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THE STICKINESS OF FOOD PRICES IN POLAND – ONLINE VS. TRADITIONAL SHOPS

The author calculated various measures of price stickiness of food products in online shops and compared them with their counterparts in traditional shops in Poland. The main findings are as follows: (1) food prices in online shops are less sticky than in traditional shops; (2) the scale of percentage price changes is also smaller in online shops, and price increases and price decreases are both smaller in absolute terms compared to traditional stores; (3) price stickiness increases and the scale of price change decreases if the impact of promotions is eliminated; and (4) using daily data leads to lower estimates of price stickiness and a greater scale of percentage change in prices compared to monthly data, thus indicating that intra-month price changes are common in online shops. These findings may have significant policy implications if declining price stickiness in online shops (observed in the case of food products) also occurs in other product categories, as it would mean that the overall price rigidity in Poland has decreased over time. In the DSGE-New Keynesian approach, such results would indicate a decrease in the transmission of monetary policy shocks to the real economy and represent an important contribution to understanding the monetary transmission mechanism in Poland.*

Keywords: monetary transmission, Internet, DSGE, Keynesian

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1. INTRODUCTION

The assumption of sticky prices is an essential element of the New Keynesian economic theory regarding the rise of business cycles (Mankiw and Romer, 1991). The literature shows that the nature of nominal rigidities determines an economy's response to a broad range of disturbances and has several implications for the conduct of monetary policy (Goodfriend and King, 1997). As stated by Clarida, Galí,

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and Gertler (1999), "the approach [..] is based on the idea that temporary nominal rigidities provide key friction that gives rise to nonneutral effects of monetary policy."

Ascari and Haber (2019) found that over the last decade, the DSGE-New Keynesian paradigm has become the new workhorse to analyse business cycle fluctuations and the effects of monetary and fiscal policy, both among academic researchers and policy institutions. They highlighted the fact that the existence of the real effects of monetary policy shocks (or demand shocks in general) rests on the assumption of sticky nominal prices and/or wages in these models. While most recent models introducing banking and financial frictions can provide alternative mechanisms for the transmission of monetary policy shocks, price stickiness remains the major reason that monetary policy affects real variables in most versions of New Keynesian models.

The economic literature points to several sources of price rigidity (see e.g. Blinder et al., 1998; Fabiani et al., 2006). Among the possible reasons quoted in the numerous theories as to why price setters withhold price adjustments, empirical studies identify the following four as the most important: (1) coordination failure (fear of losing market share to competitors who do not follow suit), (2) explicit contracts with customers (guaranteeing constant prices), (3) implicit contracts with customers (aiming at building relations), and (4) cost-based pricing (prices do not change as long as costs remain the same).

In this context, there is substantial empirical research investigating the extent of sluggish price adjustment and potential sources of price stickiness. Bils and Klenow (2004) pioneered an approach employing disaggregate price observations to study micro-level price behaviour, and the key indicators of interest refer to the frequency of price changes and the size of such changes. While further studies (Dyhne et al. 2006) analysed price stickiness and its micro-foundations (mostly in the US),Alvarez et al. (2006) presented stylised facts regarding price stickiness in the Eurozone. However, to date, only two studies have been conducted on price stickiness in Poland. Macias and Makarski (2013) used official micro data on prices gathered by the Central Statistical Office and found that prices in Poland are less sticky than in the Eurozone but more rigid than in the US. In terms of Poland in particular, the results of the surveys conducted among various enterprises in Poland show that while the frequency of price changes is similar to that in the Eurozone, the scale of the changes is greater (Jankiewicz and Kołodziejczyk, 2008). Such results may indicate that prices are slightly less sticky in Poland than in the Eurozone.

Although price rigidities documented at micro-level are important from the standpoint of the calibration of macroeconomic models (see e.g. Nakamura and Steinsson, 2008), the aforementioned literature predominantly concentrates on prices collected in traditional bricks-and-mortar stores. However, the introduction of the Internet has greatly affected consumer decisions (Ellison and Ellison, 2005). For example, online shopping offers consumers product descriptions and price comparisons at the click of a mouse, thereby essentially increasing market transparency. Additionally, bricks-and-mortar stores face some contributing factors,

such as menu costs (i.e. necessary changes to signage, price tags, and printed catalogues), that are either irrelevant or less conducive to sluggish price changes for online sellers. Thus, as online selling allows for very low costs related to changing prices and digitally adjusting "price tags" (see Levy et al., 1997; Dutta, et al., 1999), some researchers have begun focusing on analyses of the price behaviour(including price stickiness) of online stores.

Lünnemann and Wintr (2011) documented the stickiness of online prices in the US and large European markets (Germany, France, Italy, and the U.K.), to establish that internet prices are more flexible than their offline counterparts, with half of the price spells (i.e. periods when prices remain unchanged) lasting less than a month. Gorodnichenko and Talavera (2017) found that price changes in online stores are much smaller (less than half the size; approximately 10 percent) and occur much more frequently than in traditional stores. This evidence is consistent with the view that online prices are much more flexible than traditional store prices. However, contrary to the findings of other studies, Cavallo's analysis (2018) of the daily prices of 80 thousand products collected from five countries with varying degrees of inflation, including the US, showed that online prices tend to be stickier compared to in-store prices. Yet, in this context, as an increasing share of products are being sold via the Internet, a simple analysis of traditional, physical prices may, to an increasing extent, lead to the underestimation of the actual consumer price flexibility.

Although the utilization of e-stores in Poland has increased rapidly over the past decade, the author is not aware of any similar analysis of online price stickiness from Poland. Moreover, comparing the degree of price stickiness between physical stores and the Internet may indirectly contribute to a better understanding of the driving factors of price stickiness in Poland. Thus, this study focused on online prices that correspond to rapidly growing retail sectors.

