.190)
within-R^2	0.946	0.031	0.613	0.610	0.595
obs.	2730	2730	2730	2730	2583
Regular, $\tilde{\pi}_{jt}$					
	0.981***	-0.296	1.413***	1.449***	1.462***
	(0.015)	(0.797)	(0.279)	(0.204)	(0.195)
within-R^2	0.967	0.027	0.607	0.646	0.637
obs.	2730	2730	2730	2730	2513

Notes: ***, **, * denote statistical significance at 0.1%, 1% and 5% levels, respectively. Regressions are done at the NACE Rev. 2 level including month dummies and NACE Rev. 2 fixed effects. Regressions are weighted using NACE Rev. 2 PPI weights between 2010 and 2018. Standard errors are clustered at NACE Rev 2. level.

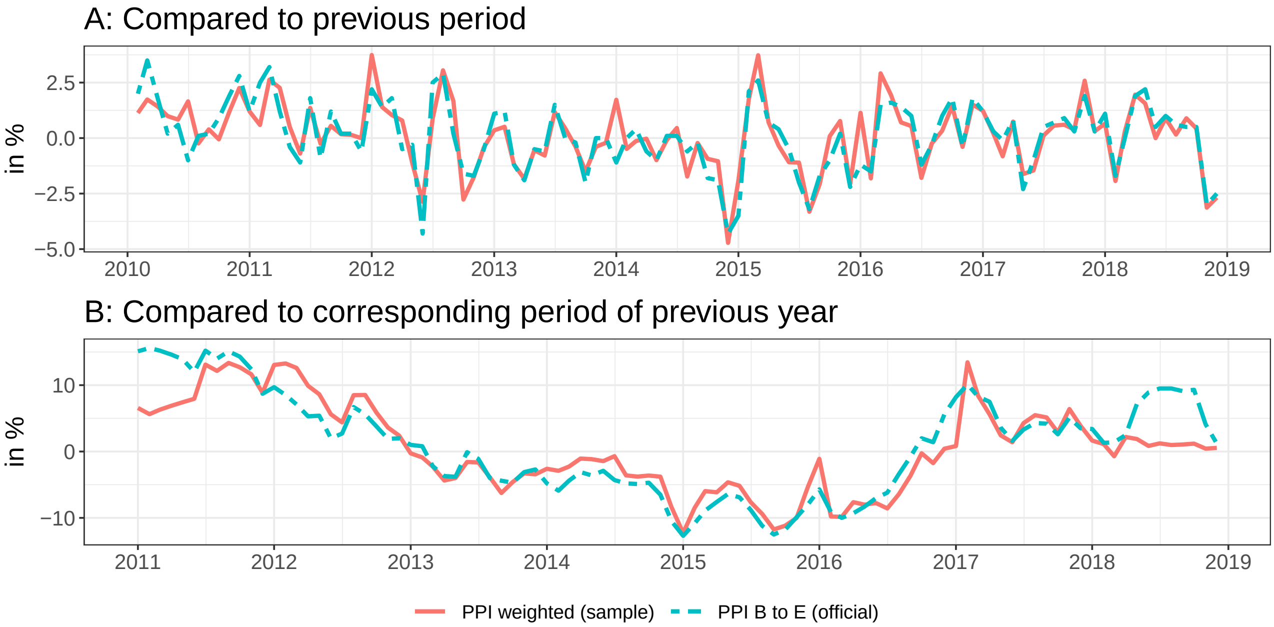
Table 4: HICP item-level regressions, counterfactual inflation rates

	$\tilde{\pi}^{\bar{f}}_{jt}$	$\tilde{\pi}^{\Delta\bar{p}}_{jt}$	$\tilde{\pi}^{\bar{\alpha},\bar{f}}_{jt}$	$\tilde{\pi}^{\Delta\bar{p}^+,\Delta\bar{p}^-}_{jt}$	$\tilde{\pi}^{\bar{f},\Delta\bar{p}^+,\Delta\bar{p}^-}_{jt}$
Benchmark, $\tilde{\pi}_{jt}$					
	1.051***	1.228***	1.154***	0.986***	1.087***
	(0.019)	(0.135)	(0.177)	(0.055)	(0.047)
within-R^2	0.866	0.028	0.234	0.751	0.674
obs.	18416	18416	18416	18416	17524
Regular, $\tilde{\pi}_{jt}$					
	1.047***	1.172***	1.341***	1.098***	1.257***
	(0.029)	(0.201)	(0.211)	(0.055)	(0.052)
within-R^2	0.705	0.090	0.272	0.748	0.561
obs.	18416	18416	18416	18416	16914

Notes: ***, **, * denote statistical significance at 0.1%, 1% and 5% levels, respectively. Regressions are done at the ECOICOP4 level including month dummies and NACE Rev. 2 fixed effects. Regressions are weighted using ECOICOP4 weights between 2010 and 2018. Standard errors are clustered at ECOICOP4 level.

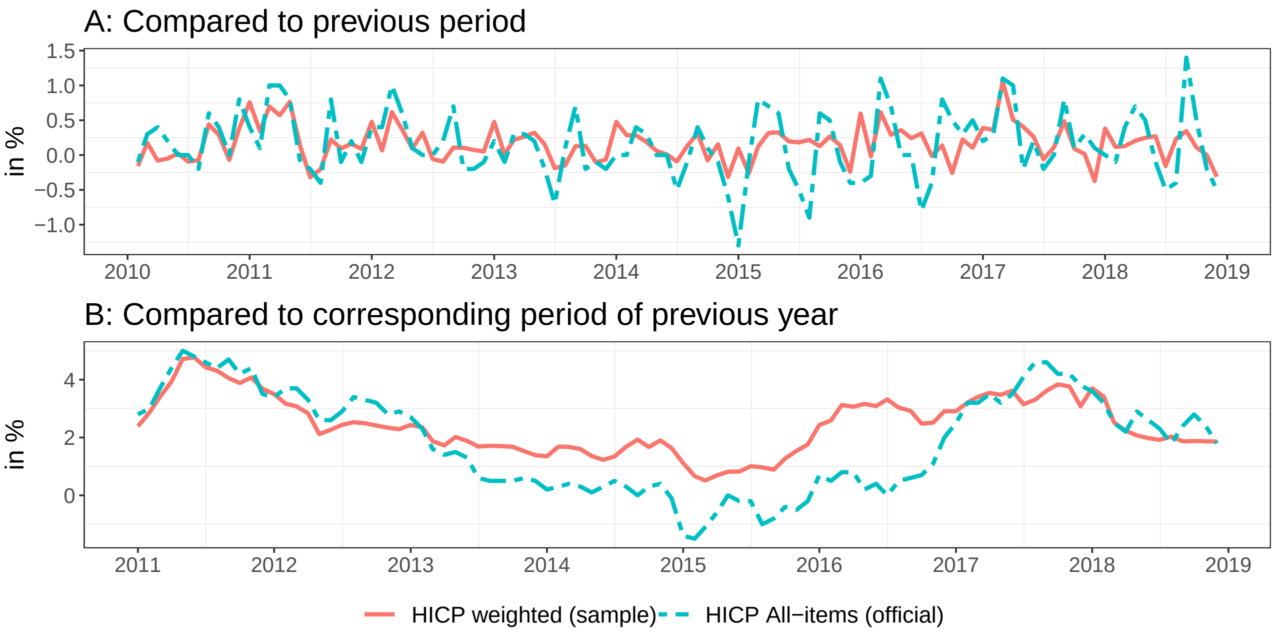
FIGURES

Figure 1: Aggregate PPI inflation rates: sample and official



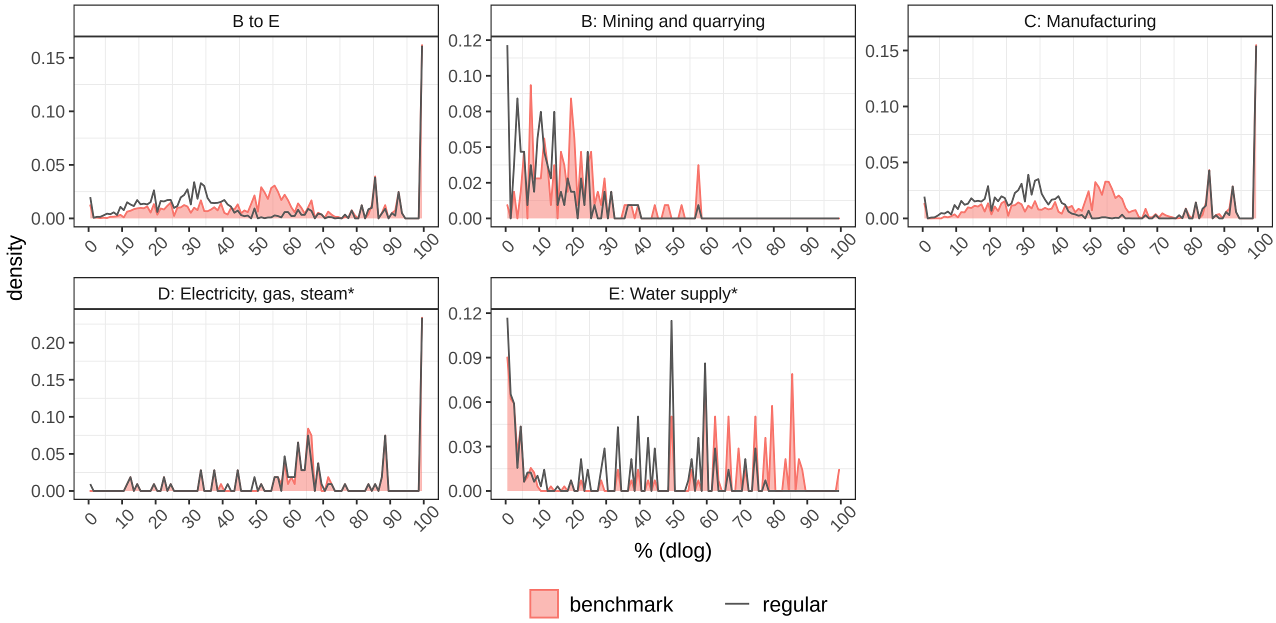
Notes: The aggregate inflation series of the sample are calculated according to the steps in appendix 5. The coverage of the PPI NACE Rev. 2 (2 digits) expenditure weights is 99.5%. The official series is obtained from Eurostat.

