

# Grocery price setting in times of high inflation: what webscraped data tell us

Christian Beer, Robert Ferstl, Bernhard Graf, Fabio Rumler<sup>1</sup>

Refereed by: Lukas Henkel, ECB

We complement the existing literature on price rigidity by calculating statistics on the frequency and size of retail price changes observed in Austria between January 2021 and August 2022, using data scraped from online shop websites. As inflation started going up in September 2021, we split our sample into two parts: January to August 2021 and September 2021 to August 2022. Moreover, we limit our analysis to grocery items, since online supermarkets are a comprehensive and reliable source of daily prices. Our preliminary findings suggest that prices changed significantly more often in the period from September 2021 onward, with about 2.6% of all food prices being adjusted on a given day when we include sale price changes (compared to 1.5% in the period before September 2021). When we exclude sale price changes, we arrive at a daily price change rate of 0.5% (versus 0.2% in the low-inflation period). This corresponds to an average price duration of 38 days including sale price changes (versus 67 days in the low-inflation period) and approximately 200 days excluding sale price changes (versus 500 days before September 2021). While the considerably higher frequency of price changes in the high-inflation period under review affected all product groups observed, the average size of price changes remained broadly stable over time. Hence, we conclude that the current high level of food price inflation is driven mainly by an increase in the frequency of price changes rather than by changes in size. This might indicate that, in the face of a large shock, the frequency of price changes is no longer constant over time – as found in previous periods – but varies with the state of the economy. In other words, it would follow that time-dependent price setting has been replaced by state-dependent price setting.

JEL classification: E31, C82, D22

Keywords: price setting, price rigidity, webscraping, online prices, inflation

Inflation is ultimately the outcome of individual firms resetting thousands of prices. It is a well-established fact that at the micro level prices tend to be rather sticky, meaning that they do not instantly adjust to changes in costs and other disturbances to the economy. The degree of price stickiness is a major determinant of how macroeconomic shocks affect the economy. In particular, together with nominal wage rigidities, the degree of price rigidities determines the speed and extent of the transmission of monetary policy to the real economy.

Knowledge about individual price setting improves our understanding of the inflation process at large. The literature on price rigidity draws mainly on micro price data obtained from consumer price index (CPI) statistics in various countries (see e.g. Nakamura and Steinsson, 2008, for the US; Gautier et al., 2022, for the euro area; and Rumler et al., 2011, for Austria). These papers typically find that overall prices adjust on average every 9 to 12 months and by an amount of approximately 10%. However, there is a great deal of heterogeneity in the price adjustment frequencies across sectors, with prices of fresh food and some energy items (such as fuels) adjusting most often and prices of some (regulated) services adjusting

<sup>1</sup> Oesterreichische Nationalbank, Business Cycle Analysis Section, christian.beer@oenb.at; Monetary Policy Section, robert.ferstl@oenb.at, fabio.rumler@oenb.at; b.graf@gmx.at. Opinions expressed by the authors of studies do not necessarily reflect the official viewpoint of the OeNB or the Eurosystem. The authors would like to thank Lukas Henkel (ECB) for helpful comments and valuable suggestions.

only very infrequently. Especially for products with frequent price adjustments, CPI-based statistics come with the drawback that they are based on monthly data by definition. With the rise in e-commerce and the availability of website scraper software for downloading large amounts of data from the internet, the availability of high-frequency micro price data has increased vastly in recent years. Webscraped data can be used to do high-frequency analyses of price trends as e.g. in The Billion Prices Project<sup>2</sup> or to nowcast inflation developments (see e.g. Macias et al., 2022).

Another limitation of the existing literature on price rigidity is that – with very few exceptions (e.g. Henkel et al., 2022) – it covers only the low-inflation period before the second half of 2021. Since summer 2021, however, the inflation process has changed dramatically in most countries, with the potential of altering the ingrained price-setting behavior of firms. After all, rising inflation may be the result of prices changing more often or more significantly, or both. Webscraped data can provide timely information on whether and how corporate price setting may have changed in the current environment.

In this paper we complement the existing literature on price rigidity using data scraped from Austrian online shop websites between January 2021 and August 2022. Specifically, we calculate statistics on the frequency and size of price changes, based on thousands of online prices observed at a daily frequency. To compare the period before the inflation surge with the ensuing high-inflation period, we split the sample into two parts: January to August 2021 and September 2021 to August 2022. As comprehensive and reliable daily price data are available in our dataset mainly from online supermarkets, we limit our analysis to grocery items. The resulting statistics on the frequency and size of price changes are measured on a daily basis and have to be interpreted as such.

This paper is structured as follows: In section 1 we describe the data and methodology used in our analysis. Section 2 presents the empirical results and discusses the implications for price rigidity and the inflation process. Section 3 concludes and draws some policy conclusions.