Given the increasing importance of online purchases in total consumer expenditure, the aim was to study Internet price rigidities in Poland and compare food price stickiness between online stores and traditional stores. The food subcomponent of the CPI is crucial to the accurate measurement of the total CPI due to its significant weight in the inflation basket and high volatility compared to other CPI categories (Narodowy Bank Polski, 2016). In addition, the potential for developing the online food trade is enormous; the estimated penetration of this category in Poland is currently around 0.7% of the FMCG market, and, according to Euromonitor International data, the average growth rate for e-grocery is between 15% and 20% year-on-year. The Polish Wallet Report by Izba Gospodarki Elektronicznej (2017) showed that 28% of Internet users bought food online, and, in the "E-grocery in Poland" (online grocery shopping) report compiled by Izba Gospodarki Elektronicznej (2018), 16% of respondents indicated that they did so regularly.

To assess the degree of food price stickiness in stores, the study applied a framework similar to Macias and Makarski (2013), allowing to compare their results (regarding physical stores) with this author's insights concerning food prices on the Internet. To measure price rigidity, the study utilised quantitative measures of the frequency and size of price adjustments in e-stores operating in Poland based on an analysis of narrowly defined products (micro data) representative of the various categories of the food CPI basket. Some of the calculated price stickiness indicators included: the frequencies of price increases, decreases, and all price changes; the average sizes of price increases and decreases; and the duration of price spells.

The main findings were as follows: (1) food prices in online shops are less sticky than in traditional shops in Poland, with the frequency of price changes of 43.1% and 28.6%, respectively; (2) however, the scale of percentage price changes is smaller in online shops, and the changes for both price increases (6.6% vs. 11.0%) and price decreases (-5.7% vs. -10.6%) are smaller in absolute terms compared to traditional stores; (3) price stickiness increases and the scale of price changes decreases if the impact of promotions is eliminated; (4) using daily instead of monthly data leads to lower estimates of price stickiness and a greater scale of percentage changes in prices, which signals that intra-month price changes are common.

The remainder of this paper is organized as follows: the next section presents the data and methodology used to calculate the stickiness of online food prices. The main results of the empirical study are presented in Section 3. This section also compares stickiness statistics between online and traditional shops. Section 4 concludes the discussion on the study.

2. MATERIAL AND METHODS

2.1. Data

The prices of food products sold online are not openly available in a pre-prepared dataset. To estimate the inflation of food products in Poland using online prices, it was necessary to gather these prices specifically for this study. To this end, the author used a web-scraping technique on one of the major supermarket chains' websites. A combination of programming languages was used to build a web-scraping script, which, in principle, imitates a human web user, navigating websites and extracting the pre-defined information. The automated procedure developed in this study scans the code of the publicly available website of the supermarket chain every day, identifies relevant pieces of information (e.g. product name, price, size, and unique ID), and stores these data in a file.

The web-scraping methodology operates in three steps. First, at a fixed time each day, the software detects all the web pages with information about individual products and their prices available on the retailer's website. The individual pages are retrieved daily. Second, the underlying code is analysed to locate each piece of relevant information using special characters in the code that identify the start and end of each variable (these are characters placed by the page programmers to give the website a particular look and feel). Specifically, the algorithm explores the hypertext markup language (HTML) format in web pages and extracts and stores the relevant portion of the code. Third, the software stores the scraped information in a database that contains one record per product per day. These variables include the product's price, date, category information, and an indicator for whether the item is on sale or not.

This web scraping procedure was repeated daily from July 2015 through to December 2019. The resulting database contains a price history of approximately 20 thousand unique food products. Naturally, not every product is available daily. Prices are recorded from the first day a product is offered to consumers until the day it is discontinued from the store. Some information can be missing owing to stock shortages on a given day, seasonal product offers, and technical problems (on the part of the supermarket chain or this study). Moreover, during the research, the supermarket chain's website changed several times, necessitating changes in the web crawlers (which have to be specially developed for each website) used in this study to adjust their underlying code. Each redesign of the web crawler takes a day or so, which resulted in some missing data. Nonetheless, there are few missing observations over the four-year study period and these should not distort the results of the analysis.

Moreover, not all the 20,000 product prices were needed to calculate price stickiness. The calculation was based on the purposely selected list of representative items for each elementary category at the lowest aggregation levels of the weighting system in the "01: food and non-alcoholic beverages" category. The study obtained very detailed information from the CSO concerning the particular kinds of products considered when collecting prices (see the Appendix). Based on this information, individual products were selected to represent price changes in each subcategory according to the COICOP classification. For this study, 221 individual products that cover all 86 elementary categories representing food prices were selected.

Only the price data collected from the supermarket chain's website were used to calculate price stickiness of food products in Poland. However, based on existing studies (Cavallo and Rigobon, 2016; Cavallo, 2017) one can conclude that webscraped prices are representative of the evolution of prices captured by official inflation statistics compiled by the statistical office. In terms of Poland, specifically, Jaworski (2021) employed a web-scraped dataset similar to the one used in this study to produce reliable estimates (nowcasts) of monthly and annual food inflation.

2.2. Calculation of price stickiness

To estimate the price stickiness of online food products, the author followed the method outlined by Macias and Makarski (2013). Applying the same process enabled comparisons between price rigidness in online stores (calculated in this study) and traditional stores (presented in that study). Although the daily observations had to be aggregated to monthly frequencies to be comparable with their data, the study also reported the results obtained using raw daily data.

