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E-commerce and the end of price rigidity?

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ABSTRACT

Online grocery platforms play an increasing role in many countries' food sectors. However, little is known about their pricing strategies. Are online prices less rigid than prices in brick-and-mortar stores, as theoretical and empirical studies from non-food sectors suggest? What does an acquisition by an internet giant imply for price adjustments in a formerly traditional offline store? Using a large data set of daily Amazon Fresh price quotes, we analyze the frequency and magnitude of price changes online. We find highly frequent and mostly small price adjustments for all major food categories sold by Amazon Fresh. For products from Whole Foods Market, which was acquired by Amazon in 2017 and whose assortment has since then been distributed online and offline, price behavior is completely different: Prices continue to be sticky and to follow traditional offline retail pricing patterns. We conclude that Amazon has indeed introduced a new way of dynamic pricing into food retail. However, at least until now this change is limited to Amazon Fresh's online channels and has not yet spread to the acquired Whole Foods Market stores.

1. Introduction

In the United States, the online grocery sector was the fastest growing of all product groups in 2018, even though the total online sales share is still modest compared with other sectors such as electronics or books (Bond, 2018). Between 30% and 50% of Americans already buy groceries online (KANTAR Worldpanel, 2017; Weinswig, 2018). By 2018, sales tripled in comparison with 2013, and the growth is expected to continue, fueled by the increased use of mobile technologies and an expansion of crowd-sourced business models to shopping and delivery (Packaged Facts, 2018). The forecasts for the United States suggest that 70% of consumers will do grocery shopping online by 2022–2024, spending over 100 billion US dollars per year (Danziger, 2018), an equivalent of 20% of projected total US retail food and grocery business (Scott Degraeve Consulting, 2017). Today, Amazon is the largest online grocery retailer in the United States, with further expansion potential thanks to Amazon's high household penetration (77% in the United States; Dumont, 2018). For internet giants such as Amazon, grocery retailing is highly attractive for a simple reason: Food is shopped more frequently and regularly than any other good (Brill, 2018). Grocery expenses make up a large share in total expenses of households (Doplbauer, 2015), which compensates for still modest shares of e-commerce in the total grocery revenues. On top of that, during the COVID-19 pandemic, online grocery shopping experienced a never seen popularity in many countries, including the United States (Biggs et al., 2020; Lusk & McCluskey, 2020). Like most online grocers, Amazon aims to transform this temporary demand spike into long-term growth (Soper, 2020).

Amazon started its subsidiary Amazon Fresh in Seattle in 2007, offering a full supermarket assortment online, including fresh produce, perishable products and frozen foods. Free delivery is available to Amazon Prime members in select regions for Amazon Fresh orders that meet the local order threshold. By 2020, the Amazon Fresh grocery delivery service was available in most major U.S. cities, and has expanded globally to urban areas in Germany, the United Kingdom, Japan, and India. This launch and the subsequent expansion has given rise to speculations whether Amazon is going to reinvent the entire grocery experience or even bring about the end of traditional supermarkets (Cahn & Cahn, 2017; Groeneveld, 2017). In particular, it could introduce the end of the rigid pricing practice characteristic for food retail: Prices remain unchanged for months or even years, only interrupted by occasional temporary sales promotions. Known for its low prices (Makortoff, 2018) and dynamic price adjustments (Marktwächter, 2018), Amazon is sometimes seen as a player of the "infinite game, where the goal is to outlast the competition" (Ladd, 2018). Since Amazon entered the stationary food retailing landscape with its

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acquisition of the organic grocery retailer Whole Foods Market Inc. (in the following "Whole Foods") in 2017, retailers across and beyond the United States have speculated even more how this acquisition may introduce a more dynamic pricing in the entire grocery industry (Ladd, 2018; Thompson, 2017).

First industry studies suggest that Amazon Fresh can be both a boost and a danger for its rivals in grocery retailing because it sets challenging prices (Butler, 2016; DISQ, 2018) and brings dynamics into an otherwise rigid sector by adjusting prices rather often (Makortoff, 2018; Marktwächter, 2018). Despite the broad media coverage, our knowledge on Amazon's online pricing strategies in the grocery sector and their transmission to newly acquired offline sites remains limited. To the best of our knowledge, this article provides the first empirical analysis of food price setting by Amazon Fresh. Besides Amazon Fresh's online-only assortment, we analyze the prices of Whole Foods products, which are distributed via both Amazon Fresh and brick-and-mortar Whole Foods stores. From scientific studies in the non-food sector, we know that pure online retailers adjust prices more frequently than pure offline retailers (Gorodnichenko, Sheremirov & Talavera, 2018; Gorodnichenko & Talavera, 2017). However, multi-channel (non-food) retailers have mostly shown one pricing strategy for both their online and their offline channels (Cavallo, 2017). Our study aims to analyze whether this is also the case for Amazon Fresh and Whole Foods Market. Does the acquisition by Amazon mean the end of price rigidity for Whole Foods? Do Whole Foods prices continue to follow traditional "sticky" retail price patterns, or have they taken over Amazon's more dynamic price setting? The latter might be an indicator that such acquisitions indeed have the potential to change pricing practices in the entire food retail sector.

We use daily price quotes collected on the Amazon Fresh website from November 2017 to February 2019 for more than 3000 products in all major food categories, resulting in a panel data set with more than 1.8 million price observations. To shed light on the scope and scale of price adjustments, we analyze the frequency and magnitude of price changes across different product groups and over time. Applying a within–between random effects logit model (Bell & Jones, 2015), we analyze the drivers of price change frequency.