## 1 Data and empirical approach

In April 2020, the OeNB started collecting product prices and related information (product name, store-specific product categorization, information on whether a price involves discounts, etc.) as provided by online stores of several Austrian retail chains on a daily basis. Although data are available for a variety of different product groups and store types, in this contribution we focus on groceries. We analyze three COICOP<sup>3</sup> 3-digit categories: food (C011), nonalcoholic beverages (C012)

<sup>2</sup> *The Billion Prices Project was an initiative at the MIT and Harvard using prices collected from hundreds of online retailers around the world on a daily basis to conduct research in macro and international economics. For more information see: <http://www.thebillionpricesproject.com>.*

<sup>3</sup> *COICOP stands for Classification of Individual Consumption by Purpose. It is a classification developed by the United Nations Statistics Division to categorize consumption expenditures and is used for the computation of the Harmonised Index of Consumer Prices (HICP). For the webscraped data, the individual products are first classified into the finest COICOP category level (elementary indices). For instance, food (C011) is composed of 118 elementary indices (e.g. chicken filet). This classification is accomplished with the help of regular expressions on the product names and shop-specific product categories. Thus, only products that are covered in the COICOP classification enter the analysis. Subsequently, the products are assigned to the higher-level COICOP categories, using the information on the structure of COICOP aggregates and country-specific weights for index compilation as provided by Statistics Austria (2021, 2022).*

and alcoholic beverages (C021). As a fourth category, we include an aggregate for unprocessed food items, consisting mainly of unprocessed meat, fish, eggs, fruits and vegetables.<sup>4</sup>

Given that our dataset was still being built up in the course of 2020, we use data from January 1, 2021, to the end of August 2022 for our analysis. Data are downloaded from the online stores of

four supermarkets of which two also have brick-and-mortar stores and two are on-line only.<sup>5</sup> Table 1 shows the number of price observations that enter the analysis.

To separately analyze and compare price setting in different inflation regimes, we divide our sample into two subperiods. A lower-inflation period until the end of August 2021, when HICP inflation averaged 2.3%, and the ensuing high-inflation period with average inflation amounting to 6.1%. In addition, we also present monthly averages of daily numbers. This allows us to smooth the strong fluctuations present in the daily data while retaining the higher information content of daily data.

There is an ongoing debate in the literature as to whether sale price changes (i.e. the markdown of prices for temporary sales promotions and discount sales) should be considered in the analysis of price rigidity. While the frequency of price changes goes up, of course, when we include sale price changes, it is not clear whether such price flexibility matters from a monetary policy perspective. For example, Nakamura and Steinsson (2008) argue that sale price changes might at times be more attributable to company-specific circumstances and less so to the general macroeconomic situation. Kehoe and Midrigan (2015) argue that the responses to monetary policy from frequent changes of micro prices during sale periods are only short-lived and the relatively high stickiness of regular prices matters more from the monetary policy perspective. Whether to include sale price changes when calculating the frequency of price changes or not has important implications for economic modeling. Since our contribution is mostly descriptive, we present all statistics for both aggregates, including and excluding sale price changes. In our dataset, sale price changes are flagged as such whenever retailers indicate that a price involves discounts. Our inspection of the data suggests that such flags are a reliable indicator for the presence of sale items for the stores analyzed.<sup>6</sup>

Webscraped data exhibit some differences from other data sources that are used in the analysis of price rigidity (e.g. CPI microdata, scanner data): Data collection is limited to selected stores and restricted to certain store types. In the case of groceries, all webscraped data are retrieved from supermarkets. This could potentially affect our results if different store types show different price-setting behaviors. Yet, supermarkets have a high market share for grocery products, suggesting high representativity of their price-setting behavior for the price-setting process in the whole sector. Furthermore, webscraped data include all products of

Table 1

### Size of dataset

Category	Number of observations	Number of unique products
Food	3,747,502	9,414
Unprocessed food	423,652	1,438
Nonalcoholic beverages	875,146	2,064
Alcoholic beverages	741,101	1,960

Source: OeNB, authors' calculations.

<sup>4</sup> For the exact definition see: [Europa - RAMON - Classification Detail List](#).

<sup>5</sup> Due to confidentiality granted to the stores from which prices are scraped, the names of these shops are not disclosed here.

<sup>6</sup> Therefore, we do not apply a sale filter as e.g. proposed by Nakamura and Steinsson (2008).

a certain store, not just a few selected ones (like HICP microdata). At the same time, webscraped data on discontinued products are not mapped to any replacement products a store may add. Therefore, we might miss implicit price changes that occur if products are replaced by similar ones. However, a big advantage of webscraped data is their high frequency and their quick availability and timeliness. Among other things, this allows for almost real-time monitoring of price developments.

The daily frequency of price changes is calculated as the ratio of the sum of observed price changes to the sum of potential price changes. The sum of potential price changes refers to all products for which prices are available on a given day and the preceding day and are thus, in theory, subject to change. To exclude sale price changes, we replace sale prices by the last regular price observed (i.e. the price on the day before the sale started) and recalculate all statistics from this modified price series.

In a first step, price changes and the frequencies are calculated at the level of elementary indices. At this stage, all products enter with the same weight. These frequencies are then aggregated to higher COICOP levels and eventually to the product groups analyzed in this article using the HICP weights provided by Statistics Austria (Statistics Austria, 2022, and equivalent information for 2021).