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The analysis of the degree of price stickiness at micro-level using individual price quotations is generally based on a frequency approach. In this situation, prices are considered sticky in the case of low frequency price changes, which means that the unchanged price lasts for a prolonged period. The following variables are defined to present the method of calculating the frequency of price changes:

 P_{ijt} is the price of product *i*, belonging to the elementary COICOP category *j*, recorded in period *t*, while x_{ijt} – a binary variable indicating that the price of product *i* belonging to the elementary COICOP category *j* was recorded both at period *t* and t-1:

$$x_{ijt} = \begin{cases} 1, & \text{if } P_{ijt} \text{ and } P_{ijt-1} \text{ were recorded;} \\ 0, & \text{if } P_{ijt} \text{ or } P_{ijt-1} \text{ were not recorded;} \end{cases}$$
(1)

 z_{ijt} – a binary variable indicating that the price of product *i* belonging to the elementary COICOP category *j* was changed in period *t* (compared to the price recorded in period *t* – 1), and the prices were recorded both at period *t* and *t* – 1:

$$z_{ijt} = \begin{cases} 1, & \text{if } x_{ijt} = 1 \text{ and } P_{ijt} \neq P_{ijt-1}; \\ 0, & \text{otherwise;} \end{cases}$$
(2)

 s_{ijt} – a binary variable indicating that the price of product *i* belonging to the elementary COICOP category *j* was lowered in period *t* (compared to the price recorded in period t-1), and the prices were recorded both at period *t* and t-1:

$$s_{ijt} = \begin{cases} 1, & \text{if } x_{ijt} = 1 \text{ and } P_{ijt} < P_{ijt-1}; \\ 0, & \text{otherwise;} \end{cases}$$
(3)

 w_{ijt} – a binary variable indicating that the price of product *i* belonging to the elementary COICOP category *j* was increased in period *t* (compared to the price recorded in period *t* – 1), and the prices were recorded both at period *t* and *t* – 1:

$$w_{ijt} = \begin{cases} 1, & \text{if } x_{ijt} = 1 \text{ and } P_{ijt} > P_{ijt-1}; \\ 0, & \text{otherwise;} \end{cases}$$
(4)

 F_{ij} is the frequency of price changes for product *i*, belonging to elementary COICOP category *j* throughout the analysed period:

$$F_{ij} = \frac{\sum_{t=2}^{T} z_{ijt}}{\sum_{t=2}^{T} x_{ijt}},$$
(5)

 F_{ij}^+ is the frequency of price increases for product *i*, belonging to the elementary COICOP category *j* throughout the analysed period:

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$$F_{ij}^{+} = \frac{\sum_{t=2}^{T} w_{ijt}}{\sum_{t=2}^{T} x_{ijt}},$$
(6)

 F_{ij}^{-} is the frequency of price decreases for product *i*, belonging to the elementary COICOP category *j* throughout the analysed period:

$$F_{ij}^{-} = \frac{\sum_{t=2}^{T} s_{ijt}}{\sum_{t=2}^{T} x_{ijt}} \,. \tag{7}$$

The frequency of price changes represents the percentage of prices that were subject to change during the analysed period. Accordingly, the frequency of price increases (decreases) represents the percentage of prices that have risen (declined). Thus, these measures can be equated with the probability of a price change in a given period.

The frequencies of price changes of individual products belonging to a given elementary COICOP category j were aggregated (via averaging) to represent the frequencies of price change of the entire elementary category j, that is, F_j .

 F_j is the frequency of price changes for the elementary COICOP' category *j* throughout the analysed period, where n_j indicates the number of individual products belonging to category *j*:

$$F_{j} = \frac{1}{n_{j}} \sum_{i=1}^{n_{j}} F_{ij}.$$
(8)

To calculate the frequency of price changes for aggregates consisting of several elementary groups, it was necessary to weigh them according to the following formula:

$$F = \sum_{j=1}^{J} \omega_j F_j, \qquad (9)$$

where ω is the weight of a given elementary category *j* in the "01: food and non-alcoholic beverages" main category.

Based on the frequency of price changes, the study also calculated the average implied price duration (i.e. price spells) according to the formula presented below:

$$T = \sum_{j=1}^{J} \left(\omega_j \frac{-1}{\ln\left(1 - F_j\right)} \right). \tag{10}$$

The author also calculated the indicators for the frequency of price changes (F_m) and implied duration (T_m) , but used the median instead of the average as the aggregation function.

3. RESULTS

Using the formulas presented in Section 2.2, the online price stickiness statistics were calculated and compared with the estimates presented in Macias and Makarski (2013). The study also reported how different approaches to the calculation of price stickiness impact on the value of the estimates.

3.1. Price stickiness using data in monthly frequency

Table 1 shows the frequencies for the selected groups calculated in line with equation (9) for online shops and compares them with estimates for traditional shops. Among the results, it was found that the frequency of price changes was greater in online shops than traditional shops for the aggregate category of "food and non-alcoholic beverages." Food prices in online shops changed, on average, in 43.1% of the months over the study period, compared to only 28.6% for items sold in traditional shops, with both price increases and price decreases occurring more frequently online. Such a tendency was observed not only for the aggregate food category, but also in 10 out of the 11 subcategories. Regular shops only changed prices more frequently than those online for products only in the "meat" category (35.2% vs. 28.6%). The food subcategory for which the online and in-store frequencies of price changes were most similar, was for "mineral waters, soft drinks, and fruit and vegetable juices" at 17%-18%.

				Frequency	of: (in %)		
Category	COICOP code	price changes	price increases	price decreases	price changes	price increases	price decreases
		Traditional shops			(Online shop	S
1	2	3	4	5	6	7	8
FOOD AND NON- ALCOHOLIC BEVERAGES	01	28.6	16.4	12.1	43.1	22.7	20.3
Bread and cereals	01.1.1	16.1	10.6	5.5	53.7	26.6	27.1
Meat	01.1.2	35.2	20.6	14.6	21.6	12.7	8.9
Fish and seafood	01.1.3	14.7	9.1	5.6	39.0	20.8	18.2
Milk, cheese and eggs	01.1.4	22.4	13.6	8.8	39.5	20.5	19.0
Oils and fats	01.1.5	26.6	15.9	10.8	50.2	24.0	26.2
Fruit	01.1.6	56.7	28.7	28.0	86.7	43.5	43.2
Vegetables	01.1.7	49.3	24.1	25.1	63.6	36.6	27.1

Table 1

Frequency of price changes - comparison between traditional and online shops

1	2	3	4	5	6	7	8
Sugar, jam, honey, chocolate and confectionery	01.1.8	22.8	13.6	9.2	42.9	24.1	18.9
Food products N.E.C.	01.1.9	15.5	9.7	5.8	44.2	22.9	21.3
Coffee, tea and cocoa	01.2.1	21.1	13.2	7.9	62.1	29.0	33.1
Mineral waters, soft drinks, fruit and vegetable juices	01.2.2	17.1	10.2	6.9	18.3	9.3	9.0

Source: The results for traditional shops were taken from Macias and Makarski (2013). The results for online shops were obtained using methods outlined in Section 2.