Our analysis contributes to existing knowledge in a few ways: First, we focus on grocery products and even differentiate between different food products, such as produce, frozen foods and prepared foods. Because the grocery sector is a latecomer in online retail worldwide, most existing studies focus on non-food products. The few available high-frequency large-scale studies either do not include groceries at all, or they use data limited to packaged non-perishable products and report results only for one aggregated Food and Beverages group (as in Cavallo, 2018). In contrast, our study analyzes price rigidity for individual product groups within the grocery assortment.

Our second contribution lies in providing more recent figures for price rigidity, analyzing price quotes until February 2019. This may be relevant because available large-scale studies suggest a gradual but rapid decrease in price rigidity over time. However, their data do not go further than 2018 (the sample in Cavallo [2018] ends in March 2018; in Gorodnichenko & Talavera [2017] in September 2013; in Lünnemann & Wintr [2011] in September 2005). Our price quotes are collected until February 2019.

Our major contribution is in analyzing (the change in) the price behavior resulting from an acquisition of an offline retailer by a large online retailer. Given two opposite pricing strategies of Amazon and Whole Foods before the acquisition (dynamic pricing with small and frequent price adjustments versus rigid prices once promotions are controlled for), understanding whether price synchronization took place and—if yes—in which direction (more or less price rigidity) it goes is of interest to both academia and industry. For academia, it provides insights into multi-channel pricing when various channels come together due to a merge of businesses with different pricing strategies. For industry, our study might reveal potential effects of further alliances between the large tech platforms and grocery retailers.

The article proceeds as follows. In the next section, we briefly review the major studies on the theory and empirics of price rigidity, with specific focus on the grocery sector and online markets. Section 3 describes the data set and the econometric model we use to estimate price change probabilities. Section 4 reports the results for price change frequency and magnitude, and the final Section 5 discusses these results and offers some conclusions.

2. Theory and empirics of price rigidity

Price rigidity, or "stickiness", a situation in which prices do not respond quickly to changes in economic conditions, is a phenomenon well documented for retailing at large (Nakamura & Steinsson, 2008) and grocery retailing in particular (Loy & Schaper, 2014). There is no shortage in theories explaining the causes of price rigidity (Blinder, 1994). Prominent theories include coordination failure (Ball & Romer, 1991), cost-based pricing with lags (Blanchard, 1983; Gordon, 1981), varying delivery lags, services or product quality (Carlton, 1990), contracts (Okun, 1981), price adjustment costs (Mankiw, 1985), procyclical elasticity (Bils, 1989), psychological pricing (Kashyap, 1995), constant marginal costs (Hall, 1986), varying inventory stocks (Blinder, 1982) and using prices as quality signals (Allen, 1988). More recent empirical studies on the causes of price rigidity confirm that there is a variety of reasons rather than one single cause (e.g., Álvarez et al., 2006; Fabiani et al., 2006; Kleshchelski & Vincent, 2009). Menu costs, i.e., the costs of changing prices, have received particular research attention, with mixed conclusions on their contribution to price rigidity in offline retail (e.g., Levy, Lee, Chen, Kauffman, & Bergen, 2011; Loy & Weiss, 2002; Nakamura & Steinsson, 2008). The development of e-commerce is expected to remove at least some of these reasons, making prices more flexible, both off- and online (Brynjolfsson & Smith, 2000). Irrespective of the causes behind price rigidity, there is abundant evidence of sticky prices across different sectors, countries, and in both on- and offline markets.

Traditional offline grocery retail is characterized by more rigid prices than, e.g., offline retail for energy products or consumer electronics (Baudry, Le Bihan, Sevestre, & Tarrieu, 2007). Among different grocery items, prices of processed food products are on average more rigid than prices of fresh, unprocessed food products (Dhyne et al., 2006). Another particularity of the grocery sector is the frequent use of temporary sales promotions (Herrmann, Moeser, & Weber, 2005).

In a geographical comparison, European offline prices are on average stickier than those in the United States, both for food (Dhyne, Konieczny, Rumler, & Sevestre, 2009) and in other sectors (Álvarez et al., 2006). Studying food prices in the Euro area, Dhyne et al. (2009) find that 28.3% and 13.7% of prices for unprocessed and processed food items, respectively, change within one month. For unprocessed foods, prices in Portugal, Luxembourg, Finland and Spain are more flexible: About 50% of prices change during a given month. In Italy, France and Germany, food prices are more rigid (Dhyne et al., 2009). Herrmann et al. (2005) confirm this finding for the case of Germany: For some products, the median duration of unchanged prices equals 116 weeks, although sales are actively used by retailers in the sample. For online prices, Lünnemann and Wintr (2011) report less pronounced differences across countries and find that European prices tend to change more often than prices in the United States for most (non-food) consumer goods.