Figure 2: Aggregate HICP inflation rates: sample and official



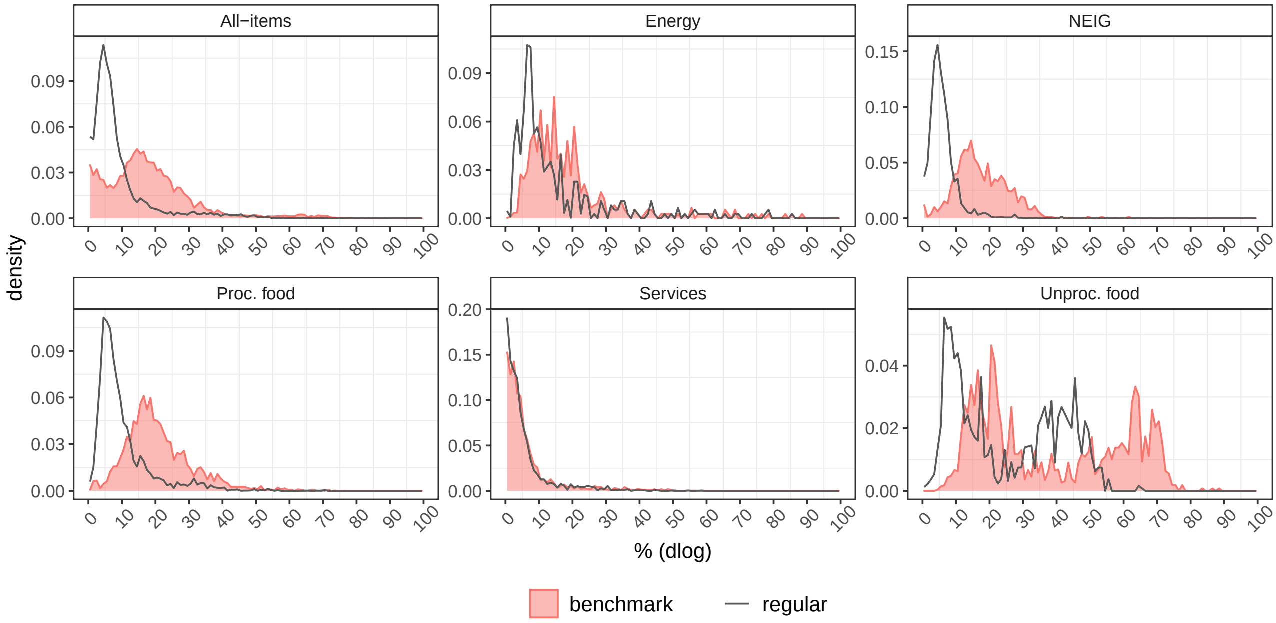
Notes: The aggregate inflation series of the sample are calculated according to the steps in appendix 5. The coverage of the HICP ECOICOP4 expenditure weights is about 73%. The official series is obtained from Eurostat.

Figure 3: Weighted distribution of the frequency of price changes, PPI



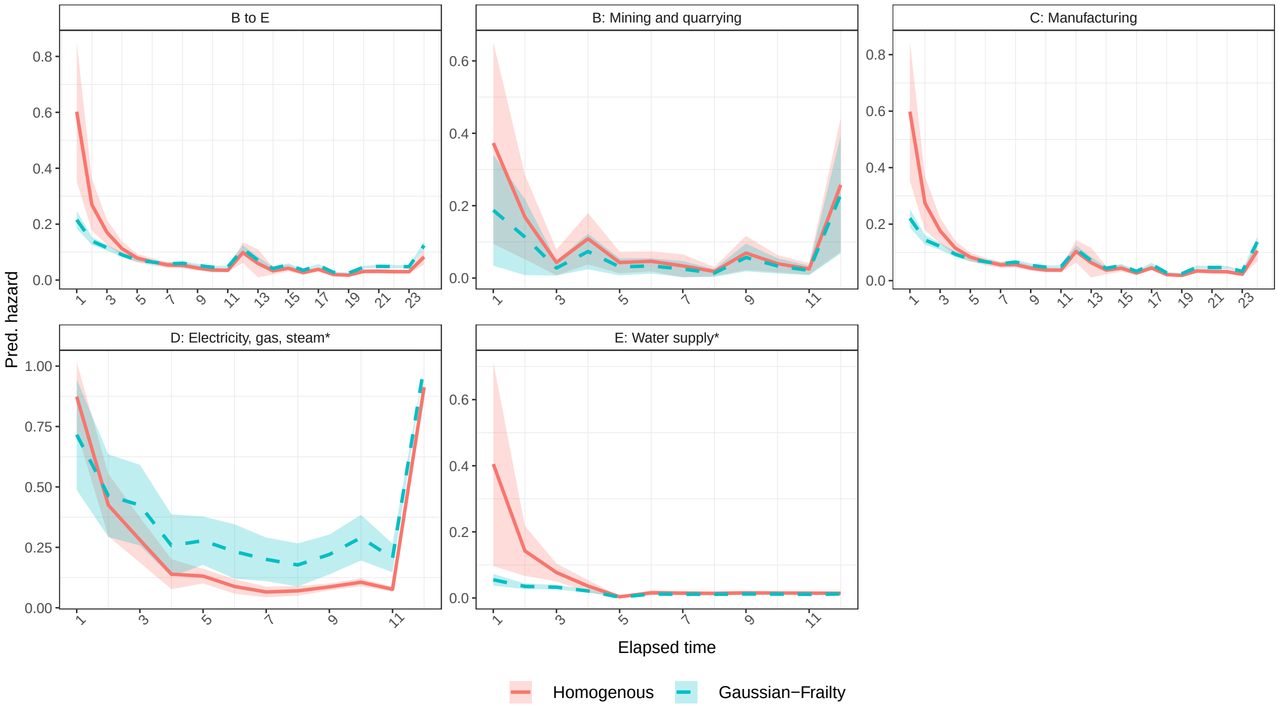
Notes: The distribution is computed as follows. 1) For each NACE division (2- digit level), a histogram is computed on intervals of width 1% between 0 and 1. 2) The final empirical distribution is the weighted average of the relative frequencies in each interval using the average weights by NACE divisions between 2010 and 2018. *The category D contains: "Electricity, gas, steam and air conditioning supply". The category E contains: "Water supply; sewerage, waste management and remediation activities".

Figure 4: Weighted distribution of the frequency of price changes, HICP



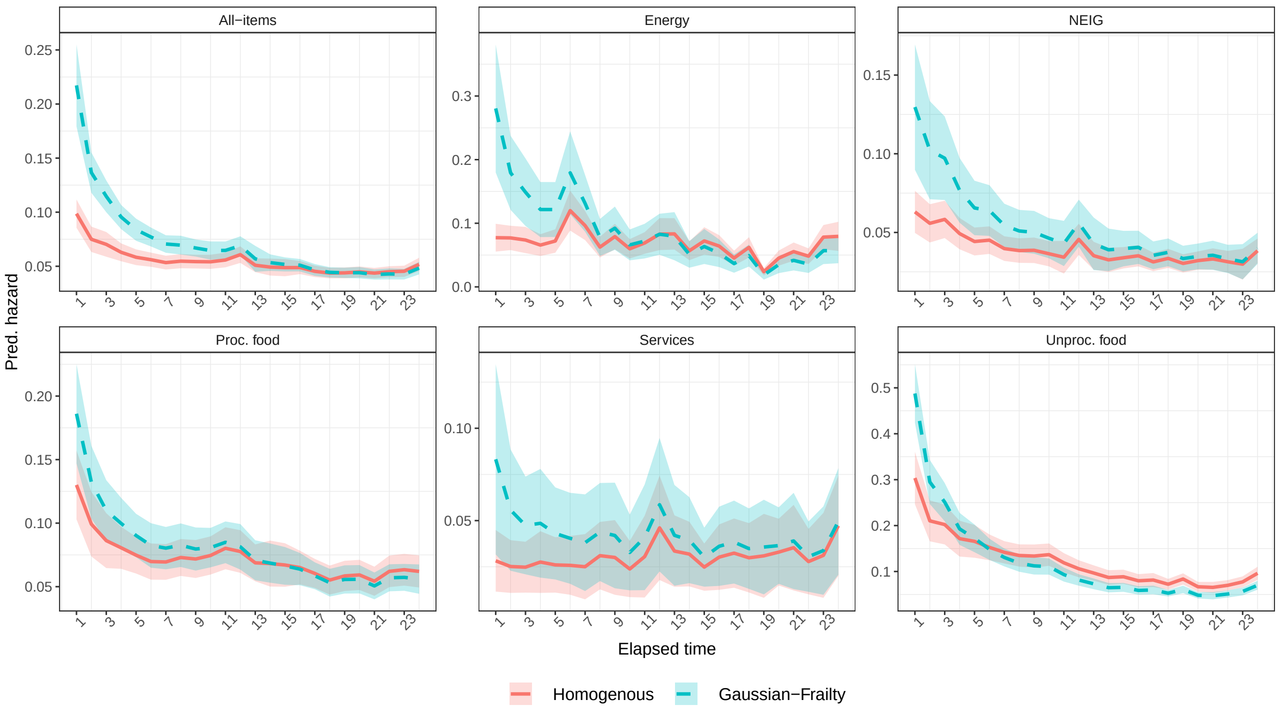
Notes: The distributions are computed as follows. 1) For each ECOICOP4 category, a histogram is computed on intervals of width 1% between 0 and 1. 2) The final empirical distribution is the weighted average of the relative frequencies in each interval using the average weights by ECOICOP4 divisions between 2010 and 2018. NEIG refers to "non-energy industrial goods".

Figure 5: Predicted hazard rates, PPI



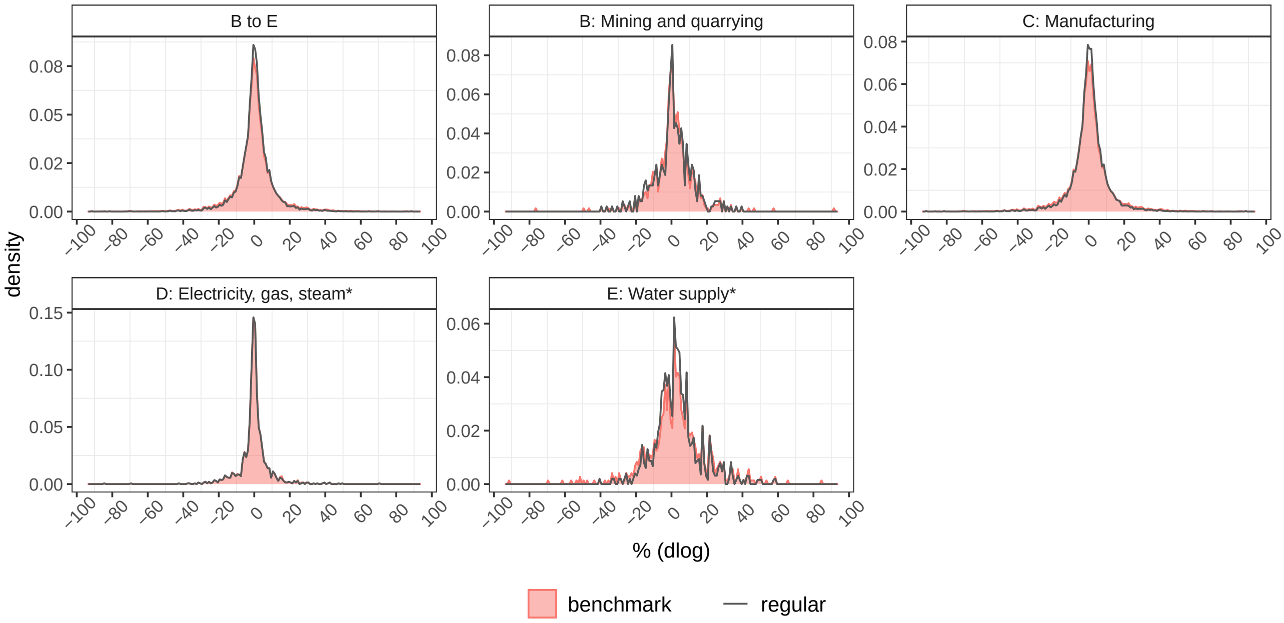
Notes: The hazard rates are predicted from discrete proportional hazard models. I control for the PPI index for each estimate. I truncate the price periods to 24 months in the model when possible, otherwise to 12 months when few price change events occur between 12 and 24 months. The x-axis indicates the truncation chosen. Survival time is modeled by monthly dummies. The hazard rates are obtained as the average of the month-article level predictions. The 95% confidence intervals are calculated using the standard deviation of these predictions. *The category D contains: "Electricity, gas, steam and air conditioning supply". The category E contains: "Water supply; sewerage, waste management and remediation activities".