The duration of price spells is more intuitive to interpret than the frequency of price spells, and the findings should be consistent with the approach based on the frequency of price changes. However, there were some discrepancies due to the nonlinear relation between frequency and implied price spells; see equation (10). Table 2 presents the implied duration of price spells. Looking at the aggregate category, the implied duration of price spells was shorter in online shops (3.5 months on average and median of 3.2 months) compared to traditional shops (3.9 and 3.7 months, respectively). Hence, the difference in price spells between online and traditional shops was about half a month, or about 12%.

_	COICOP	Implied duration of price spells (in months)				
Category	code	average	median	average	median	
		Traditional shops		Online shops		
1	2	3	4	5	6	
FOOD AND NON-ALCOHOLIC BEVERAGES	01	3.9	3.7	3.5	3.2	
Bread and cereals	01.1.1	6.0	4.1	1.6	1.5	
Meat	01.1.2	2.6	1.8	4.1	4.1	
Fish and seafood	01.1.3	6.3	4.4	3.9	5.2	
Milk, cheese and eggs	01.1.4	4.1	2.8	4.4	2.6	
Oils and fats	01.1.5	3.3	2.3	1.7	1.4	
Fruit	01.1.6	1.5	1.0	0.4	0.4	

Table 2

Implied duration of price spells - comparison between traditional and online shops

Table 2, cont.

1	2	3	4	5	6
Vegetables	01.1.7	2.2	1.6	2.7	2.6
Sugar, jam, honey, chocolate and confectionery	01.1.8	4.4	3.0	7.4	7.4
Food products N.E.C.	01.1.9	6.1	4.2	2.2	1.8
Coffee, tea and cocoa	01.2.1	4.4	3.0	1.9	1.6
Mineral waters, soft drinks, fruit and vegetable juices	01.2.2	5.5	3.8	7.2	6.7

Source: The results for traditional shops were taken from Macias and Makarski (2013). The results for online shops were obtained using methods outlined in Section 2.

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	COLCOR	Percentage scale of price changes (%)				
Category	COICOP code	increase	decrease	increase	decrease	
	couc	Traditio	nal shops	Online shops		
FOOD AND NON-ALCOHOLIC BEVERAGES	01	11.0	-10.6	6.6	-5.7	
Bread and cereals	01.1.1	9.7	-10.0	6.6	-6.3	
Meat	01.1.2	8.9	-8.9	5.4	-2.6	
Fish and seafood	01.1.3	9.7	-9.3	5.4	-5.1	
Milk, cheese and eggs	01.1.4	8.2	-8.2	5.4	-4.9	
Oils and fats	01.1.5	9.2	-8.5	6.8	-5.8	
Fruit	01.1.6	19.4	-17.6	11.1	-11.0	
Vegetables	01.1.7	23.4	-21.2	10.0	-10.5	
Sugar, jam, honey, chocolate and confectionery	01.1.8	10.0	-8.5	4.9	-4.2	
Food products N.E.C.	01.1.9	10.6	-10.1	5.0	-4.6	
Coffee, tea and cocoa	01.2.1	8.7	-8.6	10.2	-9.8	
Mineral waters, soft drinks, fruit and vegetable juices	01.2.2	9.2	-9.8	6.4	-6.6	

 Table 3

 Scale of price changes – comparison between traditional and online shops

Source: The results for traditional shops were taken from Macias and Makarski (2013). The results for online shops were obtained using methods outlined in Section 2.

A strong diversification was implied in the duration of price spells between subcategories. The categories of "fish and seafood," "milk, cheese, and eggs" and "vegetables" had a similar duration for traditional and online stores, whereas "bread and cereals," "fruit," "oils and fats," "food products not elsewhere classified" and "coffee, tea, and cocoa," the duration of price spells in traditional shops was between two and four times longer than in online stores. On the contrary, for "meat," "sugar, jam, honey, chocolate, and confectionery," and "mineral waters, soft drinks, and fruit and vegetable juices," the implied duration of price spells in traditional shops was only half of that observed online.

The third element that needs to be compared is the scale of the price changes (see Table 3). In traditional shops, the average percentage scales of both price increases and decreases were larger than in online shops. For the main category of "food and non-alcoholic beverages", the average price increase was 11.0% compared to only 6.6% in online shops. The average price decrease was -10.6% in traditional shops and -5.7% in online shops. A similar situation persisted in 10 out of the 11 subcategories (apart from "coffee, tea, and cocoa"). The scale of percentage price increases was generally similar to the scale of price decreases (a difference smaller than one percentage point) in online shops in all categories but "meat", where price hikes were more pronounced on average. In traditional shops, tendencies in that respect were slightly different. The scales of upward and downward price changes were similar in all categories except "fruit", "vegetables", and "sugar, jam, honey, chocolate, and confectionery", for which the price hikes were greater.

3.2. Impact of promotions on price stickiness estimates

Macias and Makarski (2013) reported that "promotions" (temporary decreases in prices) comprise a factor that significantly impacts on estimates of price stickiness. Thus, the next step of analysis was to determine how excluding promotions from the data affected the price stickiness estimates, however these results were not compared with those of Macias and Makarski (2013). Their dataset did not contain explicit information about products being "on-sale" (i.e. temporary price reduction) at a given time and they identified promotions using a filter that isolated events of significant price changes. Macias and Makarski (2013) recognized that such an approach is not ideal and may create some bias in the results. On the contrary, this study had explicit information about whether there was a promotion for a particular product in online shops, and what was the scale of the price cut. It also noted both the regular and lowered prices observed on a given day.