Over time, price rigidity seems to have decreased in the United States: For the years 1988–2005, Nakamura and Steinsson (2008) analyze various product categories, including food items. In their sample, most prices remain unchanged for 8–11 months (excluding temporary sales), with the majority of price changes being price increases. In Bils and Klenow's (2004) sample of 350 categories of goods and services for the years 1995–1997, the estimated average duration of a price spell is 7 months and the median duration is 4.3 months (5.5 months excluding sales). One reason for shortening price spells over time is a higher degree of automation in retail transaction processing, and consequently lower menu costs (Doms, Jarmin, & Klimek, 2004; Nakamura, 1999). In more recent years, the rise of e-commerce has led to an additional decrease in price rigidity, both on- and offline. E-commerce makes physical menu costs of price adjustments negligible, enhancing higher price flexibility online (Bergen, Kauffman, & Lee, 2005; Brynjolfsson & Smith, 2000). Even managerial and customer costs that some authors ascribe to a typically neglected part of menu costs (Chakrabarti & Scholnick, 2005) become less relevant when price setting algorithms are employed instead of manual price reviews (Calvano, Calzolari, Denicolò, & Pastorello, 2019). However, also offline price adjustments have become more frequent, because a greater diffusion of e-commerce can result in more competitive pressure by offering easier access to price information (Dhyne et al., 2006). This situation can reduce retail markups and put downward pressure on prices in the whole sector (Ater & Rigbi, 2018; Cavallo, 2018).

Overall, previous studies suggest that online prices are more flexible than offline prices. Gorodnichenko and Talavera (2017) find for electronic items in North America that price changes online are on average twice as small as typically reported for regular stores, with price changes occurring more frequently online than offline (once every three weeks). Also, Gorodnichenko et al. (2018) conclude that online prices are more flexible than prices in conventional stores for a broad spectrum of consumer goods in the Unites States and the UK. In their sample from the years 2010–2012, the average duration of online price spells was about 7–20 weeks, and therefore about two times shorter than previously reported for similar product categories in earlier offline studies (Nakamura & Steinsson, 2008). However, for multi-channel retailers, there seems to be little difference between their online and offline distribution channels: Studying 56 large multi-channel retailers in 10 countries, Cavallo (2017) finds that price levels online and offline are identical about 70% of the time. He finds that price changes are not always synchronized but have similar frequencies and similar average magnitudes on- and offline.

Following the rise of online retailing, a growing body of literature uses big data possibilities to investigate the nature of online price adjustments and the way they influence traditional retailing. Lünnemann and Wintr (2011) collect about five million price quotes from price comparison websites in France, Italy, Germany, the UK and the United States to analyze price stickiness in information technology products, consumer and entertainment electronics, small household appliances and consumer durables. In their sample, prices remain unchanged for 13–79 days. The authors suggest that the probability of a price change online is a function of the duration of a price spell, the weekday (most price changes on Thursdays in the United States and on Tuesdays in Europe), being a pure online retailer, as well as having many retailers selling the same product (higher perceived competition) and using psychological prices. The authors show that lower costs of a price change result in a shorter average price spell and smaller average sizes of price changes. Also, in their sample, price changes on the internet are on average smaller than those in traditional retail stores, although they typically exceed annual inflation rates.

A recent study by Cavallo (2018) uses the Billion Prices Project database (Cavallo & Rigobon, 2016) to figure out the way online competition affects the degree of price dispersion and frequency of price adjustments across different US locations (by ZIP code). It is the first large-scale online study that singles out groceries as a special product group, although groceries are defined as packaged non-perishable products only (earlier research on the food e-retailing used much smaller sample sizes; see, e.g., Bissinger, 2019; Fedoseeva, Herrmann, & Nickolaus, 2017). In this study, Cavallo (2018) shows that also online, the food sector deviates in several ways from other product groups. For instance, the food and beverage category is an exception when it comes to geographical price differences across locations. The share of identical prices in food and beverages across different US locations is only 84% on Amazon and 76% at other retailers, whereas the respective shares for all other sectors are 91% and 78% (for recreation and electronics: 99% of products with uniform pricing across different locations). The results further suggest that there is a lower geographical price dispersion if the product can be found on Amazon. The "Amazon effect" also seems to contribute to a higher pass-through of aggregate nationwide shocks, including exchange rates, to retail prices. As with geographical price dispersion, the Amazon pressure also increases the frequency of price adjustments: The price spell duration for Walmart's products that are also available on Amazon is shorter for all product groups, including food and beverages. Furthermore, Cavallo (2018) demonstrates that the aggregate frequency of price changes at multi-channel retailers has been increasing steadily over the observation period (2008–2017) for most product groups. Only for groceries, this development started later, in the year 2015. The author attributes this delay to a late but aggressive Amazon expansion in the fresh produce segment. Our study investigates whether the acquisition of Whole Foods, which is a part of this expansion, has further decreased the rigidity of grocery prices.

3. Data and methods

Our data consist of daily price quotes collected from the Amazon Fresh website for the location New York City (NY, ZIP Code 10001).[1] The data set covers the period from November 20, 2017 to February 1, 2019. Eight major food product categories are included in the sample: Bakery, Dairy, Deli, Frozen Foods, Meat & Seafood, Prepared Foods[2], Produce, and Whole Foods. The category "Whole Foods" includes the major food product categories of the Whole Foods Market assortment, as available via Amazon Fresh. This assortment represents mostly organic products, both packaged and fresh and both processed and unprocessed items.[3] All prices for products within those categories are collected, even if the assortment changes over time or an item falls into more than one category: Ice cream, for example, would be listed both in dairy products and in frozen foods. For all products, their unique Amazon Standard Identification Number (ASIN) code is recorded to ensure that identical products, even when listed in different categories, can be identified as such. When Amazon changed some category names in June 2018, we match the observations by their ASIN and continue to report the original categories (Table 1).