Figure 6: Predicted hazard rates, CPI



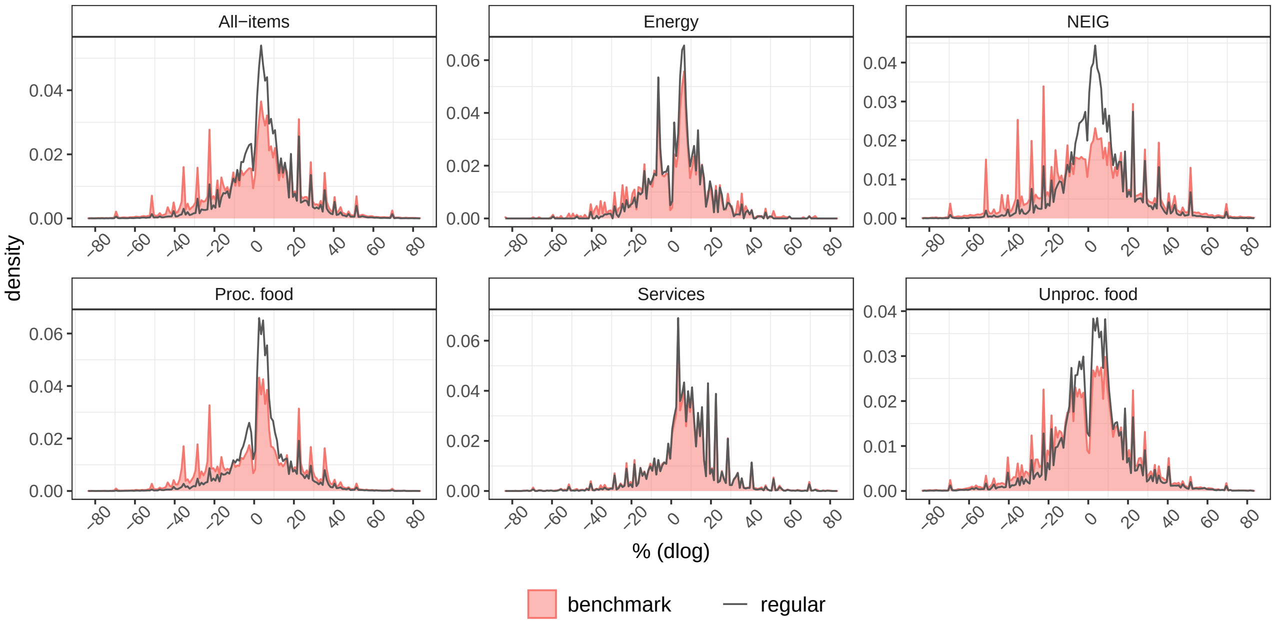
Notes: The hazard rates are predicted from discrete proportional hazard models. I control for the CPI index for each estimate. I truncate the price periods to 24 months. Survival time is modeled by monthly dummies. The hazard rates are obtained as the average of the month-article level predictions. The 95% confidence intervals are calculated using the standard deviation of these predictions. NEIG refers to "non-energy industrial goods".

Figure 7: Weighted distribution of the size of non-zero price changes, PPI



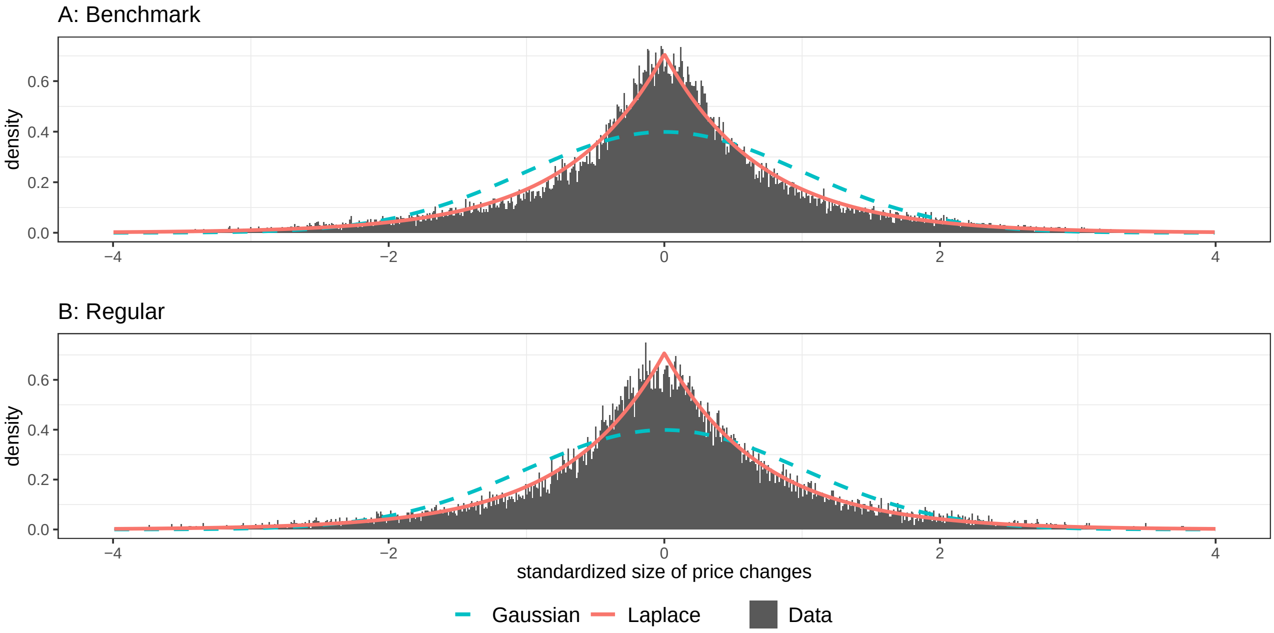
Notes: The distribution is computed as follows. 1) For each NACE division (2- digit level), a histogram is computed on intervals of width 1% ranging from minus the ceiling of the largest between min/max size of all size of price changes and plus the ceiling of the largest between min/max size of all size of price changes. 2) The final empirical distribution is the weighted average of the relative frequencies in each interval using the average weights by NACE divisions between 2010 and 2018. *The category D contains: "Electricity, gas, steam and air conditioning supply". The category E contains: "Water supply; sewerage, waste management and remediation activities".

Figure 8: Weighted distribution of the size of non-zero price changes, HICP



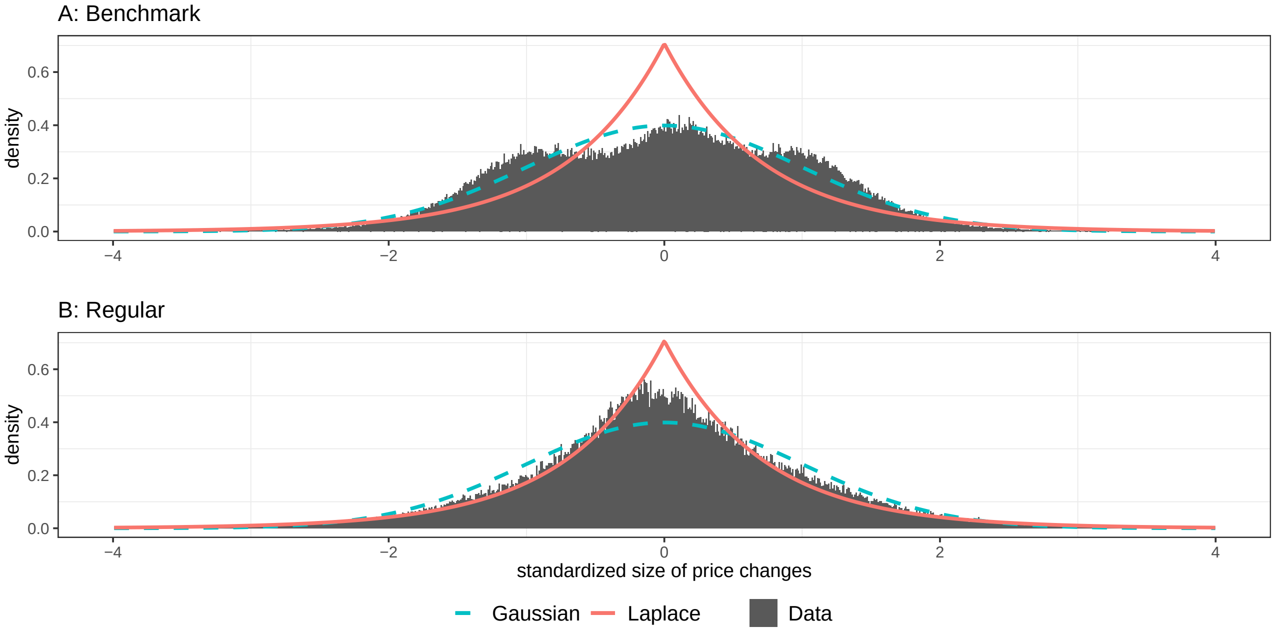
Notes: The distribution is computed as follows 1) For each ECOICOP4 category, a histogram is computed on intervals of width 1% ranging from minus the ceiling of the largest between min/max size of all size of price changes and plus the ceiling of the largest between min/max size of all size of price changes. 2) The final empirical distribution is the weighted average of the relative frequencies in each interval using the average weights by ECOICOP4 divisions between 2010 and 2018. NEIG refers to "non-energy industrial goods".

Figure 9: Histograms of standardized non-zero price changes, PPI



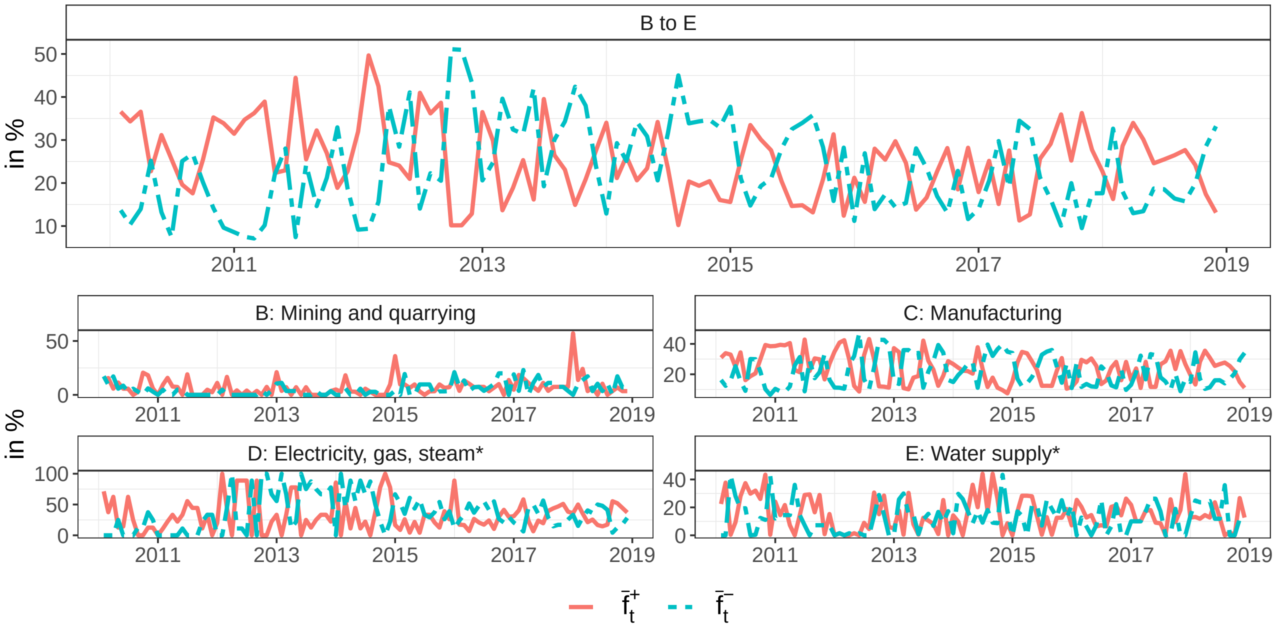
Notes: Non-zero price changes are standardized at the NACE Rev. 2 (2-digit) division level. I remove divisions with less than 10 observations of price changes per month. I also eliminate price changes with absolute values less than 0.1%, and those outside the 99th percentile of absolute price changes.