Table 4 presents the main estimates regarding price stickiness calculated for online shops with data after eliminating the impact of promotions. If a price of a given product was lowered, the author used the regular, i.e. "before promotion" price level. As expected, such an approach decreased the calculated frequency of price changes to 26.2% compared to 43.1% when promotions were included in the case of the aggregate "food and non-alcoholic beverages" category. The frequencies of price increases (14.6% vs. 22.7%) and price decreases (11.6% vs. 20.3%) were also lower after eliminating the impact of promotions. Consequently, the average

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Category	COICOP	Frequency of: (%)			Implied duration of price spells (months)		Percentage scale of price changes (%)	
entrger y	code	price changes	price increases	price decreases	average	median	increase	decrease
FOOD AND NON- -ALCOHOLIC BEVERAGES	01	26.2	14.6	11.6	5.2	4.9	5.6	-4.5
Bread and cereals	01.1.1	29.6	15.0	14.7	3.9	3.5	3.5	-2.8
Meat	01.1.2	17.3	11.2	6.1	5.3	5.5	4.7	-2.2
Fish and seafood	01.1.3	28.2	15.8	12.4	4.7	3.6	5.3	-5.4
Milk, cheese and eggs	01.1.4	20.3	11.2	9.1	7.6	5.9	4.7	-3.0
Oils and fats	01.1.5	27.1	13.1	14.0	4.5	3.5	5.1	-3.7
Fruit	01.1.6	59.0	29.7	29.3	1.6	1.5	11.0	-10.8
Vegetables	01.1.7	43.2	25.8	17.4	3.8	3.7	9.6	-9.6
Sugar, jam, honey, chocolate and confectionery	01.1.8	23.5	12.7	10.9	8.2	8.0	5.1	-4.3
Food products N.E.C.	01.1.9	22.4	12.8	9.5	4.6	4.3	3.3	-2.6
Coffee, tea and cocoa	01.2.1	19.2	12.3	6.9	6.6	6.2	7.4	-9.3
Mineral waters, soft drinks, fruit and vegetable juices	01.2.2	13.5	6.7	6.8	7.4	7.4	7.4	-6.7

Table 4 Impact of promotions on price stickiness in online shops

Source: own calculations.

(5.2 vs. 3.5 months) and median (4.9 vs. 3.2 months) implied durations of price spells were more than a month longer if one eliminated the impact of promotions. Additionally, the absolute percentage scales of price increases (5.6% vs. 6.6%) and price decreases (-4.5% vs. -5.7%) were lower than those in the standard dataset. This result is intuitive, as the exclusion of large (usually double-digit) promotions limits the overall scale of price decreases. Without promotions, there were also no significant price jumps that normally would be observed after the promotion ended.

Overall, the results regarding the impact of promotions on price stickiness statistics, although not directly comparable, were consistent with the findings of Macias and Makarski (2013).

3.3. Price stickiness calculated using data in daily frequency

Contrary to Macias and Makarski (2013), the use of daily data enabled the author to estimate stickiness more precisely than when using only monthly data, as no information was lost regarding intra-month price changes, and those changes can significantly influence the results. For example, a price cut and a consecutive return to the original price within one month were not registered as a price change based on monthly data. Therefore, using daily data contributed to a more accurate estimate of the duration of price spells.

Category	COICOP code	-	duration lls (months)	Percentage scale of price changes (%)	
	coue	average	median	increase	decrease
FOOD AND NON- -ALCOHOLIC BEVERAGES	01	2.2	1.9	16.3	-15.2
Bread and cereals	01.1.1	1.2	1.1	15.1	-14.5
Meat	01.1.2	2.3	2.4	13.8	-10.7
Fish and seafood	01.1.3	3.7	4.9	10.2	-9.9
Milk, cheese and eggs	01.1.4	3.7	1.9	14.4	-13.4
Oils and fats	01.1.5	1.4	1.3	16.2	-14.9
Fruit	01.1.6	0.4	0.4	28.7	-29.4
Vegetables	01.1.7	2.6	2.3	24.4	-25.7
Sugar, jam, honey, chocolate and confectionery	01.1.8	1.0	1.0	12.9	-12.5
Food products N.E.C.	01.1.9	1.6	1.3	11.4	-12.7
Coffee, tea and cocoa	01.2.1	1.5	1.2	19.6	-19.5
Mineral waters, soft drinks, fruit and vegetable juices	01.2.2	4.3	3.9	16.9	-14.0

Table 5	

Implied duration of price spells and scale of price changes calculated on daily online data

Source: own calculations.

Table 5 shows that the average and median duration of price spells estimated using daily data was half of the observed respective durations calculated using monthly data. For the aggregate category of "food and non-alcoholic beverages", the median implied a duration of price spells of only 1.9 months and, on average, amounted to 2.2 months. The differences regarding estimates of price stickiness varied depending on the subcategory. The shortening of price spells duration was most pronounced in the case of "bread and cereal" (5.2 times shorter average duration and 3.9 times shorter median duration of price spells), "sugar, jam, honey, chocolate, and confectionery" (4.3 and 3.1 times shorter, respectively), "food products not elsewhere classified" (3.7 and 3.3 times shorter, respectively), and fruit (3.6 and 2.5 times shorter, respectively).

Moreover, the percentage scales of both price increases and price decreases were larger in daily data calculations, with price increases, on average, 2.5 times larger and price decreases 2.7 times larger than monthly data. Such tendencies were observed for all the subcategories: the scale of price changes calculated with daily data was between 1.9 and 4.1 times larger than with monthly data.