Whereas most of the products are only distributed online by Amazon Fresh, many Whole Foods products are distributed on- and offline[4]. They are available in the brick-and-mortar Whole Foods stores, and online via Amazon Fresh for pickup or delivery in selected US cities.

To get a sufficiently long observation period and hence meaningful insights on price rigidity, we only include products that are available at least for the duration of a whole year (min. 365 days), starting at the earliest date available. This way, all seasonal and only temporarily available products are excluded, and we focus on the basic assortment that is available all year long. Within the observed period (min. 365 days, max. 437 days, depending on the product), we allow for maximal 15 missing observations per product to ensure an almost continuous

[1] Because we always log on from the same location and the same device, this work does not cover aspects of individual price discrimination based on user characteristics, including discounts for Amazon Prime members.

[2] The category "Prepared Foods" is not analyzed separately due to the small number of observations.

[3] Whole Foods Market sells many, but not exclusively, organic products. The claim is to sell only "natural" foods, according to self-created quality standards. See Whole Foods Market (2019) for a list of unacceptable food ingredients, such as artificial flavors, sweeteners and preservatives.

[4] Our Whole Foods sample includes 1408 products before and 704 products after filtering for year-round availability. This is less than their full assortment because we focus on the essential food items and exclude all non-food items, alcoholic beverages and health supplements. Therefore, our analysis and conclusions are limited to the essential food assortment available on the Amazon Fresh website, and cannot be generalized to the overall Whole Foods assortment.

observation period. Missing observations can occur due to technical issues in the data collection or due to temporal unavailability of some products. For the missing observations, we assume the previous day's price, which implies that price changes for these products might be recorded with a one-day delay. Because missing data are limited in our sample, such an approach does not lead to any systematic bias.[5]

To study the phenomenon of price rigidity in our sample data, we are primarily interested in the price change frequency, i.e., how often prices are adjusted. To assess the frequency of price changes, we define a binary price change indicator I_{it} (Eq. (1)), such that

$$I_{it} = \begin{cases} 0 & if \ \ p_{it} = p_{it-1} \\ 1 & if \ \ p_{it} \neq p_{it-1} \end{cases}. \tag{1}$$

This price change indicator is only comparable (e.g., across different product groups) if applied to a standardized period. To allow for a straightforward interpretation and comparability with other studies, we calculate it for the whole time period available, but report it for a standardized period of a whole year (365 days), indicating how often a product price changes on average within one year $\left(\left(\sum_1^T I_{it} = 1/\sum_1^T \Delta p_{it}\right)^* 365\right)$.[6]

Moreover, we apply a logit model to assess which factors influence the probability of observing a non-zero price change ($I_{it} = 1$)in our sample. To account for the panel structure of our data, we follow Bell and Jones (2015) and apply a random effects model that allows for distinguishing the within and between effects. This within–between random effects logit model can model heterogeneity at both the cluster and the observation level (Bell, Fairbrother, & Jones, 2019). In our panel data, the individual products i (3199 entities, level 2) are measured on several days, i.e., observations, t (437 days, level 1) according to Eq. (2):

$$y_{it} = \beta_0 + \beta_{1w}\left(x_{it} - \overline{x}_i\right) + \beta_{2B}\overline{x}_i + \beta_3 z_i + (v_{i0} + \epsilon_{it}) \tag{2}$$

where y_{it} is the dependent binary variable, with 1 for price change ($I_{it} = 1$) and 0 for constant prices ($I_{it} = 0$), linked to the explanatory variables through a logit function. x_{it} is a vector of time-variant (level 1) independent variables. We include the following time-variant variables: *price* level in USD, effective exchange rate *(fx)*[7], dummy variables for *cyberweek* and federal holidays *(fedholiday)*[8], *weekdays* (reference = *Monday*), and *months* (reference = *January*). z_i is a vector with time-invariant (level 2) independent variables. In our case, these are the product categories (reference = *Bakery*). x_{it} is divided into two effects: The average within effect is represented by β_{1w}, the average between effect by β_{2B}. β_3 represents the effect of the time-invariant variable z_i (group category); it can also be seen as a between effect because there is no variation within a product i (i.e., level 2). β_0 represents the intercept. We allow for a random effect v_{i0} attached to the intercept, but we assume homogeneous effects across the level 2 entities (products), i.e., we do not include random slopes on an individual product level. ϵ_{it} are the model's level 1 residuals, assumed to be normally distributed and homoscedastic. Including the explicit variables, our model is specified as follows (Eq. (3)):

$$\begin{aligned} logit(I_{it}) = {} & \beta_0 + \beta_{1w1}\left(price_{it} - \overline{price_i}\right) + \beta_{1w2}\left(fx_{it} - \overline{fx_i}\right) + \beta_{1w3}\left(cyberweek_{it} - \overline{cyberweek_i}\right) + \beta_{1w4}\left(fedholiday_{it} - \overline{fedholiday_i}\right) \\ & + \beta_{1w5}\left(weekday_{it} - \overline{weekday_i}\right) + \beta_{1w6}\left(month_{it} - \overline{month_i}\right) + \beta_{2B1}\left(\overline{price_i}\right) + \beta_{2B2}\left(\overline{fx_i}\right) + \beta_{2B3}\left(\overline{cyberweek_i}\right) + \beta_{2B4}\left(\overline{fedholiday_i}\right) + \beta_{2B5}\left(\overline{weekday_i}\right) \\ & + \beta_{2B6}\left(\overline{month_i}\right) + \beta_3(category_i) + (v_{i0} + \epsilon_{it}) \end{aligned} \tag{3}$$