## 2 Results

### 2.1 The frequency of price changes increased markedly in the high-inflation period

Table 2

#### Frequency of price changes

	Including sale price changes	Excluding sale price changes
	%	
Food		
2021-01 – 2021-08	1.5	0.2
2021-09 – 2022-08	2.5	0.5
Unprocessed food		
2021-01 – 2021-08	3.7	0.4
2021-09 – 2022-08	4.8	0.5
Nonalcoholic beverages		
2021-01 – 2021-08	0.6	0.1
2021-09 – 2022-08	1.9	0.3
Alcoholic beverages		
2021-01 – 2021-08	0.7	0.2
2021-09 – 2022-08	2.8	0.3

Source: OeNB, authors' calculations.

Note: Average daily frequency.

Table 2 shows the average frequency of daily price changes for the selected time span, both including and excluding sale price changes.<sup>7</sup> For example, including sale price changes, 2.5% of the prices of all food items changed on a given day on average in the high-inflation period. Excluding sale price changes, the ratio drops to 0.5%. This would imply that, on average, food prices remain constant for about 38 days and even for 200 days when only nonsale price changes are considered.<sup>8</sup> For all product categories, the frequency of price changes is considerably higher in the second (high-inflation) period compared to the first (low-inflation) period. This already indicates that rising inflation was accompanied by a rise in the frequency of

<sup>7</sup> Our data also include information on quantity discounts. We do not consider quantity discounts to be general discounts, as they only benefit consumers who purchase at least a certain quantity of a product. Therefore, we do not take them into account when calculating the statistics presented in this study.

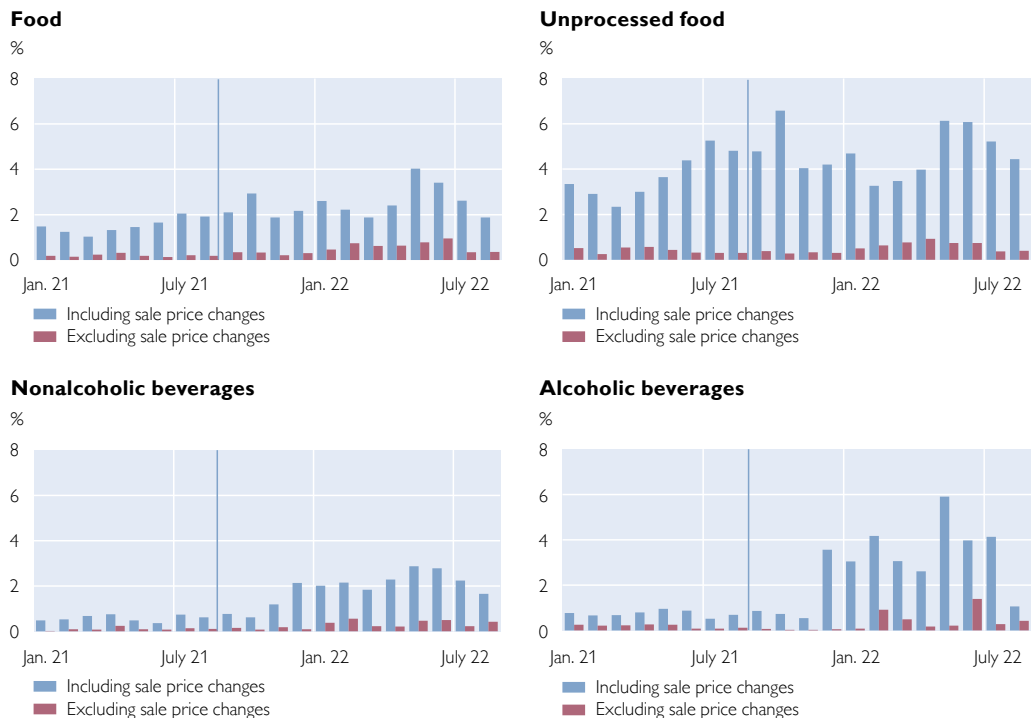
<sup>8</sup> We convert the average frequency of price changes ( $F$ ) into an average duration of price spells ( $D$ ) with the simple formula  $D=1/F$ .

price changes. By and large, the numbers including and excluding sale price changes show the same pattern, but at different scales. For food, the frequency of price changes more than doubled from the first to the second period when sale price changes are excluded, while the difference was less pronounced when sale price changes are included. In contrast, beverages and in particular alcoholic beverages actually exhibited a rising frequency of price changes when sale price changes are included. Thus, before the inflation surge, prices of food items were altered more often than those of beverages. This pattern obviously changed in the high-inflation period when the frequencies of price adjustments of food and beverages became more aligned.