CONCLUSIONS

To the best of the author's knowledge, this study is the first to provide quantitative measures of the frequency and size of price adjustments in online shops in Poland, as the one previous paper (Macias and Makarski, 2013) providing statistics regarding consumer price stickiness in Poland was an analysis of prices in traditional shops. Hence, the author included their data and compared price-setting patterns between traditional and online channels.

The main findings regarding the data and the comparisons with traditional prices are as follows: (1) the stickiness of food prices in online shops was lower compared to traditional shops, with frequencies of price changes equal to 43.1% and 28.6%, respectively; (2) the scale of percentage price changes was smaller in online shops, and both price increases (6.6% vs. 11.0%) and price decreases (-5.7% vs. -10.6%) were smaller in absolute terms compared to traditional shops; (3) price stickiness increased and the scale of price changes decreased if the impact of promotions was eliminated; (4) using daily instead of monthly data led to lower estimates of price stickiness and a greater scale of percentage changes in prices, which signals that intra-month price changes were common.

A potential caveat is that different periods were analysed. Macias and Makarski (2013) used monthly data spanning 2004 to 2008, whereas this study examined a dataset covering the period from 2015 to 2019, and did not pinpoint the reasons why price stickiness was lower in this sample, by asking: "Is it because it is possible for online prices to change in a different way, or that the economy may have become more flexible in the seven-year period separating the samples?" This choice was made because it is difficult to say so with certainty, and the author did not consider answers to these questions as an objective of this study. The uncertainty regarding the source of lower price rigidity does not invalidate the main finding that price stickiness of food prices is lower now than previously.

In this study, the higher frequency and smaller price changes for online prices are consistent with "menu" costs being smaller for online sellers than for traditional shops. Given that online prices are likely to play an increasingly important role in the future, macroeconomists should incorporate the properties of a broader set of goods, including goods sold online, when they characterise the micro-foundations of their macroeconomic models.

Furthermore, these findings may have significant policy implications if declining price stickiness in online shops (observed for food products) also occurs for other product categories, as it would indicate that the overall price rigidity in Poland has decreased over time. In the New Keynesian DSGE theory, such results would signify a decrease in the transmission of monetary policy shocks to the real economy. Such a finding would be important, thus contributing to the knowledge of the mechanism of monetary transmission in Poland (see Chmielewski et al., 2018).

Finally, estimating price stickiness statistics for categories of inflation basket other than food products and studying their tendencies over the last few years are avenues for further research. However, access to official data gathered by the Central Statistical Office regarding the prices of individual products is restricted, and therefore, estimating price stickiness based on the latest official data remains outside the study's capabilities at this time.

REFERENCES

- Alvarez, L. J., Dhyne, E., Hoeberichts, M., Kwapil, C., Le Bihan, H., Lünnemann, P., Martins F., Sabbatini R., Stahl H., Vermeulen, P., Vilmunen, J., *Sticky prices in the euro area: a summary of new micro-evidence*, Journal of the European Economic Association, 4(2-3), pp. 575-584, 2006.
- Ascari, G., Haber, T., Sticky prices and the transmission mechanism of monetary policy: a minimal test of New Keynesian models, Economics Series Working Papers, No. 869, University of Oxford, Department of Economics. Available at https://econpapers.repec.org/RePEc:oxf:wpaper:869, 2019.
- Bils, M., Klenow, P. J., *Some evidence on the importance of sticky prices*, Journal of Political Economy, 112(5), pp. 947-985. Available at http://klenow.com/StickyPrices.pdf, 2004.
- Blinder, A., Canetti, E. R., Lebow, D. E., Rudd, J. B., Asking about prices: a new approach to understanding price stickiness, Russell Sage Foundation, New York 1998.
- Cavallo, A., Are online and offline prices similar? Evidence from large multi-channel retailers, American Economic Review, Vol. 107, No. 1, pp. 283-303, 2017.
- Cavallo, A., *Scraped data and sticky prices*, Review of Economics and Statistics, 100(1), pp. 105-119, 2018.
- Cavallo, A., Rigobon, R., The billion prices project: using online prices for measurement and research, Journal of Economic Perspectives, 30(2), pp. 151-178, 2016.
- Chmielewski, T., Kapuściński, M., Kocięcki, A., Łyziak, T., Przystupa, J., Stanisławska, E., Wróbel, E., Mechanizm transmisji polityki pieniężnej w Polsce [Transmission mechanism of monetary policy in Poland], Materiały i Studia, National Bank of Poland, 2018.