Figure 10: Histograms of standardized non-zero price changes, HICP



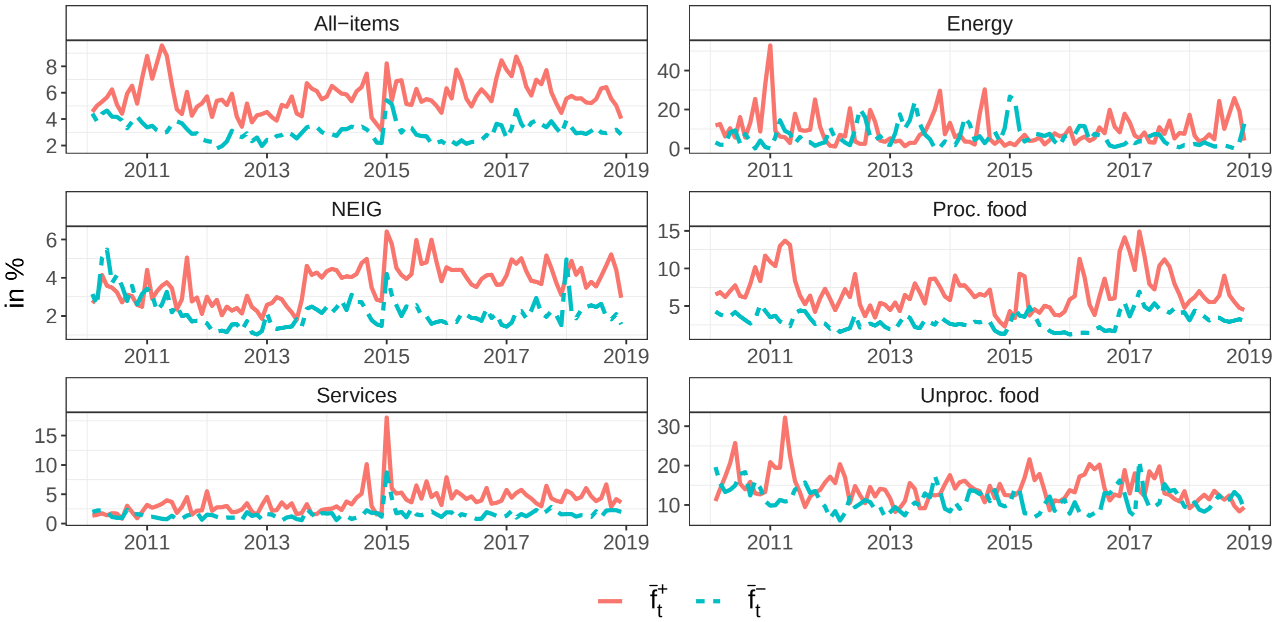
Notes: Non-zero price changes are standardized at the ECOICOP4 division level. I remove divisions with less than 10 observations of price changes per month. I also eliminate price changes with absolute values less than 0.1%, and those outside the 99th percentile of absolute price changes.

Figure 11: Weighted average frequency of price increases and decreases, PPI



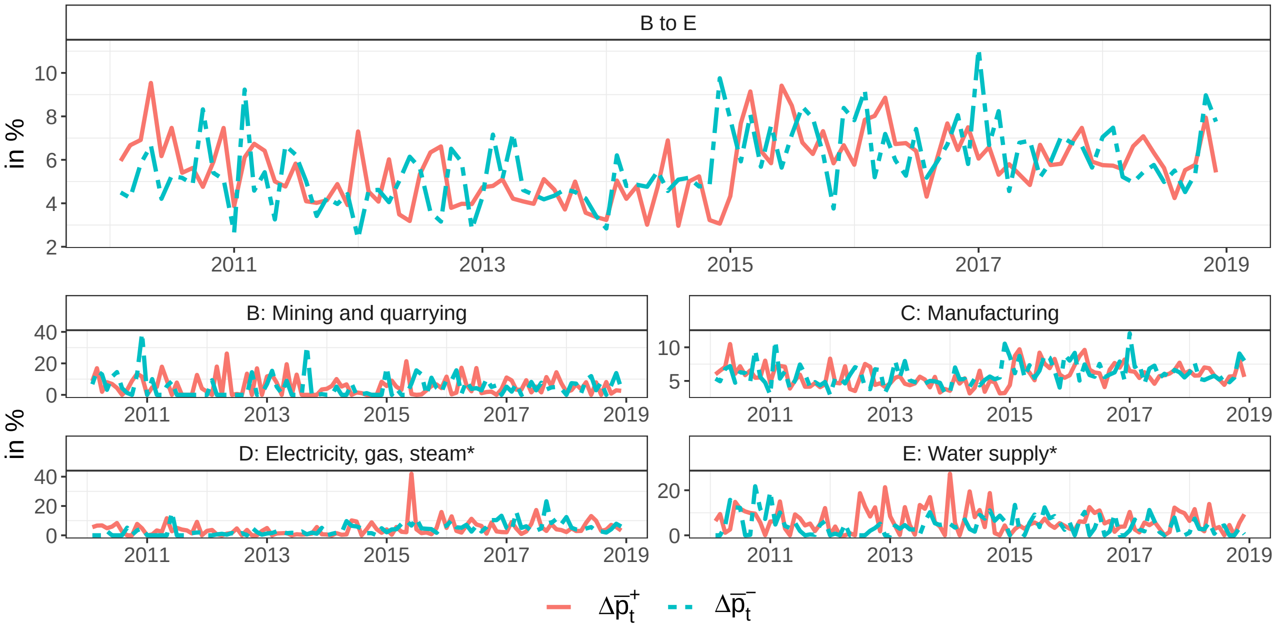
Notes: "Regular" series. The average frequency of price increases (red solid lines) is calculated in two steps: 1) $f_{jt}^+ = \frac{1}{N_{jt}} \sum_n^{N_{jt}} I_{njt}^+$ for n items and j NACE Rev. 2 (2-digit) divisions. I_{njt}^+ are price increase indicators; i.e. $I_{njt}^+ = 1$ if $p_{njt} > p_{njt-1}$, and 0 otherwise. 2) $\bar{f}_t^+ = \sum_j^J \omega_{jt} f_{jt}^+$. The average frequency of price decreases (blue dashed lines) is computed in two steps: 1) $f_{jt}^- = \frac{1}{N_{jt}} \sum_n^{N_{jt}} I_{njt}^-$ where I_{njt}^- are price decrease indicators; i.e. $I_{njt}^- = 1$ if $p_{njt} < p_{njt-1}$, and 0 otherwise. 2) $\bar{f}_t^- = \sum_j^J \omega_{jt} f_{jt}^-$. *The category D contains: "Electricity, gas, steam and air conditioning supply". The category E contains: "Water supply; sewerage, waste management and remediation activities".

Figure 12: Weighted average frequency of price increases and decreases, HICP



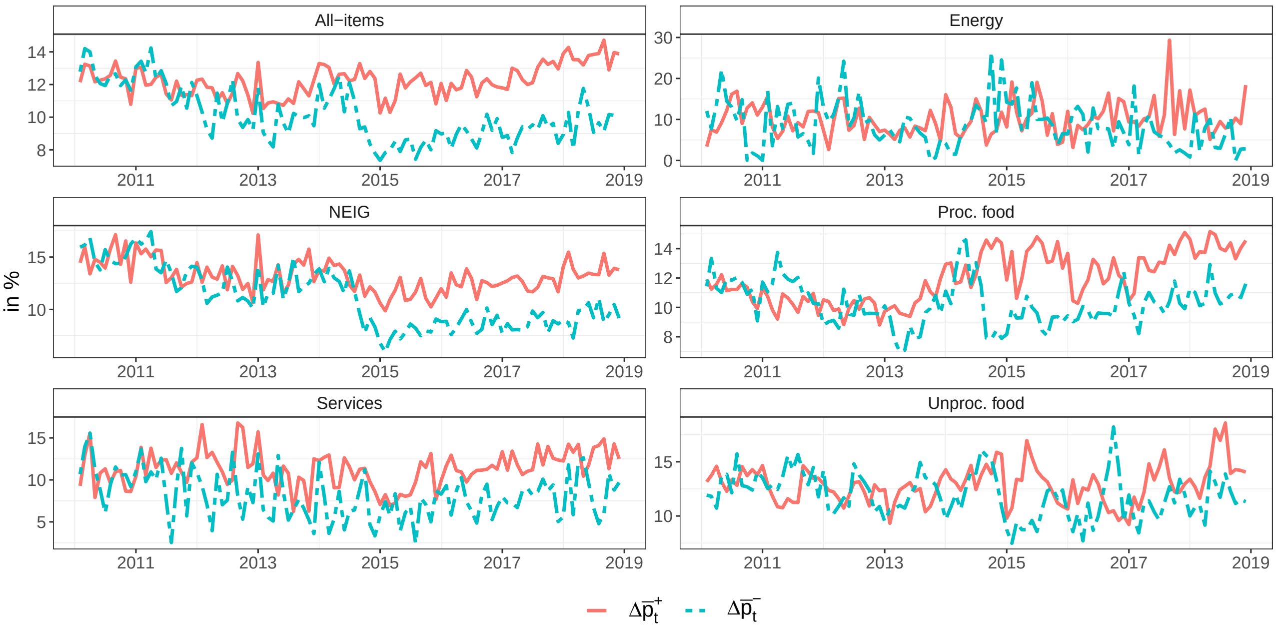
Notes: "Regular" series. The average frequency of price increases (red solid lines) is calculated in two steps: 1) $f_{jt}^+ = \frac{1}{N_{jt}} \sum_n^{N_{jt}} I_{njt}^+$ for n items and j ECOICOP4. I_{njt}^+ are price increase indicators; i.e. $I_{njt}^+ = 1$ if $p_{njt} > p_{njt-1}$, and 0 otherwise. 2) $\bar{f}_t^+ = \sum_j^J \omega_{jt} f_{jt}^+$. The average frequency of price decreases (blue dashed lines) is computed in two steps: 1) $f_{jt}^- = \frac{1}{N_{jt}} \sum_n^{N_{jt}} I_{njt}^-$ where I_{njt}^- are price decrease indicators; i.e. $I_{njt}^- = 1$ if $p_{njt} < p_{njt-1}$, and 0 otherwise. 2) $\bar{f}_t^- = \sum_j^J \omega_{jt} f_{jt}^-$. NEIG refers to "non-energy industrial goods".