Chart 1 shows the monthly averages of daily price changes from January 2021 to August 2022. We see that the high-inflation period exhibits considerably higher frequencies both including and excluding sale price changes, as was evident from table 2. But the chart also visualizes variations within the low- and high-inflation periods and similarities and differences across product groups. For instance, the frequency of price changes (including sale price changes) peaked in May 2022 in all product groups except nonalcoholic beverages, before starting to decline again. Or, the increase in the price change frequency of beverages was more abrupt and started later than that for food.

Chart 1

### Frequency of price changes



Source: OeNB, authors' calculations.

Note: The vertical line separates the low- and high-inflation periods.

Table 3

### Frequency of price increases and decreases

	Frequency of increases or decreases				Share of increases	
	Including sale price changes		Excluding sale price changes		Including sale price changes	Excluding sale price changes
	Increases	Decreases	Increases	Decreases		
	%					
Food						
2021-01 – 2021-08	0.7	0.8	0.1	0.1	47.5	51.9
2021-09 – 2022-08	1.3	1.2	0.4	0.1	55.4	86.5
Unprocessed food						
2021-01 – 2021-08	1.8	2.0	0.2	0.2	47.0	58.1
2021-09 – 2022-08	2.3	2.5	0.4	0.1	48.3	73.0
Nonalcoholic beverages						
2021-01 – 2021-08	0.3	0.3	0.1	0.1	47.9	45.6
2021-09 – 2022-08	1.1	0.8	0.3	0.0	56.0	91.9
Alcoholic beverages						
2021-01 – 2021-08	0.4	0.3	0.1	0.1	51.9	68.5
2021-09 – 2022-08	1.5	1.3	0.3	0.1	53.0	84.6

Source: OeNB, authors' calculations.

Note: Average daily frequency.

For the evolution of inflation, it is not only the frequency of overall price changes that matters but also the balance of price increases and decreases. After all, the overall frequency of price changes would remain constant if price increases are offset by price decreases. This is why table 3 provides separate breakdowns for the frequency of price increases and decreases. In the low-inflation period, the frequency of increases remained broadly balanced with the frequency of decreases. In other words, the share of price increases in all price changes is close to 50% (last two columns of table 3). This is also the case in the high-inflation period, but only if we include sale price changes. If we exclude sale price changes, the data exhibit a sharp increase in the frequency of increases in the high-inflation period, compared with a broadly stable decrease in the frequency of decreases (or even a drop for nonalcoholic beverages). As a consequence, the share of nonsale price increases is way above 50% in the high-inflation period.

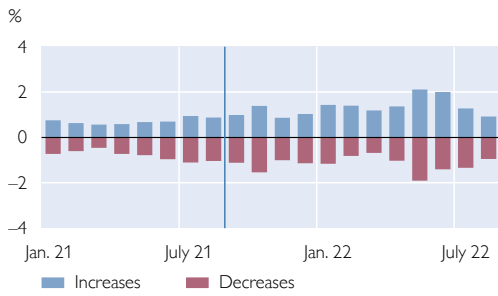
Chart 2 shows the frequency of price increases and decreases including sale price changes, and chart 3 shows the corresponding data excluding sale price changes.<sup>9</sup> Like the overall frequency of price changes visualized in chart 1, the frequency of increases (including sale price changes) peaked in May or June 2022 and dropped thereafter for all categories, while remaining above the low-inflation period levels. The same pattern is visible when we exclude sale price changes: Especially for food, the frequency of both price increases and decreases declined considerably in the last two months, July and August 2022, but price increases continued to be substantial (except for alcoholic beverages in August 2022).

<sup>9</sup> For graphical reasons, we put the statistics for decreases on the negative y-axis, although it is a positive number.