- Clarida, R., Gali, J., Gertler, M., The science of monetary policy: a New Keynesian perspective, Journal of Economic Literature, 37(4), pp. 1661-1707, 1999.
- Dhyne, E., Alvarez, L. J., Le Bihan, H., Veronese, G., Dias, D., Hoffmann, J., Jonker N., Lunnemann, P., Rumler, F., Vilmunen, J., *Price changes in the euro area and the United States: Some facts from individual consumer price data*, The Journal of Economic Perspectives, 20(2), pp. 171-192, 2006.
- Dutta, S., Bergen, M., Levy, D., Venable, R., *Menu costs, posted prices, and multiproduct retailers*, Journal of Money, Credit, and Banking, Vol. 31, No. 4, pp. 683-703, 1999.
- Ellison, G., Ellison, S., *Lessons about markets from the Internet*, The Journal of Economic Perspectives, 19(2), pp. 139-158. Available at http://www.jstor.org/stable/4134941, 2005.
- Fabiani, S., Druant, M., Hernando, I., Kwapil, C., Landau, B., Loupias, C., Martins, F., Mathä, T., Sabbatini, R., Stahl, H., Stokman, A., *What firms' surveys tell us about price-setting behavior in the euro area*, International Journal of Central Banking, 2(3), pp. 3-47, 2006.
- Goodfriend, M., King, R. G., The new neoclassical synthesis and the role of monetary policy, NBER Macroeconomics Annual, 12, pp. 231-96. Available at http://www.nber.org/chapters/c11040, 1997.
- Gorodnichenko, Y., Talavera, O., Price setting in online markets: Basic facts, international comparisons, and cross-border integration, American Economic Review, 107(1), pp. 249-82, 2017.
- Izba Gospodarki Elektronicznej, *Polish Wallet Report, July 2017*. Retrieved 3 April 2020, https://www. ecommercepolska.pl/files/2415/0037/5980/Raport Portfel Polaka.pdf, 2017.
- Izba Gospodarki Elektronicznej, Mobile E-grocery in Poland online grocery shopping. Accessed 13 April 2020, https://www.ecommercepolska.pl/files/4415/1775/0535/E-grocery_w_Polsce_ Zakupy_spozywcze_online_raport.pdf, 2018.
- Jankiewicz, Z., Kołodziejczyk, D., Mechanizmy kształtowania cen w przedsiębiorstwach polskich na tle zachowań firm ze strefy euro, [Mechanisms of price creation in Polish enterprises at the background of firms' behaviours in the euro zone], Bank i Kredyt, No. 2, pp. 19-42. Available at https://ssl.nbp.pl/publikacje/materialy i studia/ms295.pdf, 2008.
- Jaworski, K., *Measuring food inflation during the COVID-19 pandemic in real time using online data: a case study of Poland*, British Food Journal, 123(13), pp. 260-280, 2021.
- Levy, D., Bergen, M., Dutta, S., Venable, R., *The magnitude of menu costs: direct evidence from large* US supermarket chains, The Quarterly Journal of Economics, 112(3), pp. 791-824, 1997.
- Lünnemann, P., Wintr, L., *Price stickiness in the US and Europe revisited: Evidence from internet prices*, Oxford Bulletin of Economics and Statistics, 73(5), pp. 593-621, 2011.
- Macias, P., Makarski, K., Stylizowane fakty o cenach konsumenta w Polsce [Stylized facts about consumer prices in Poland], Materiały i Studia, No. 295, National Bank of Poland, 2013.
- Mankiw, N. G., Romer, D., Imperfect competition and sticky prices [in:] Mankiw, G., Romer, D. (eds.), New Keynesian Economics, Vol. 1. The MIT Press, 1991.
- Nakamura, E., Steinsson, J., *Five facts about prices: a re-evaluation of menu cost models*, The Quarterly Journal of Economics, 123(4), pp. 1415-1464, 2008.
- Narodowy Bank Polski (2016). *Metodyka obliczania miar inflacji bazowej publikowanych przez* Narodowy Bank Polski [The method of calculating the base inflation rates published by National Bank of Poland], Instytut Ekonomiczny NBP, Warszawa 2016.

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APPENDIX

The food products used by the Statistical Office in the calculation of consumer price indices for "food and non-alcoholic beverages" category

ECOICOP code	Elementary food group	Number of representative products	Food products
1	2	3	4
01.1.1		Brea	ad and cereals
01.1.1.1	Rice	3	Different types of rice
01.1.1.2.1	Wheat flour	3	Wheat flour
01.1.1.2.2	Other flours	1	Rye flour
01.1.1.2.3	Groats and grains	3	Different types of groats (e.g. wheat, buckwheat)
01.1.1.3	Bread	4	Rye, wheat-rye, wheat bread (type: bread and rolls)
01.1.1.4	Other bakery products	13	Other types of bread, e.g. toasted, crispy; Yeast and sponge cake products, dessert cakes; Other bakery products, e.g. waffles, gingerbread, cookies, sticks
01.1.1.5	Pizza and other flour products	3	Frozen pizza; Other flour products, e.g. dumplings, patties (stuffed with different types)
01.1.1.6	Pasta and macaroni products	4	Different types of pasta (including soy); Pasta with extras (dish)
01.1.1.7	Cereals	5	Different types of flakes (e.g. corn), flakes with additives, bran
01.1.1.8	Other cereal products	4	Bread crumbs, powder concentrates, potato flour
01.1.2			Meat
01.1.2.1.1	Beef meat	3	Different species with and without bone
01.1.2.1.2	Veal meat	2	Different species with and without bone
01.1.2.2	Pork meat	6	Different species with and without bone
01.1.2.3	Sheep and goat meat	1	Sheep or lamb meat
01.1.2.4.1	Chickens, roosters, chickens	3	Chickens, whole chickens and parts thereof
01.1.2.4.2	Other poultry	3	Turkey meat (parts), duck meat (whole)
01.1.2.5	Other meats	1	Rabbit meat
01.1.2.6	Offal and offal preparations	5	Liver, headcheese, black pudding, liver

1	2	3	4
01.1.2.7.1	Cold cuts, except poultry	13	Different types of sausages, sausages, sausages (e.g. steamed sirloin, ham), luncheon meat, bacon
01.1.2.7.2	Poultry sausages	3	Different types of sausages, sausages
01.1.2.8.1	Mixed minced meat	1	Minced pork and beef meat
01.1.2.8.2	Other meat preparations	4	Pates, tripe, canned meat
01.1.3		Fis	h and seafood
01.1.3.1	Fresh or chilled fish	3	Various types of fish, whole and parts thereof (fresh or chilled)
01.1.3.2	Frozen fish	4	Various types of fish, whole and parts thereof (frozen)
01.1.3.3	Fresh or chilled seafood	1	Shrimps (fresh or chilled)
01.1.3.4	Frozen seafood	1	Shrimps (frozen)
01.1.3.5	Dried, smoked or salted fish and seafood	5	Different types of fish, whole and parts thereof (smoked or salted)
01.1.3.6	Other preparations of fish and seafood	7	Various types of canned fish, fillets in sauce, pastes, fish sticks, caviar
01.1.4		Milk,	cheese and eggs
01.1.4.1	Full fresh milk	3	Cow's milk with a fat content of 3.2% – 3.5% (various levels of processing)
01.1.4.2	Fresh low-fat milk	4	Cow's milk, goat's milk with different fat content (different degree of processing)
01.1.4.3	Condensed and powdered milk	1	Condensed milk
01.1.4.4	Yoghurt	4	Different types of yogurt and yogurt drinks (natural, fruit)
01.1.4.5.1	Ripened and processed cheese	5	Ripening, blue cheese, processed cheese, in marinade
01.1.4.5.2	Curd	6	Cottage cheese with different fat content, cottage cheese, feta cheese, goat cheese type
01.1.4.6.1	Sour cream	3	Sour cream, different fat content, cream
01.1.4.6.2	Drinks and other dairy products	4	Fermented milk drinks (e.g. kefir), homogenized cheese, dairy desserts with additives (e.g. chocolate)
01.1.4.7	Eggs	1	Eggs