Figure 13: Weighted average size of price increases and decreases, PPI



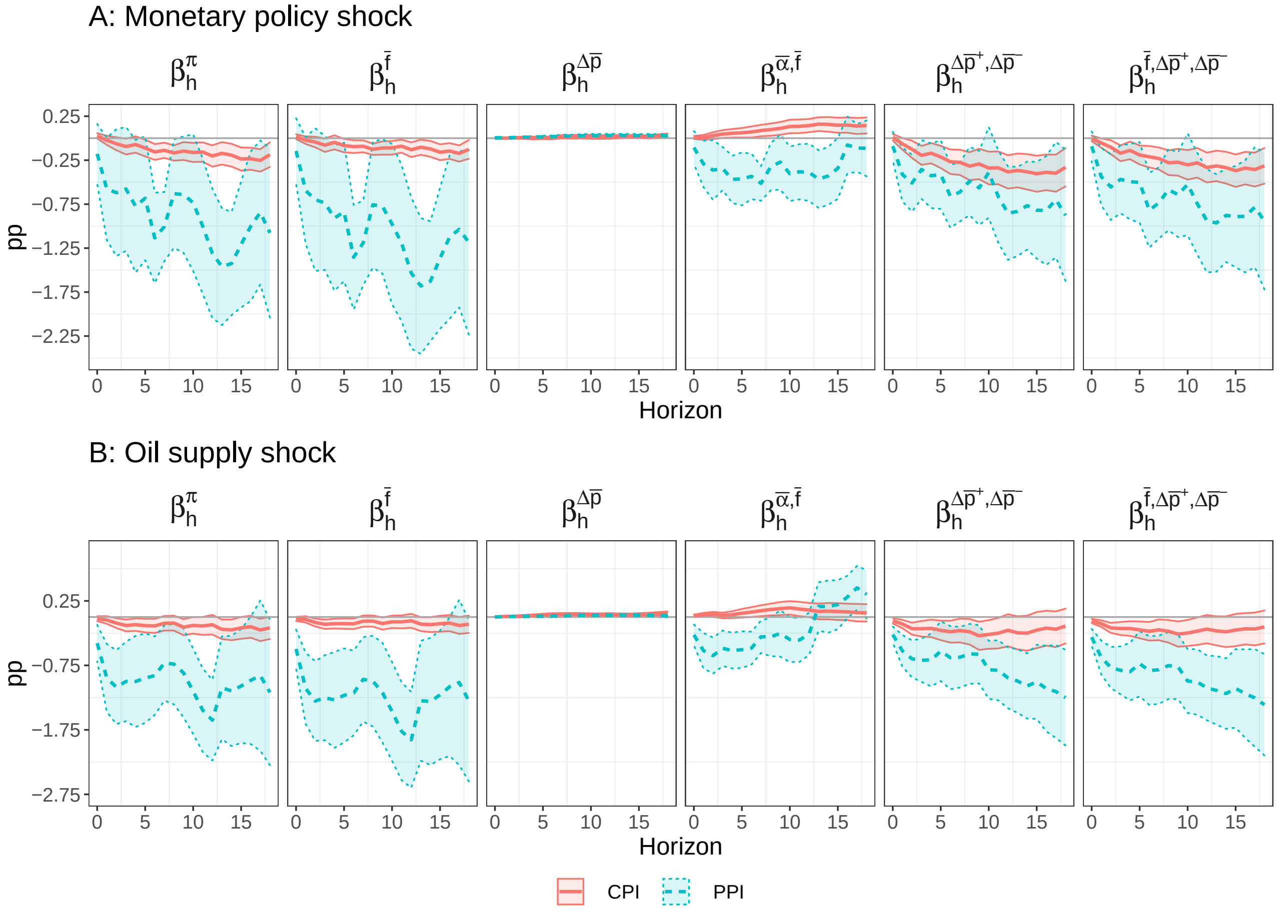
Notes: "Regular": series. The average size of price increases (red solid lines) is calculated in two steps: 1) $\Delta p_{jt}^+ = \frac{1}{N_{jt}} \sum_n^{N_{jt}^+} (p_{njt} - p_{njt-1})^+ \ / \ f_{jt}^+$ for n items and j NACE Rev. 2 (2-digit) divisions. f_{jt}^+ is computed as in (9). 2) $\bar{\Delta}p_t^+ = \sum_j^J \omega_{jt} \Delta p_{jt}^+$. The average size of price decreases (blue dashed lines) is computed in two steps: 1) $\Delta p_{jt}^- = \frac{1}{N_{jt}} \sum_n^{N_{jt}^-} (|p_{njt} - p_{njt-1}|)^- \ / \ f_{jt}^-$. 2) $\bar{\Delta}p_t^- = \sum_j^J \omega_{jt} \Delta p_{jt}^-$. *The category D contains: "Electricity, gas, steam and air conditioning supply". The category E contains: "Water supply; sewerage, waste management and remediation activities".

Figure 14: Weighted average size of price increases and decreases, HICP



Notes: "Regular" series. The average size of price increases (red solid lines) is calculated in two steps: 1) $\Delta p_{jt}^+ = \frac{1}{N_{jt}} \sum_n^{N_{jt}^+} (p_{njt} - p_{njt-1})^+ \ / \ f_{jt}^+$ for n items and j ECOICOP4 divisions. f_{jt}^+ is computed as in (9). 2) $\bar{\Delta}p_t^+ = \sum_j^J \omega_{jt} \Delta p_{jt}^+$. The average size of price decreases (blue dashed lines) is computed in two steps: 1) $\Delta p_{jt}^- = \frac{1}{N_{jt}} \sum_n^{N_{jt}^-} (|p_{njt} - p_{njt-1}|)^- \ / \ f_{jt}^-$. 2) $\bar{\Delta}p_t^- = \sum_j^J \omega_{jt} \Delta p_{jt}^-$. NEIG refers to "non-energy industrial goods".

Figure 15: Responses of counterfactual inflation to positive monetary and oil supply shocks



Notes: The local linear regressions are described in equation (7). β_h^{π} refers to the response of: inflation, $\beta_h^{\bar{f}}$ counterfactual inflation with constant overall frequency, $\beta_h^{\Delta\bar{p}}$ counterfactual inflation with constant overall size, $\beta_h^{\bar{\alpha},\bar{f}}$ counterfactual inflation with constant overall frequency and frequency of price increases and decreases, $\beta_h^{\Delta\bar{p}^+,\Delta\bar{p}^-}$ counterfactual inflation with constant size of price increases and decreases, $\beta_h^{\bar{f},\Delta\bar{p}^+,\Delta\bar{p}^-}$ counterfactual inflation with constant overall frequency and size of price increases and decreases. The colored areas correspond to two standard errors using calendar-based (month-year) clusters.

APPENDICES

A – DATA: ADDITIONAL INFORMATION

The procedure for cleaning the PPI database is as follows. First, I remove duplicates and consider a price change to be zero when it results from a change of less than 1 euro cent in January 2015 (in absolute value). If this were ignored, the frequency statistics would be completely skewed by the changeover to the euro. Second, I discard all observations of an item if any of its records is outside the 1st to 99th percentile of the absolute price growth distribution (excluding zero price growth). Third, I remove price records of a NACE Rev. 2 category at the 4-digit level if its average number of observations is less than 5 between 2010 and 2018. Otherwise, the statistics are too inaccurate.

I process the noise in the HICP database by following these steps. First, I remove duplicates and round to zero the price change below 1 euro cent in January 2015 (in absolute value). This is done for the reason outlined above. Second, I remove the seasonal prices. Third, I drop all observations from an item if any of its records falls outside the 1st to 99th percentile of the absolute price growth distribution (excluding zero price growth). Fourth, I retain the price records of an item-type if more than 25 of them are observed in a month. Fifth, I drop the data for an ECOICOP4 category if they are not observed for at least 100 months, i.e., more than eight years.[29]

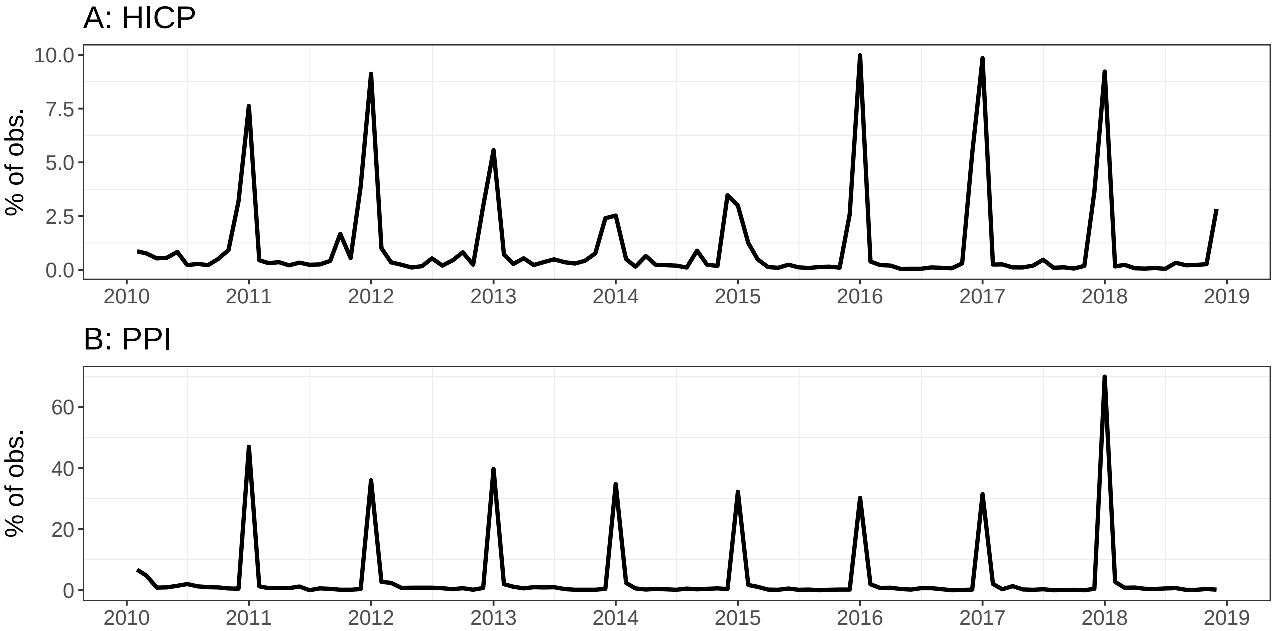
On the other hand, sales (promotions), and product substitutions and entries strongly influence micro-price statistics (Nakamura and Steinsson (2008); Kehoe and Midrigan (2015)). To better highlight their importance in both databases, I produce a ”regular” series of price changes. In this regard, Figure A1 shows the percentage of new item entries in the data for each month. New item observations are very high in January, especially in the PPI microdata, creating severe left-censoring. To smooth out this problem in the PPI, I use the information about the base price in December of the previous year. If the base price in January of the year n is not the same as the item price in December $n-1$, then the product has been replaced. Therefore, if there is a price difference between the base price and the item price in January of year n, it is due to product replacement. In that case, I set the price change between December $n-1$ and January n to 0.[30] In addition, I change any price difference to 0 when a flag identifying product replacements appears. Finally, other information in the form of a sentence indicating reasons may be provided when a price changes. Since a lot of information is mixed in, I do a text search for keywords related to sales (promotions), seasonality, product replacements and ”other important reasons”. I replace price change with 0 for all occurrences. When smoothing out the effects of sales, the following month's price change must also be taken into account. Indeed, it is common to encounter V-shaped price variations. For example, suppose an item is priced at 1 euro in the first month. The second month, it is reduced to a price of 0.5 euro. In the third month, the price returns to 1 euro. This shows that the price change in the second month is entirely due to the sale, and therefore the current price has not changed from the first month. When this happens, I adjust the price changes to 0 for months 1 and 2.

For HICP prices, there is no December base price. On the other hand, there are many ”flags” that allow one to correctly identify if there is a specific reason for a price change. This can be due to sales, product or customer replacement, etc. It is even indicated when ”the price has actually changed”. I use this information to adjust price changes to 0 when necessary. A more detailed description of the method and the flags can be found in Jouvanceau (2021). Note that observations of these ”flags” before August 2013 are rare (all flags for sales are missing). Thus, the ”regular” series largely coincide with the ”benchmark” series prior to that date.