Please note that the between effect of the purely time-varying (and not product-dependent) variables (*fx*, *cyberweek*, *fedholiday*, *weekday*, *month*) is not meaningful in itself. However, for unbalanced panels as ours (for one product, there might be more observations in January than for other products), it is still important to include those between effects ($\beta_{1B2}, \beta_{1B3}, \beta_{1B4}, \beta_{1B5}, \beta_{B6}$) in the estimation. Otherwise, the within effect ($\beta_{1w2}, \beta_{1w3}, \beta_{1w4}, \beta_{1w5}, \beta_{1w6}$) would be biased (Bell & Jones, 2015; Bell et al., 2019).

In addition to the frequency, we report some statistics on the price change magnitude, aiming to give complementary insights into the pricing behavior. The magnitude of price changes can be measured in absolute or relative terms. However, for absolute values in USD ($\Delta p_t^{abs} = p_t - p_{t-1}$), there is a lack of comparability among various products. For relative measures, one can choose either raw returns, i.e., percentage changes ($\Delta p_t^{raw} = (p_t - p_{t-1})/p_{t-1}$), or logarithmic returns ($\Delta p_t^{log} = \ln(p_t/p_{t-1})$). Raw returns may be more intuitive because they can be interpreted directly as percentage changes. However, their negative deviations cannot be smaller than −1, or −100%, whereas there is no upper bound. Overall, for raw returns, price increases are measured larger than price decreases: A temporary sales price change from regularly 3.99 to 2.99 USD and back would be measured as a price decrease of −25.06%, and then as a price increase of +33.44%. The log return would be ±0.2885 and therefore treat this as a symmetric price

[5] Sensitivity analysis with non-continued time series data leads to qualitatively similar results (available on request).

[6] An alternative measure is the price spell, i.e., an uninterrupted sequence of unchanged price quotes for a particular product, often measured in days. However, this measure requires censoring and relatively long observation periods (Lünnemann & Wintr, 2011). In our case, a price spell is considered left-censored if the observation period does not start with a price change, and right-censored if the last observation is not a price change. Because this censoring could lead to a systematic underestimation of price spells, we stick to the alternative measure of price change frequencies per year and derive the implied price spell in the latter interpretation.

[7] The effective exchange rate measures the US dollar's relative strength against a basket of currencies belonging to the country's most important trading partners. For weekends, last Friday's exchange rate applies (https://www.poundsterlinglive.com/bank-of-england-spot/historical-effective-exchange-rates/USD-history).

[8] *Cyberweek* is the week after Thanksgiving, in which many online stores offer promotional sales prices. As federal holidays, we include the 10 official US-wide holidays (https://web.archive.org/web/20160126083035/http://hr.commerce.gov/Employees/Leave/DEV01_005944=).

adjustment in which the direction of price change does not influence its magnitude. Although all measures were calculated, in this article we only report log returns due to their independency of the price change direction and their time consistency (Hamilton, 1994). For small log returns, approximate raw-log equality applies, so that log returns can approximately be interpreted as percentage changes (Hudson & Gregoriou, 2015). To assess the magnitude of price changes, we compare distributions of price changes between different product categories and test whether the magnitude of price increases and decreases is statistically different, i.e., whether there are asymmetries in price adjustment. This is done by means of Wilcoxon rank sum tests (Mann & Whitney, 1947) and Kolmogorov–Smirnov tests (Conover, 1971; Smirnov, 1939). Please note that we do not make any specific distributional assumptions for price change magnitudes. Appendix A provides a detailed analysis of how price changes are distributed in our sample.

4. Results

4.1. Price change frequency

To give a first impression of the price change frequency, Fig. 1 shows the average number of price changes per product per year. On average, a single product undergoes 20.4 price changes in one year, which would imply an average price spell of about 18 days. The share of price changes of different signs is balanced with only slightly more increases than decreases (10.4 vs. 10.0 price changes per year). Among individual categories, we observe some heterogeneity in the frequency of price changes. Produce and Dairy products show the most price changes per year (26.4 and 26.3, respectively, implying a price spell of about two weeks), followed by Frozen Foods (23.3) and Bakery (19.0). Deli and Meat & Seafood experience less frequent price changes (14.7 and 9.3 times, respectively), which correspond to price spells of about 25 and 39 days, respectively. Similarly high frequencies of online price adjustments have already been reported for household appliances, technology products, consumer and entertainment electronics, and consumer durables (Lünnemann & Wintr, 2011) but rarely for grocery products. For instance, Cavallo (2018) reports grocery prices to remain unchanged for about six months.

Price setting in the Whole Foods category seems to follow different patterns: Less than one price change (0.7) per product per year takes place in this product group, indicating highly sticky prices similar to findings from offline food retail studies (Herrmann et al., 2005; Nakamura & Steinsson, 2008).[9] This fundamental difference is depicted in Fig. 1.[10]

These descriptive statistics give a good first impression of price change frequencies and indicate that Amazon's acquisition of Whole Foods has not changed the latter's price setting strategy.