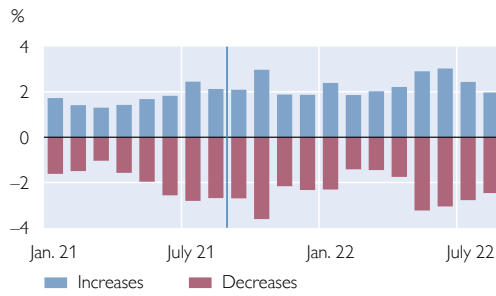
Chart 2

### Frequency of price increases and decreases including sale price changes

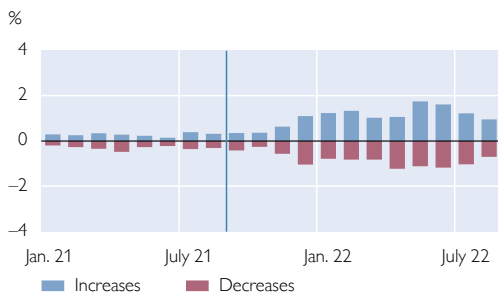
#### Food



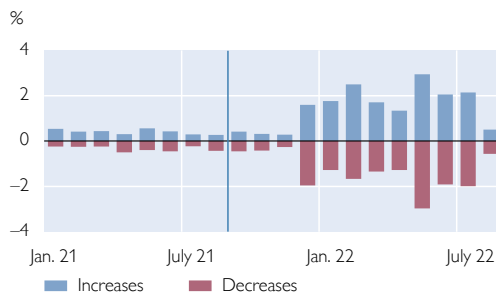
#### Unprocessed food



#### Nonalcoholic beverages



#### Alcoholic beverages



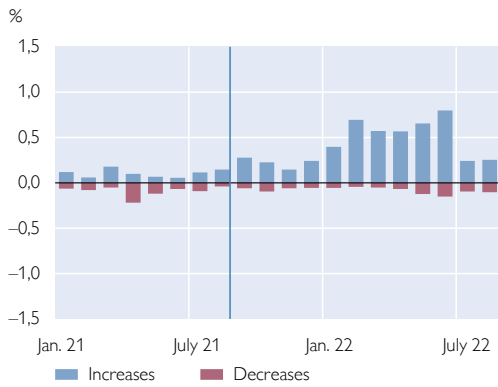
Source: OeNB, authors' calculations.

Note: The vertical line separates the low- and high-inflation periods.

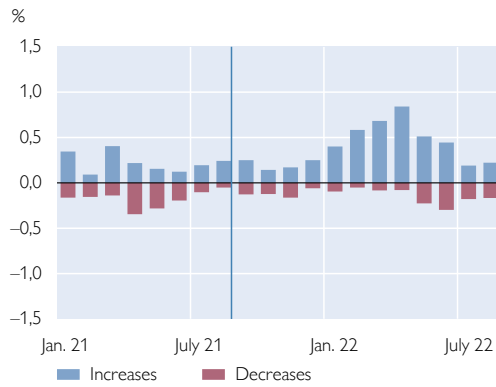
Chart 3

### Frequency of price increases and decreases excluding sale price changes

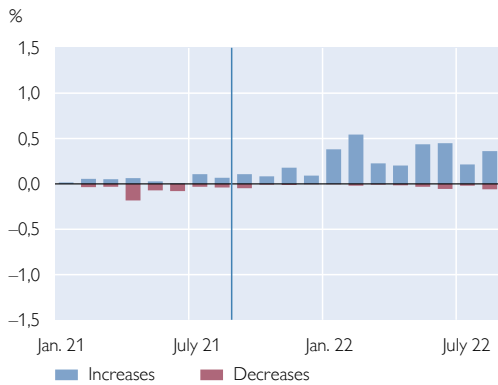
#### Food



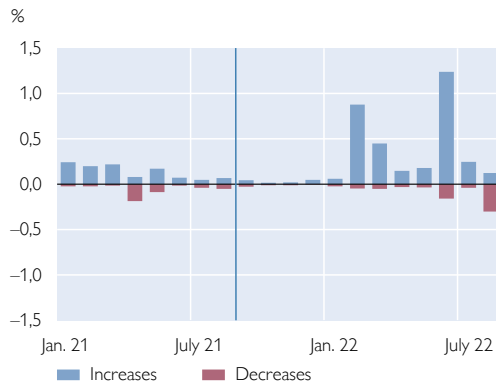
#### Unprocessed food



#### Nonalcoholic beverages



#### Alcoholic beverages



Source: OeNB, authors' calculations.

Note: The vertical line separates the low- and high-inflation periods.



## 2.2 Little variation in the size of price changes over time

Apart from the frequency of price changes, inflation is also driven by the size of price changes. Judging from menu cost models of price adjustment, we would expect the magnitude of price changes to exceed a certain size given by the menu costs (see e.g. Golosov and Lucas, 2007). Table 4 shows the average size of daily price changes (in log changes compared to the previous day) conditional on a price change. Average price changes are relatively high, ranging from 20% to 30% when we include sale price changes and 10% to 15% when we exclude sale price changes. In other words, retail prices are adjusted relatively infrequently but if they do change, the price changes are relatively large, as suggested by menu cost models. This is broadly consistent with the findings in the literature based on monthly data, where Gautier et al. (2022) find a median price increase of 10% for unprocessed food in the euro area between 2011 and 2017 and a median decrease of 11% (both excluding sale price changes), compared to 9.6% (for increases) and 10.6% (for decreases) in the low-inflation period.

When we include sale price changes, the average size of price changes appears to be broadly symmetric between increases and decreases in both time periods. When we exclude sale price changes, this is no longer the case: price decreases are usually larger than price increases, in particular for beverages. However, we do not find a systematic increase or decrease in either the low-inflation or the high-inflation period. In the high-inflation period, the calculations yielded a lower median size of both price increases and decreases for food items but a somewhat higher median size of price increases for beverages.