[29] Note that the cleaning procedure is different for the CPI and PPI statistics because there are about 7.5 million price records for the former, compared to about 250,000 for the latter.

[30] Note that I change the price to 0 and do not drop the price observation so that the statistics are comparable between the ”benchmark” (unadjusted) and ”regular” price series.

Figure A1: Percentage of new items each month



B – STATISTICS

As emphasized in Klenow and Kryvtsov (2008), the inflation rate can be decomposed into the frequency and size of non-zero price changes. I compute these margins from the most disaggregated levels at which the HICP and PPI weights are available, namely ECOICOP4 and NACE Rev. 2 (division level, 2 digits), respectively. For every month t, the division-level inflation rates are computed as:

$$\begin{aligned}\tilde{\pi}_{jt} &= \frac{1}{N_{jt}}\sum_{n}^{N_{jt}}(p_{njt}-p_{njt-1}) \\ &= \left(\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I_{njt}\right)\times\left(\frac{\frac{1}{N_{jt}}\sum_{n}^{N_{jt}}(p_{njt}-p_{njt-1})}{\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I_{njt}}\right) \triangleq f_{jt}\times\Delta p_{jt}. \end{aligned} \tag{8}$$

for n items and j ECOICOP4 or NACE Rev. 2 (2-digit) divisions. Prices are transformed into their natural logarithm p_{njt}. I_{njt} are price change indicators; i.e. $I_{njt}=1$ if $p_{njt}\neq p_{njt-1}$, and 0 otherwise. I define f_{jt} as the frequency of price changes and Δp_{jt} as the size of non-zero price changes. The frequency can be further decomposed as follows:

$$f_{jt}=\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I_{njt}=\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I^{+}_{njt}+\frac{1}{N_{jt}}\sum_{n}^{N_{jt}} I^{-}_{njt}\triangleq f^{+}_{jt}+f^{-}_{jt}. \tag{9}$$

where I^{+}_{njt} are price increase indicators; i.e. $I^{+}_{njt}=1$ if $p_{njt}>p_{njt-1}$, and 0 otherwise. I^{-}_{njt} are price decrease indicators; i.e. $I^{-}_{njt}=1$ if $p_{njt}<p_{njt-1}$, and 0 otherwise. The size of non-zero price changes breaks down into:

$$\begin{aligned}\Delta p_{jt} &= \frac{\frac{1}{N_{jt}}\sum_n^{N_{jt}}(p_{njt}-p_{njt-1})}{\frac{1}{N_{jt}}\sum_n^{N_{jt}} I_{njt}} \\ &\triangleq \frac{f_{jt}^+}{f_{jt}} \times \underbrace{\frac{\frac{1}{N_{jt}}\sum_n^{N_{jt}^+}(p_{njt}-p_{njt-1})^+}{f_{jt}^+}}_{\Delta p_{jt}^+} - \frac{f_{jt}^-}{f_{jt}} \times \underbrace{\frac{\frac{1}{N_{jt}}\sum_n^{N_{jt}^-}(|p_{njt}-p_{njt-1}|)^-}{f_{jt}^-}}_{\Delta p_{jt}^-}. \end{aligned} \tag{10}$$

where Δp_{it}^+ and Δp_{it}^- are the size of upward and downward price changes, respectively. N_{jt}^+ is the number of price increases and N_{jt}^- of price decreases. To reconstruct the j inflation rates, I proceed as follows:

$$\tilde{\pi}_{jt} = f_{jt}^+ \times \Delta p_{jt}^+ - f_{jt}^- \times \Delta p_{jt}^-. \tag{11}$$

The aggregate weighted inflation rate is given by:

$$\pi_t = \sum_j^J \omega_{jt}\tilde{\pi}_{jt} \tag{12}$$

where ω_{jt} are the HICP or PPI weights between 2010 and 2018 at ECOICOP4 or NACE division levels as appropriate.[31]

[31]Note that after cleansing the consumer prices cover about 73% of the HICP weights at the ECOICOP4 level on average between 2010 and 2018. The producer prices cover about 99.5% of the PPI weights at the NACE Rev. 2 (2-digit) on average between 2010 and 2018. Therefore, weights are normalized where relevant. Cases where aggregate statistics or inflation are not weighted are calculated by arithmetic averages.

C – ADDITIONAL: CROSS-SECTIONAL STATISTICS

Table A1: Aggregate weighted statistics by MIG, PPI

	$\bar{f}$	$\bar{f}^{+}$	$\bar{f}^{-}$	$dur.$	$\Delta\bar{p}$	$\Delta\bar{p}^{+}$	$\Delta\bar{p}^{-}$	%$inc.$	%$Adj.$	$obs.$
Benchmark	%	%	%	$m.$	%	%	%	%	%	
Intermediate goods	48.5	25.2	23.2	1.4	0.3	7.4	-7.7	52	-	39029
Energy	84.7	42.9	41.8	0.4	0.3	4.9	-4.8	51.9	-	11955
Capital goods	27.5	13.9	13.6	3.6	0.6	13.2	-13	50.9	-	11225
Durable consumer goods	24.2	12.4	11.8	4.8	0.3	10.3	-10.3	51.2	-	9272
Non-durable consumer goods	49.9	25.7	24.2	1.4	0.2	9	-9	51.2	-	54607
Regular	%	%	%	$m.$	%	%	%	%	%	
Intermediate goods	38	20.1	17.8	2	0.4	6.2	-6.3	53	10.1	39029
Energy	84	42.5	41.6	0.4	0.2	4.9	-4.8	51.7	0.8	11955
Capital goods	18.5	9.8	8.7	5.5	0	8.8	-10	52.4	10.2	11225
Durable consumer goods	16.8	9	7.8	6.5	0.3	7.4	-7.9	54.3	8.1	9272
Non-durable consumer goods	25.9	14.4	11.6	3	0.7	7.3	-7.1	55.6	22	54607

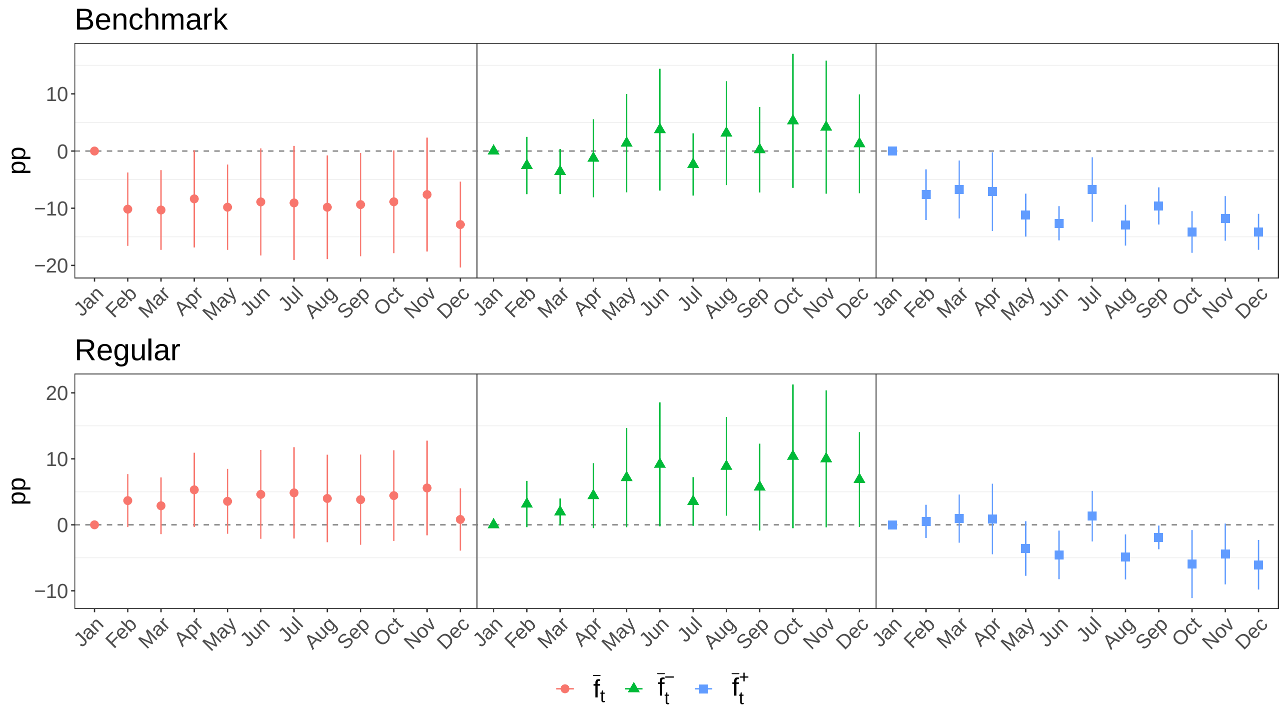
Notes: MIG is the abbreviation for "main industrial grouping". The aggregate weighted average frequency of price changes is calculated as: 1) $f_{jt} = \frac{1}{N_{jt}} \sum_{n}^{N_{jt}} I_{njt}$. 2) $\bar{f} = \sum_{t}^{T} \sum_{j}^{J} \omega_{jt} f_{jt}$. The other statistics in this table are aggregated in the same way (see appendix 5 for further details). "%$inc.$" refers the share of price increases in the total price changes. "%$Adj.$" refers to the share of prices adjusted to produce the "regular" statistics in each category. "$m.$" refers to a month. "$dur.$" gives the implied average duration using: $dur = -1/ln(1-f)$ where f is the weighted median frequency at each category level. The sample covers an average of 99.5% of the PPI NACE Rev. 2 (2-digit) weights between 2010 and 2018; the weights for each category are normalized. "Benchmark" refers to raw price changes, "Regular" refers to series adjusted for the phenomena described in section 2.

D –TIME SERIES: SEASONALITY AND TREND

Seasonality and trends in frequency and size statistics are explored by regressions with month and year fixed effects, respectively. The regressions include ECOICOP4/NACE Rev. 2 fixed effects and are weighted appropriately.