1	2	3	4
01.1.5		0	bils and fats
01.1.5.1	Butter	2	Butter with 82-83% fat content, clarified butter
01.1.5.2	Margarine and other vegetable fats	2	Margarines for spreads and other culinary purposes
01.1.5.3	Olive oil	1	Olive oil
01.1.5.4	Other edible oils	5	Different types of vegetable oil (e.g. rapeseed, sunflower)
01.1.5.5	Other animal fats	2	Lard
01.1.6			Fruit
01.1.6.1.1	Citrus fruits	4	E.g. lemons, oranges
01.1.6.1.2	Bananas	1	Bananas
01.1.6.1.3	Apples	1	Apples
01.1.6.1.4	Berries	4	E.g. strawberries, grapes
01.1.6.1.5	Stone fruits	6	E.g. cherries, cherries, avocados
01.1.6.1.6	Other fruits	5	E.g. watermelon, pears, kiwi
01.1.6.2	Frozen fruits	2	Frozen fruits and fruit mixtures
01.1.6.3	Dried fruits and nuts	6	E.g. raisins, nuts, sunflower seeds
01.1.6.4	Fruit preserves	3	Canned fruits, salted nuts
01.1.7		Y	Vegetables
01.1.7.1.1	Lettuce	3	Different types of lettuce (e.g. iceberg, mixed salad)
01.1.7.1.2	Cabbage	4	Different species of cabbage (e.g. Chinese)
01.1.7.1.3	Cauliflower	2	Cauliflower, broccoli
01.1.7.1.4	Tomatoes	1	Tomatoes
01.1.7.1.5	Cucumbers	2	Fresh cucumbers
01.1.7.1.6	Carrots	1	Carrot
01.1.7.1.7	Beetroot	1	Beetroot
01.1.7.1.8	Onions	2	Including with chives
01.1.7.1.9	Other vegetables and mushrooms	15	E.g. parsley, green beans, peppers, radish, garlic, mushrooms, ginger, fresh herbs
01.1.7.2	Frozen vegetables and mushrooms	5	Frozen vegetables and mixtures, frozen soups
01.1.7.3.1	Sauerkraut	1	Sauerkraut
01.1.7.3.2	Other vegetable and mushroom preparations	12	E.g. peas, beans, dried mushrooms, vegetable marinades, pickled vegetables, concentrates, vegetable salads, grated horseradish

1	2	3	4
01.1.7.4.1	Potatoes	1	Potatoes
01.1.7.4.2	Potato preparations	2	E.g. potato dumplings, fries
01.1.7.5	Chips	2	Different types of crisps and crisps (e.g. potato, corn)
01.1.7.6	Other tuber vegetables and tuber vegetable preparations	1	Sweet potatoes
01.1.8	S	ugar, jam, honey,	chocolate and confectionery
01.1.8.1	Sugar	3	Different types of sugar
01.1.8.2	Jams, marmalades and honey	4	Honey, jam, plum jam
01.1.8.3	Chocolate	5	Different types of chocolate (e.g. bitter, milk), chocolate boxes
01.1.8.4	Confectionery	9	Chocolate and non-chocolate sweets, halva, chewing gums, chocolate creams, jellies
01.1.8.5	Ice cream	2	Ice cream
01.1.8.6	Artificial sugar substitutes	1	Sweetener
01.1.9		Food products	not elsewhere classified
01.1.9.1	Sauces, spices	7	Soy sauces, mayonnaise, ketchup, mustard, sauces for dishes, liquid spices, vinegar
01.1.9.2.1	Salt	1	Salt
01.1.9.2.2	Spices and culinary herbs	7	E.g. pepper, bay leaves, marjoram, cinnamon, powdered spices (e.g. for chicken dishes)
01.1.9.3	Food for children	4	Baby products: milk powder, dinner dish, fruit dessert
01.1.9.4	Ready meals	3	Dinner dishes (e.g. stuffed cabbage), including soy and frozen dishes
01.1.9.9	Other food products not elsewhere classified	12	Food concentrate industry products (e.g. powder sauces for dishes), condiment concentrates for dishes (e.g. broths), powdered soups, powder dessert concentrates (e.g. pudding, jelly), gelatin, yeast
01.2		Non-alc	oholic beverages
01.2.1.1	Coffee	7	Different types of coffee – natural roasted, cappuccino, cereal coffee
01.2.1.2	Теа	6	Different types of tea – natural, fruit – granulated, leafy or in teabags
01.2.1.3	Cocoa and chocolate powder	3	Natural and added cocoa, also instant

1	2	3	4
01.2.2.1	Mineral or spring waters	4	Mineral, sparkling, still and flavoured water
01.2.2.2	Non-alcoholic beverages not elsewhere classified	7	Non-carbonated and non-carbonated soft drinks, tea drinks, fruit syrups, energy drinks
01.2.2.3.1	Fruit juices	5	Various types of fruit juices, including multi- fruit
01.2.2.3.2	Vegetable and fruit, and vegetable juices	3	Various types of vegetable juices, including multi-vegetable and fruit and vegetable juices

Source: The Central Statistical Office of Poland.