To investigate the price change frequency in more detail, we model the influence of product categories and other factors on the probability of observing a price change by applying a within–between random effects logit model. In the model, we make use of all available observations for year-round available products, which results in an unbalanced panel with 3199 individual products with varying time dimensions of 350–437 daily observations per product and over a million observations in total. The remainder of this section presents the results of the within–between random effects logit[11] model. Table 2 shows the estimates of the within effects (β_{1w}), indicating how the probability of observing a price change within an individual product can be explained by the different time-variant factors x_{it}. Table 3 summarizes the between effects (β_{2B}) for these time-variant factors, i.e., how the mean of x_{it} influences the probability of a price change between the individual products. Table 3 also lists the estimates of the time-invariant product category effect (β_3) and the intercept (β_0), which can also be considered between effects (Bell et al., 2019).

For the first time-variant variable in the tables, *price*, more expensive goods experience fewer price changes, i.e., have more rigid prices (between effect: *imean(price)* $= -0.049$; see Table 3). Also, if a given good is currently at a higher price level than normally, a price change is less likely compared with a time with a lower price level (within effect: *price* $= -0.113$; see Table 2).

For the time-variant variables fixed to a certain date, the within effects are of interest for our interpretation. The within estimate tells us whether price changes for a given product are either more or less likely on a given weekday, in a given month, or during cyberweek or federal holidays. The between effect is influenced by the number of observations available for different products, e.g., on a certain weekday. It is needed in the model to prevent a bias on the within coefficients, and it is reported in Appendix B (Table B2). Because in our sample the two effects are not equal in size, a standard random effects model would yield uninterpretable averages of the within and the between effect (Krishnakumar, 2006; Neuhaus & Kalbfleisch, 1998).

Looking at the within effects for the time-variant variables (Table 2), we get the following results: Among the weekdays, price changes are least likely to occur on Fridays (−0.374), Wednesdays (−0.221) and Thursdays (−0.205), followed by Sundays (−0.138). On Tuesdays, the probability of a price change is not significantly different from the reference day Monday, and most price changes occur on Saturdays (+0.118). However, these results should be interpreted with care, because for days with missing data we assume the previous day's price. In such cases, price changes are detected on the following day, and hence attributed to the wrong weekday. Consequently, the size of the effect may be over- or underestimated for some weekdays. For the monthly dummies, we find that price changes are most likely in the beginning of the year (February, followed by January and March) and least likely in December and in the summer months (June, July and August). However, because we only have slightly more than a year of observations, we cannot clearly conclude that this is a repeated seasonal pattern. During cyberweek, which is characterized by promotional sales in other online retail segments such as electronics, we find a negative effect (−0.731), indicating that there are even fewer price changes than in the rest of the year. It seems that for regularly purchased goods such as groceries, a once-a-year sales event is not as suitable as for durable consumer goods. However, we did not control for other promotional activities other than direct single price changes (e.g., discount on the overall purchase, "buy 1, get 1 free", etc.). Federal holidays have no significant effect. The variable "effective exchange rate" has a positive effect (0.126), indicating that in times of a strong US dollar, the

[9] It could be that the difference between Whole Foods and the other categories is not because of the retail channel, but because of differences between organic and non-organic products. To control for this possibility, we compare the price change frequency between organic products sold in the Whole Foods category and organic products sold in all other Amazon Fresh categories (using the search word "organic" in the product name). We find that on average, organic non–Whole Foods products have 23.9 price changes per year, whereas organic Whole Foods products have 0.6 price changes per year. Both Wilcoxon and Kolmogorov–Smirnov tests find this difference highly significant. This difference is even more pronounced than the whole sample difference between Whole Foods (0.7) and all other categories (21.3). Hence, we can rule out that organic products are per se priced differently, with either more or less frequent price adjustments, than non-organic products.

[10] In contrast to the other categories, the Whole Foods category covers a wide range of products. Splitting Whole Foods into subcategories, we find that there are more price changes per year for Dairy (1.9) and Meat & Seafood (1.3). For Whole Foods Produce, there are only 0.04 price changes per year (for details, see Appendix B, Table B1). Although these differences are statistically significant, the gap to all other non–Whole Foods categories remains large for all subcategories.

[11] The same model was run with a probit function, leading to qualitatively similar results.

Table 1
Number of products per category.

Category	Original number of products	Final number of products after filtering
Dairy	1906	741
Deli	727	89
Frozen Foods	1920	1025
Meat & Seafood	909	456
Prepared Foods	237	16
Produce	545	114
Whole Foods	1408	704
Sum (gross number of products)	**8001**	**3312**
Duplicates in >1 category	1656	113
Net number of unique products	**6345**	**3199**

Notes: In the final sample, only products with at least 350 observations within 365 days are considered (year-round assortment only). "Deli" refers to fine foods and specialties, "Produce" includes fresh fruits and vegetables.

probability of price changes is higher.

Although the sign and relative size of the coefficients are good indicators of the direction and magnitude of the effect, odds ratios (OR) may be easier to interpret. For the time-invariant product categories (between effect, Table 3), we get the following results: For products in the category Dairy, the odds of a price change are 99.8% (OR − 1) higher, ceteris paribus, compared with a product in the reference category Bakery. For Produce and Frozen Foods, the odds are 77.7% and 72.7% higher, respectively, whereas Deli prices do not behave significantly different from prices for Bakery products. For Meat & Seafood, the price change probability is 26.3% lower. For Prepared Foods, the odds are also significantly decreased (−83.7%), but the small number of observations (16 products) does not allow us to draw general conclusions.