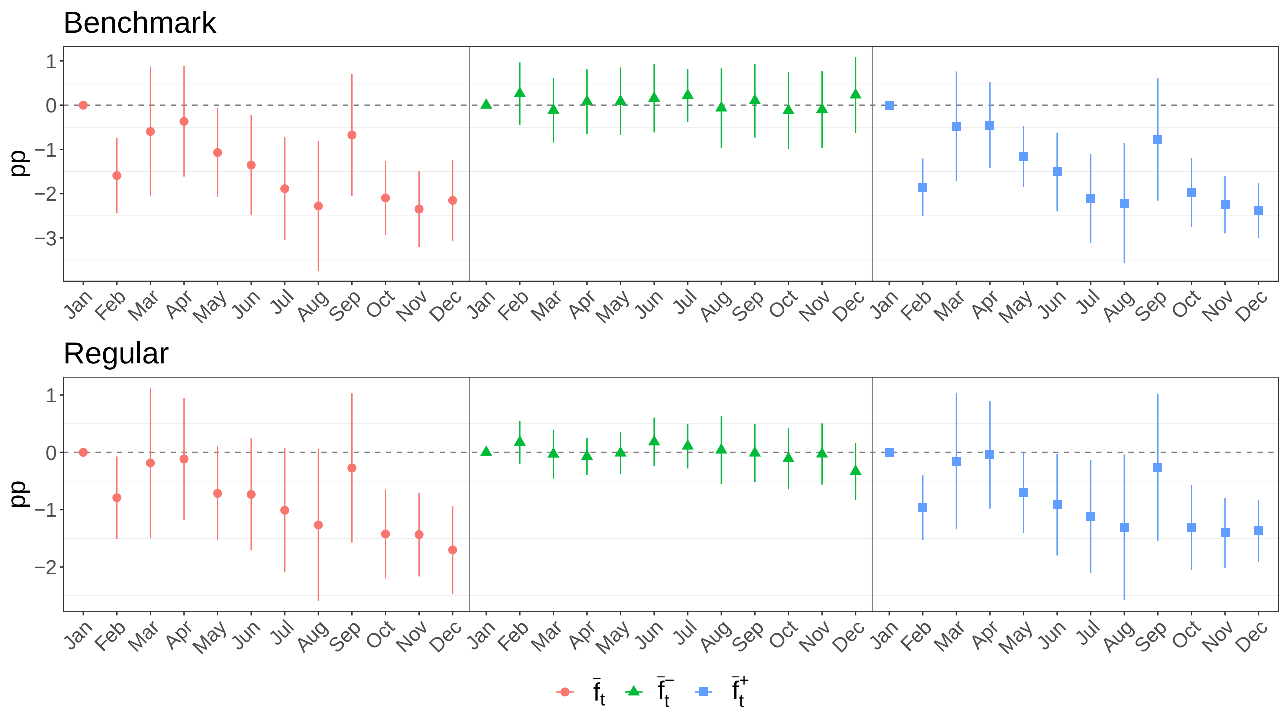
Comparing the average frequency of price increases to other months shows a strong "January effect" in the PPI (10 pp, Figure A2). This may be primarily the result of item rotations and additions, as shown in the adjusted frequency regressions and Figure A1. In the HICP, price increases are also more frequent on average in January (about 2pp, Figure A3). From a trend perspective, the average frequency of price changes has remained stable since 2010 in the PPI (Figure A4). Note, however, that while the average frequency of downward price changes increased by about 10pp between 2012 and 2016, at the same time, the frequency of upward price changes decreased by the same amount. The trend for consumer prices is rather erratic (Figure A5). It should be noted, however, that the frequency of price increases has significantly increased since 2015 ("benchmark" panel), a phenomenon potentially linked to the introduction of the euro (Jouvanceau (2021)).

Figure A2: Frequency of price changes month-effects, PPI



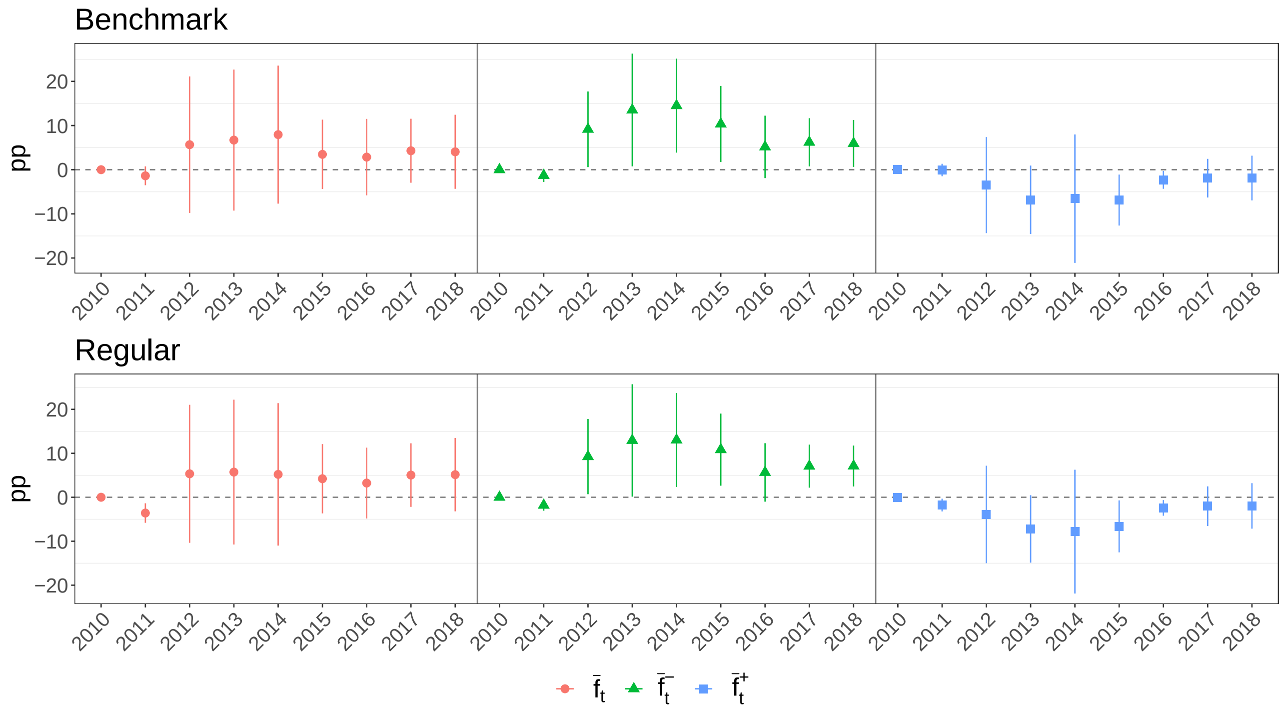
Notes: Regressions are done at the NACE Rev. 2 level including month dummies and NACE Rev. 2 fixed effects. Regressions are weighted using NACE Rev. 2 PPI weights between 2010 and 2018. Standard errors are clustered at NACE Rev 2. level. Error bars are 95% confidence intervals.

Figure A3: Frequency of price changes month-effects, CPI



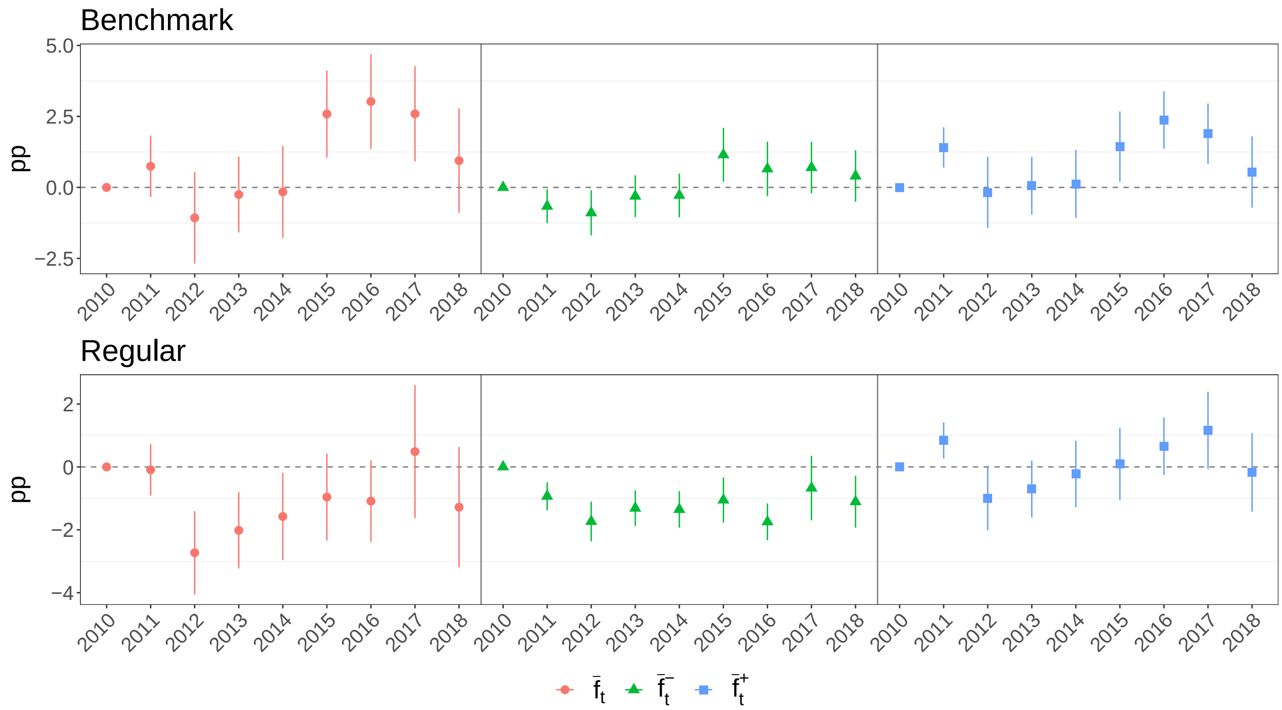
Notes: Regressions are done at the ECOICOP4 level including month dummies and ECOICOP4 fixed effects. Regressions are weighted using ECOICOP4 weights between 2010 and 2018. Standard errors are clustered at ECOICOP4 level. Error bars are 95% confidence intervals.

Figure A4: Frequency of price changes year-effects, PPI



Notes: Regressions are done at the NACE Rev. 2 level including year dummies and NACE Rev. 2 fixed effects. Regressions are weighted using NACE Rev. 2 PPI weights between 2010 and 2018. Standard errors are clustered at NACE Rev 2. level. Error bars are 95% confidence intervals.

Figure A5: Frequency of price changes year-effects, CPI

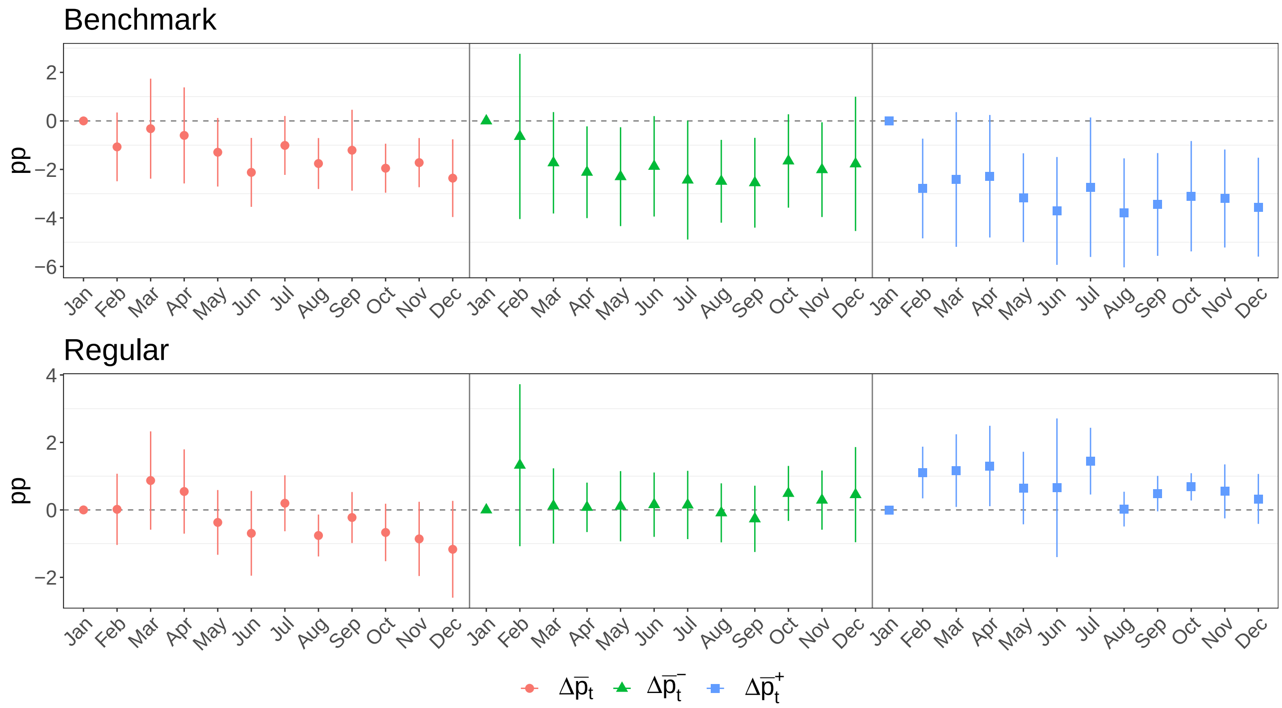


Notes: Regressions are done at the ECOICOP4 level including year dummies and ECOICOP4 fixed effects. Regressions are weighted using ECOICOP4 weights between 2010 and 2018. Standard errors are clustered at ECOICOP4 level. Error bars are 95% confidence intervals.