Data including sale price changes reflect the typical size of sale price changes (20%, 25% and 30%) and the subsequent price increase after the end of the sale period. From chart 4 we conclude that the average size of price changes is relatively constant over time, without significant differences between the high-inflation and

Table 4

### Size of price increases and decreases

	Mean (including sale price changes)		Median (including sale price changes)		Mean (excluding sale price changes)		Median (excluding sale price changes)	
	Increases	Decreases	Increases	Decreases	Increases	Decreases	Increases	Decreases
	%							
Food								
2021-01 – 2021-08	29.7	27.2	28.6	28.5	11.8	13.4	9.6	10.6
2021-09 – 2022-08	25.7	28.9	22.8	28.8	9.1	13.1	7.3	8.5
Unprocessed food								
2021-01 – 2021-08	35.3	31.3	28.6	28.6	14.0	15.0	10.6	11.8
2021-09 – 2022-08	33.8	31.0	28.9	28.9	11.9	18.2	8.5	14.4
Nonalcoholic beverages								
2021-01 – 2021-08	24.9	24.2	22.4	22.4	8.9	12.1	4.6	9.5
2021-09 – 2022-08	26.0	31.2	28.5	28.8	8.4	13.5	6.9	7.4
Alcoholic beverages								
2021-01 – 2021-08	19.6	21.8	18.2	20.1	9.7	14.7	6.0	10.6
2021-09 – 2022-08	22.8	26.1	28.5	28.7	8.0	12.1	6.5	8.7

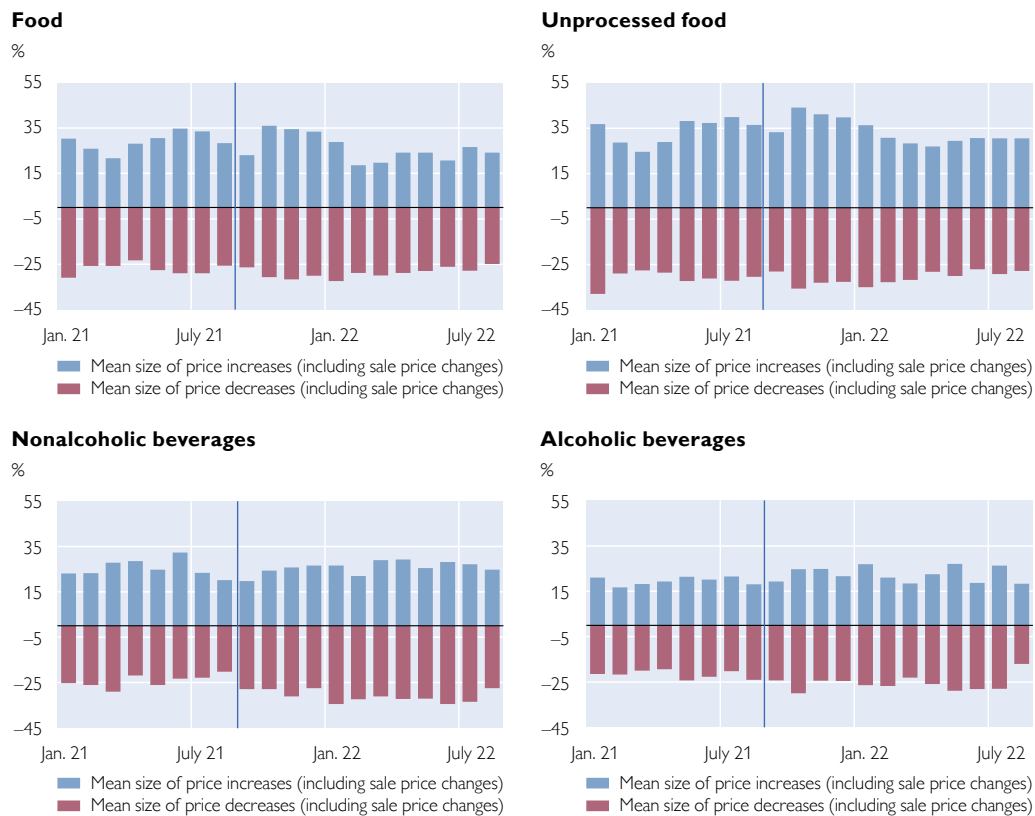
Source: OeNB, authors' calculations.



the low-inflation periods. This suggests that the recent inflation increase is driven by a higher frequency of price increases rather than an increase in the size of price changes. A similar result was found by Wulfsberg (2016), namely that in times of high and volatile inflation, the frequency of price changes is a bigger driver of inflation than the magnitude of price changes.