The largest influence has the Whole Foods category. For Whole Foods products (OR = 0.009), the odds of a price change are 99.1% (OR − 1) smaller, ceteris paribus, compared with a product in the reference category Bakery. In line with our descriptive findings, this results shows

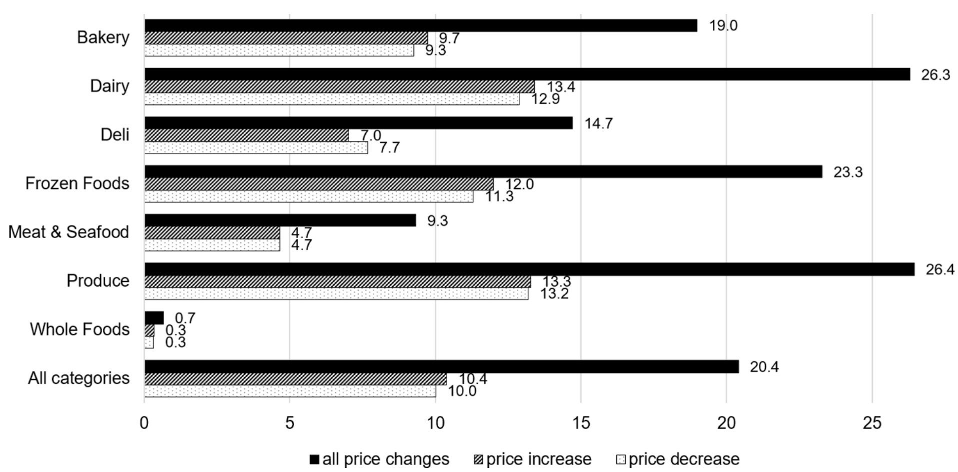

Fig. 1. Average number of price changes per product in one year, per category.

Table 2
Determinants of price change probability: within effects estimates.

Independent variable	Estimate	S.E.	z-value	p-value	Significance level	Odds ratio	(95% confidence interval)
Price	−0.113	0.010	−10.953	0.000	***	0.893	(0.88–0.91)
Effectivefx	0.126	0.007	19.157	0.000	***	1.134	(1.12–1.15)
Cyberweek	−0.731	0.050	−14.495	0.000	***	0.481	(0.44–0.53)
Fedholidays	−0.002	0.034	−0.061	0.951		0.998	(0.93–1.07)
Tuesday	0.018	0.020	0.907	0.365		1.018	(0.98–1.06)
Wednesday	−0.221	0.021	−10.553	0.000	***	0.801	(0.77–0.84)
Thursday	−0.205	0.021	−9.751	0.000	***	0.815	(0.78–0.85)
Friday	−0.374	0.022	−17.069	0.000	***	0.688	(0.66–0.72)
Saturday	0.118	0.020	5.888	0.000	***	1.125	(1.08–1.17)
Sunday	−0.138	0.021	−6.606	0.000	***	0.871	(0.84–0.91)
February	0.508	0.026	19.839	0.000	***	1.663	(1.58–1.75)
March	−0.187	0.027	−6.843	0.000	***	0.829	(0.79–0.87)
April	−0.279	0.028	−9.982	0.000	***	0.756	(0.72–0.80)
May	−0.343	0.030	−11.324	0.000	***	0.710	(0.67–0.75)
June	−0.789	0.037	−21.138	0.000	***	0.454	(0.42–0.49)
July	−0.635	0.039	−16.206	0.000	***	0.530	(0.49–0.57)
August	−0.690	0.042	−16.584	0.000	***	0.502	(0.46–0.54)
September	−0.313	0.038	−8.226	0.000	***	0.731	(0.68–0.79)
October	−0.347	0.043	−8.102	0.000	***	0.707	(0.65–0.77)
November	−0.380	0.046	−8.195	0.000	***	0.684	(0.62–0.75)
December	−1.284	0.037	−34.366	0.000	***	0.277	(0.26–0.30)

Dependent variable = price change ($p_t \neq p_{t-1}$), entities: 3199, time period: 11/21/2017 to 2/1/2019 ($t = 437$ days), model family: binomial, link: logit, specification: within–between.
Significance codes: '***' 0.001, '**' 0.01, '*' 0.05, ' ' 1.
Reference categories: Monday for weekdays, January for months.
Model fit: AIC: 267525.64, BIC = 268119.88, Pseudo-R^2 (fixed effects) = 0.51, Pseudo-R^2 (total) = 0.61, Entity Interclass Correlation (ICC) = 0.28.

Table 3
Determinants of price change probability: between effects estimates.

Independent variable	Estimate	S.E.	*z*-value	*p*-value	Significance level	Odds ratio	(95% confidence interval)
Dairy	0.692	0.098	7.055	0.000	***	1.998	(1.65–2.42)
Deli	−0.091	0.515	−0.177	0.860		0.913	(0.33–2.51)
Frozen Foods	0.546	0.095	5.775	0.000	***	1.727	(1.43–2.08)
Meat & Seafood	−0.306	0.123	−2.493	0.013	*	0.737	(0.58–0.94)
Prepared Foods	−1.816	0.379	−4.794	0.000	***	0.163	(0.08–0.34)
Produce	0.575	0.139	4.138	0.000	***	1.777	(1.35–2.33)
Whole Foods	−4.668	0.178	−26.259	0.000	***	0.009	(0.01–0.01)
imean(price)	−0.049	0.010	−5.117	0.000	***	0.952	(0.93–0.97)
(Intercept)	−38.231	26.143	−1.462	0.144		2.49E − 17	(0–4.47E + 05)