Next I ran similar weighted ECOICOP4/NACE Rev. 2 fixed effects regressions for the average size of non-zero price changes. The findings point to a small "January effect" in the PPI arising from item turnover/addition (Figure A6). For the HICP, price changes are higher in January, March and September (Figure A7). In addition, I look at the annual trends. Figure A8 shows that the average size has trended downward since

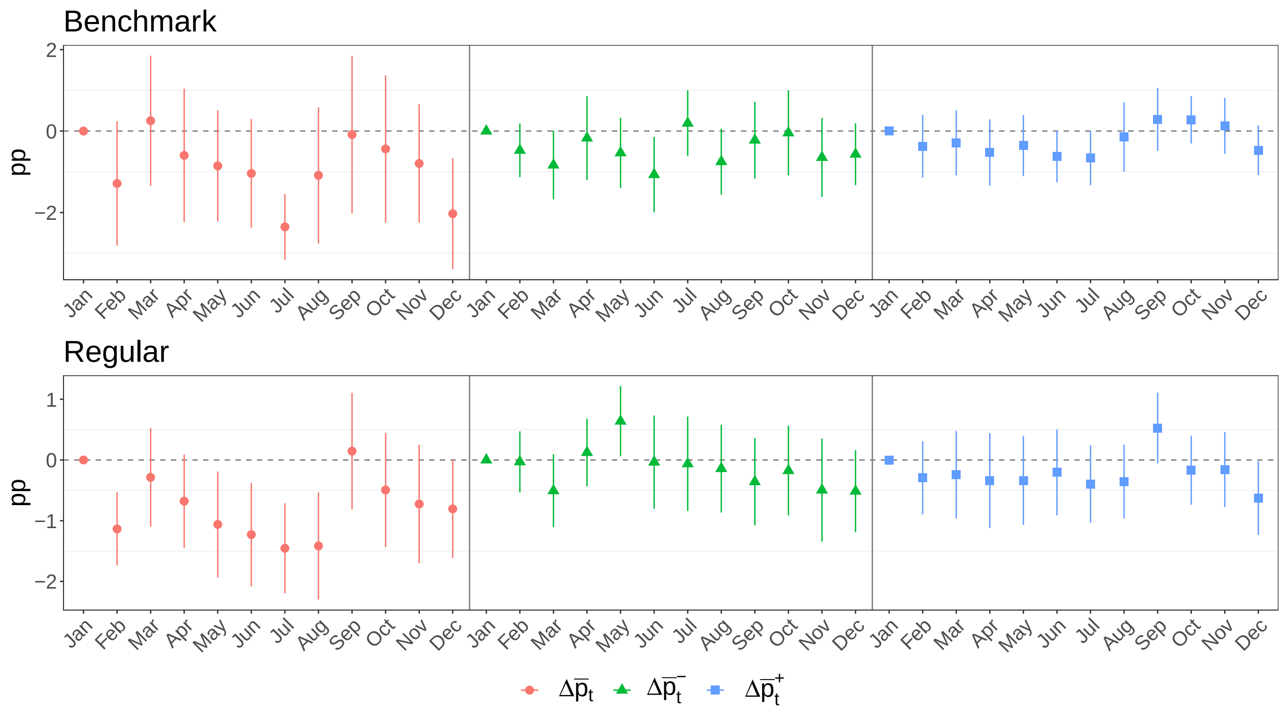
2010, peaking at -2.5pp in 2014. This change is primarily due to a decrease in the size of price increases. Conversely, a positive trend of 2pp characterized average consumer prices (Figure A9). The average size of price increases and decreases only increased from 2015. The significant changes in frequency, observed in Figure A5, indicate that they had an impact on average prices.

Figure A6: Size of non-zero price changes month-effects, PPI



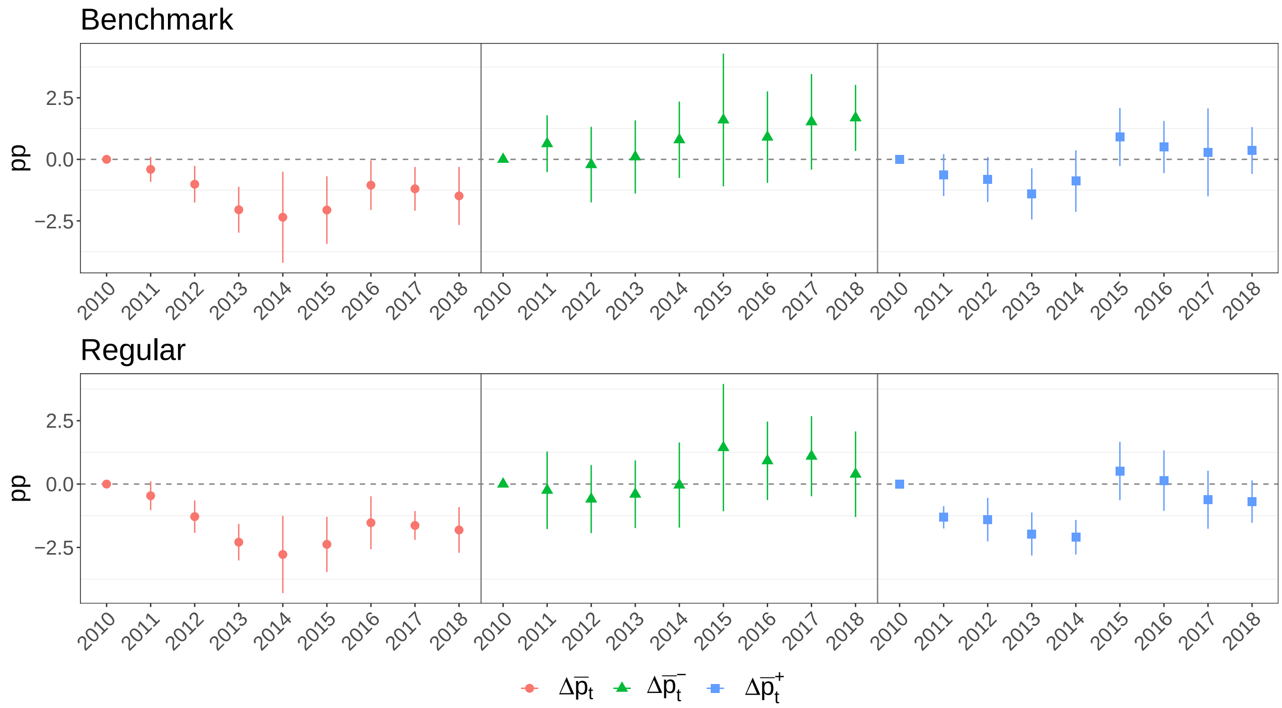
Notes: Regressions are done at the NACE Rev. 2 level including month dummies and NACE Rev. 2 fixed effects. Regressions are weighted using NACE Rev. 2 PPI weights between 2010 and 2018. Standard errors are clustered at NACE Rev 2. level. Error bars are 95% confidence intervals.

Figure A7: Size of non-zero price changes month-effects, CPI



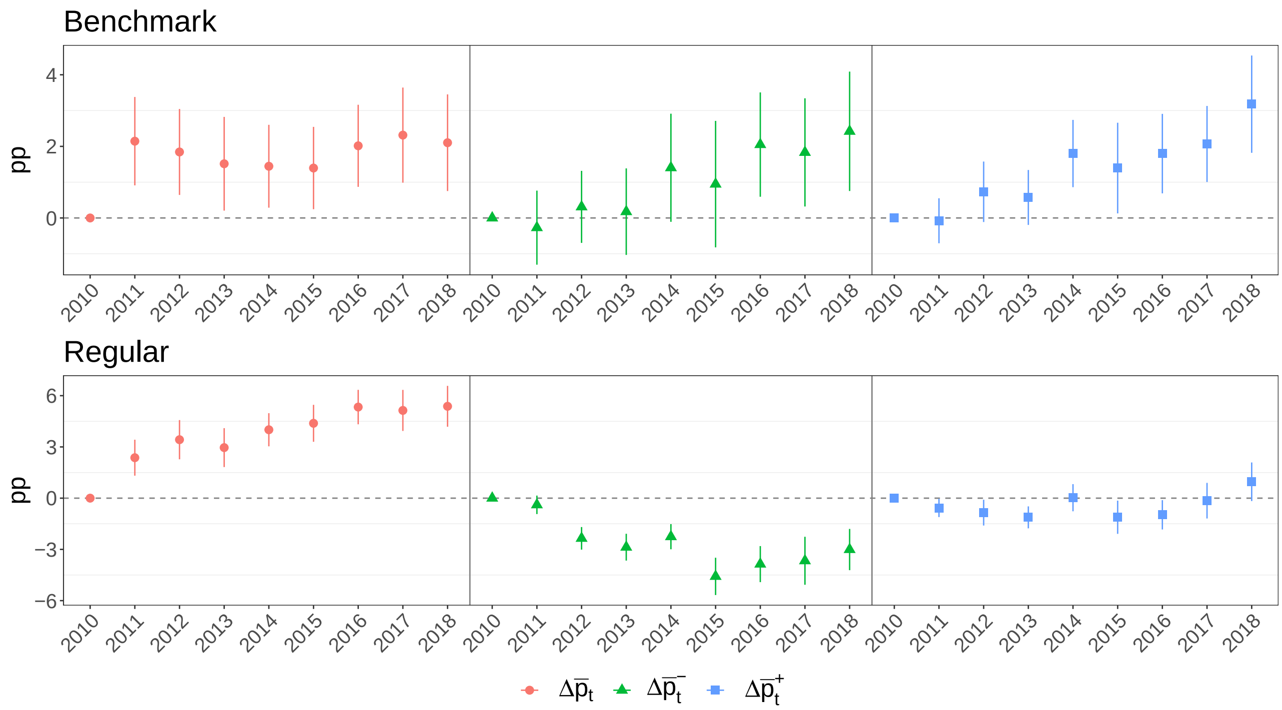
Notes: Regressions are done at the ECOICOP4 level including month dummies and ECOICOP4 fixed effects. Regressions are weighted using ECOICOP4 weights between 2010 and 2018. Standard errors are clustered at ECOICOP4 level. Error bars are 95% confidence intervals.

Figure A8: Size of non-zero price changes year-effects, PPI



Notes: Regressions are done at the NACE Rev. 2 level including year dummies and NACE Rev. 2 fixed effects. Regressions are weighted using NACE Rev. 2 PPI weights between 2010 and 2018. Standard errors are clustered at NACE Rev 2. level. Error bars are 95% confidence intervals.

Figure A9: Size of non-zero price changes year-effects, CPI



Notes: Regressions are done at the ECOICOP4 level including year dummies and NACE Rev. 2 fixed effects. Regressions are weighted using ECOICOP4 weights between 2010 and 2018. Standard errors are clustered at ECOICOP4 level. Error bars are 95% confidence intervals.