Chart 4

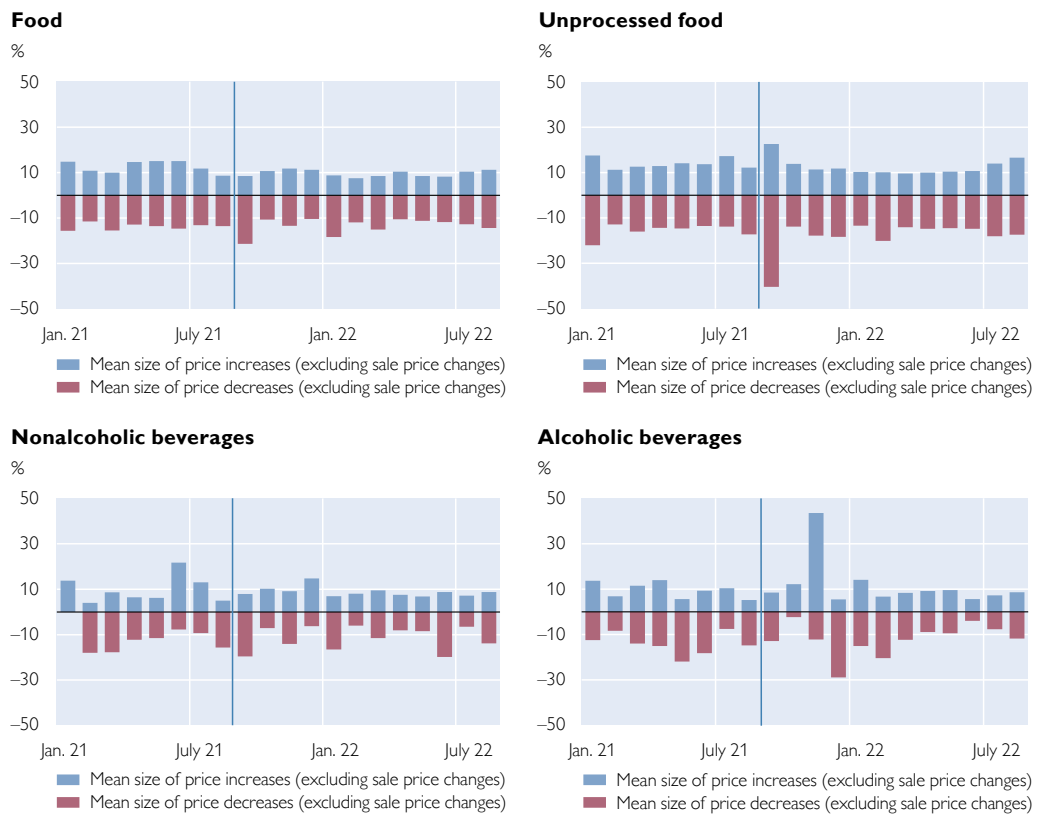
### Size of price increases and decreases including sale price changes



Source: OeNB, authors' calculations.

Note: The vertical line separates the low- and high-inflation periods.

### Size of price increases and decreases excluding sale price changes



Source: OeNB, authors' calculations.

Note: The vertical line separates the low- and high-inflation periods.

## 3 Conclusions

The degree of price rigidity in an economy is a major determinant of the speed and extent of the transmission of monetary policy to the real economy. Thus, the analysis of firms' price setting at the micro level has become a central field of macroeconomic and monetary research. So far, this research is primarily based on micro price data from official CPI statistics obtained from statistical institutes. Our addition to the literature is that we use webscraped data (micro price data from online stores) to analyze questions of price rigidity. This kind of data has advantages and disadvantages compared to CPI micro data, the biggest advantage being that the data are available at a higher frequency (in our case daily) than the official (monthly) data.

Based on daily data from online stores of major Austrian supermarket chains, we calculate price rigidity statistics for the period from January 1, 2021, to August 31, 2022. Due to the availability of reliable data that are already categorized into COICOP groups, we limit our analysis to grocery products. For food products, we find that on average about 2% of all prices are changed per day. This implies that, on average, food product prices remain constant for about 50 days. At around 1.5%, the frequency of price adjustments is somewhat lower for (nonalcoholic and alcoholic) beverages. Most of these price changes are, however, attributable to sale price changes (i.e. the markdown of prices for temporary sales promotions and discount sales). When we exclude all sale-related price changes, the frequency of

food price adjustments drops to 0.4%. In other words, we can attribute about 80% of all price changes to sale price changes. While part of the literature on price rigidity argues that sale price changes should be ignored or considered as mere noise in price-setting studies, given that sale prices are usually very short-lived and will be reversed after some time, other studies argue that sale price changes are an important element of price flexibility and should be included in the analysis of price rigidity. Depending on one's standpoint, one can draw very different conclusions on the degree of price rigidity that ultimately feeds into numerical models of the macro-economy. Part of the large difference between the frequency with and without sale price changes is specific to our analysis based on daily data, given that in studies based on monthly CPI data, sale price changes account for only about one-third of all price changes of food products (see Gautier et al., 2022). This indicates that at a higher observation frequency, sale price changes become an even more important element of retail price setting.

The period under investigation in this study is characterized by a rapid increase in inflation to levels unprecedented in recent decades. However, the whole literature on price rigidity of the past 20 years emerged during a period of relatively low and stable inflation rates. Given the extent of the shift in inflation, it is conceivable that the price-setting process may have changed, putting into question the stylized facts established so far. To see how price setting before and after the inflation shock differs, we calculate all statistics separately for the period of comparatively moderate inflation until August 2021 and the ensuing high-inflation period since September 2021. We can clearly see that the frequency of price adjustments increased substantially in the high-inflation period – for all product groups, both including and excluding sale price changes. Differentiating between price increases and decreases, we furthermore see that the rise in the frequency of price adjustments was relatively stronger for price increases. This pattern is particularly pronounced when sale price changes are excluded. At the same time, the average size of price adjustments changed relatively little over time. This indicates that rising inflation was mainly the result of an increase in the frequency of price changes, in particular of price increases.<sup>10</sup> If this finding is confirmed in other studies, it would indeed change our understanding of the price-setting process, confirming the view that, in the face of large shocks, time-dependent price setting (implying a constant frequency over time) is replaced by state-dependent price setting, which allows the frequency of price changes to vary with the state of the economy (Alvarez et al., 2019).

What are the macroeconomic consequences of our descriptive evidence on changes in the frequency and size of price adjustments? As the degree of price flexibility is a key determinant of the slope of the Phillips curve, time variation in price flexibility, as found in this paper, may have consequences on the pass-through of macroeconomic shocks (Petrella et al., 2019). Specifically, when price flexibility rises, the slope of the Phillips curve gets steeper, making it possibly more difficult for monetary policy to stabilize inflation. Furthermore, there is a possible – but less well-established – link between changes in the frequency of price adjustments and the formation of individuals' inflation expectations and perceptions (D'Acunto et al., 2021). As agents are found to base their inflation expectations and perceptions

<sup>10</sup> This is, however, only indicative as a numerical decomposition of inflation into the contribution of the frequency and size of price adjustments found in the literature using CPI data (e.g. Gautier et al., 2022; and Klenow and Krivtsov, 2008) is not directly possible with daily observations given that inflation is measured at a monthly frequency.

primarily on prices of groceries, sudden changes in the frequency of grocery price adjustments can lead to shifts in inflation expectations of consumers and firms affecting their spending, investment, price- and wage-setting decisions. Lastly, the nature of price stickiness can also have important consequences for the welfare costs of inflation (Nakamura et al., 2018). According to the New Keynesian model, a strongly varying size of price adjustments entails large welfare costs of nonzero rates of inflation as it leads to inefficient price dispersion. When inflation is mostly driven by the frequency rather than the size of price changes, as found in Nakamura et al. (2018) and in this paper, the welfare costs of nonzero inflation are much smaller, and the optimal rate of inflation needs to be reassessed.

## References

- Alvarez, F., M. Beraja, M. Gonzalez-Rozada and P. Neumeyer. 2019.** From Hyperinflation to Stable Prices: Argentina's Evidence on Menu Cost Models. In: *The Quarterly Journal of Economics* 143(1). 451–505.
- Bils, M. and P. Klenow. 2004.** Some evidence on the importance of sticky prices. In: *Journal of Political Economy* 112(5). 947–985.
- D'Acunto, F., U. Malmendier, J. Ospina and M. Weber. 2021.** Exposure to Grocery Prices and Inflation Expectations. In: *Journal of Political Economy* 129(5). 1615–1639.
- Gautier, E., C. Conflitti, B. Fabo, R. Faber, 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 2669.
- Henkel, L., E. Wieland, A. Błażejowska, C. Conflitti, B. Fabo, L. Fadejeva, J. Jonckheere, P. Karadi, P. Macias, J. O. Menz, P. Seiler and K. Szafranek. 2022.** Price Setting during the COVID-19 Pandemic. ECB Occasional Paper. Forthcoming.
- Golosov, M. and R. E. Lucas. 2007.** Menu Costs and Phillips Curves. In: *Journal of Political Economy* 115. 171–199.
- Kehoe P. and V. Midrigan. 2015.** Prices are sticky after all. In: *Journal of Monetary Economics* 75. 35–53.
- Klenow, P. and O. Kryvtsov. 2008.** State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation? In: *The Quarterly Journal of Economics* 123(3). 863–904.
- Macias, P., D. Stelmasiak and K. Szafranek. 2022.** Nowcasting food inflation with a massive amount of online prices. In: *International Journal of Forecasting*. Forthcoming.
- Nakamura, E. and J. B. Steinsson. 2008.** Five Facts about Prices: A Reevaluation of Menu Cost Models. In: *Quarterly Journal of Economics* 123. 1415–1464.
- Nakamura, E., J. Steinsson, P. Sun and D. Villar. 2018.** The elusive costs of inflation: Price dispersion during the US great inflation. In: *The Quarterly Journal of Economics* 133(4). 1933–1980.
- Petrella, I., E. Santoro and L. P. Simonsen. 2019.** Time-varying Price Flexibility and Inflation Dynamics. EMF Research Papers 28. Economic Modelling and Forecasting Group.
- Rumler, F., J. Baumgartner and A. Stiglbauer. 2011.** Patterns and Determinants of Price Changes: Analysing Individual Consumer Prices in Austria. In: *German Economic Review* 12(3). 336–350.
- Statistics Austria, 2022.** Warenkorb und Gewichtung des H/VPI für 2022. [6\\_Warenkorb\\_H\\_VPI\\_WK\\_2022.pdf \(statistik.at\)](#).
- Wulfsberg, F. 2016.** Inflation and Price Adjustments: Micro Evidence from Norwegian Consumer Prices 1975–2004. In: *American Economic Journal: Macroeconomics* 8(3): 175–194.