Dependent variable = price change ($p_t \neq p_{t-1}$), entities: 3199, time period: 11/21/2017 to 2/1/2019 ($t = 437$ days), model family: binomial, link: logit, specification: within–between.
Significance codes: '***' 0.001, '**' 0.01, '*' 0.05, ' ' 1.
Reference categories: Bakery for categories. Between effects for the other time-varying variables and for the random effect estimate υ_{i0} are reported in Appendix B, Table B2.
Model fit: AIC: 267525.64, BIC = 268119.88, Pseudo-R^2 (fixed effects) = 0.51, Pseudo-R^2 (total) = 0.61, Entity Interclass Correlation (ICC) = 0.21.

that Whole Foods products continue to have highly sticky prices, as known from stationary food retail. The frequent price adjustments apply only to the pure online categories but have not yet spread to Whole Foods. We can rule out that this is only due to the organic nature of Whole Foods products. We separately analyzed price change probabilities for all other (non–Whole Foods) organic products available on Amazon Fresh by searching for "organic" in the product name. This exercise has shown that in the Amazon Fresh assortment, organic products do not behave significantly different from non-organic products.[12]

Among the online-only categories, we see that perishable products (Dairy, Produce) or those with costly storage (Frozen Foods) are the categories with most frequent price changes. It could be that here, price setting is also used as part of an inventory management strategy, aiming to reduce the total costs of servicing the market (see, e.g., Gallego & Hu, 2014; Herbon, Levner, & Cheng, 2014).

Comparing the size effects across all parameters, we see that product categories are the best predictors of the price change frequency. Although the price level and weekly and seasonal patterns seem to play some role, product categories have by far the largest effect on price change frequencies.

4.2. Price change magnitude

To illustrate the price change magnitudes, Fig. 2 shows histograms of non-zero price changes by size, measured as log returns. Graph *a)* illustrates how large the price changes are in the whole sample. It shows that the majority of price changes are clustered between zero and ±0.1, indicating small price changes of less than 10%. The relatively symmetric curve suggests that there is a similar distribution for price increases and decreases.

The following graphs (*b*) to (*g*) represent the individual online-only product categories and display similar bell-curve distributions. Although these are sometimes flatter with relatively more large price changes (e.g., Bakery and Produce) or steeper with more small price changes (e.g., Frozen Foods), they all show similar symmetric patterns. This image changes if we look at the Whole Foods category, presented by the final graph (*h*). Unlike the other categories, there is no peak around zero with price changes smaller than 0.1. Rather, we observe large single spikes between ±0.25 and ±0.75.

Table 4 documents to what extent mean and median price changes differ between individual categories. For the whole sample, the absolute median is at 0.1056, i.e., about half of all observed price changes are smaller than 10%. For all product groups, the mean lies above the median, which can be attributed to a few very large price changes, potentially promotional sales. The median absolute price change is the smallest for Meat & Seafood, Frozen Foods and Dairy (each about 0.10), followed by Deli (0.11), Produce (0.13) and Bakery (0.16). Whole Foods is an exception again, with the largest median price change of over 0.35. In contrast to the frequent and small price changes in the other categories, Whole Foods prices continue to follow traditional retail pricing patterns with only a few, large price adjustments.

To test whether price increases and decreases are differently distributed, we test the distribution of positive against negative returns (in absolute terms) for the whole sample and per category (Table 5). We apply both Wilcoxon rank sum tests (Mann & Whitney, 1947) and two-sample Kolmogorov–Smirnov tests (Conover, 1971; Smirnov, 1939) to compare the distributions of price change magnitudes, without having to assume any specific distribution. Both tests test the null hypothesis of identical distributions for negative and positive returns and come to similar results: Positive and negative price changes do not behave significantly differently for the whole sample and within most of the individual categories. The only exceptions are Meat & Seafood and Dairy products, for which price changes appear to be somewhat asymmetrical, with higher price increases than decreases.

4.3. Temporary sales promotion

Our extracted price records do not distinguish between temporary sales promotions and permanent price adjustments. In food retail, temporary price reductions are a frequent and well-studied phenomenon, and they are unrelated to cost changes but rather serve as marketing tools (e.g., Hosken & Reiffen, 2001). We therefore try to identify temporary sales promotions ex-post, using the following definition: Price decreases that are reversed to the previous original price within max. 14 calendar days are treated as temporary sales. Using this definition, about 4.24% of all price changes in our data set fall into the category of promotional sales (either price reduction or subsequent price rise). The relative importance of temporary sales differs among the product categories (Table 6): Whole Foods have the highest share of promotional price changes with 7.75% of all price changes, compared with less than 4% in the categories Produce and Frozen Foods. This is another indicator that Whole Foods Market continues to apply "offline-style" pricing. Price changes are not only more seldom and larger in size but also more commonly used as temporary sales promotions.

As Table 7 shows, the magnitude of these promotional price changes is significantly higher than for non-temporary changes, with a mean price change (log return) of 0.327 compared with 0.157, and a median of 0.255 compared with 0.097. Because temporary sales are most common in the Whole Foods category, this is at least one explanatory factor why their price changes are higher than in other categories (compare Fig. 2

[12] Detailed results are available on request.

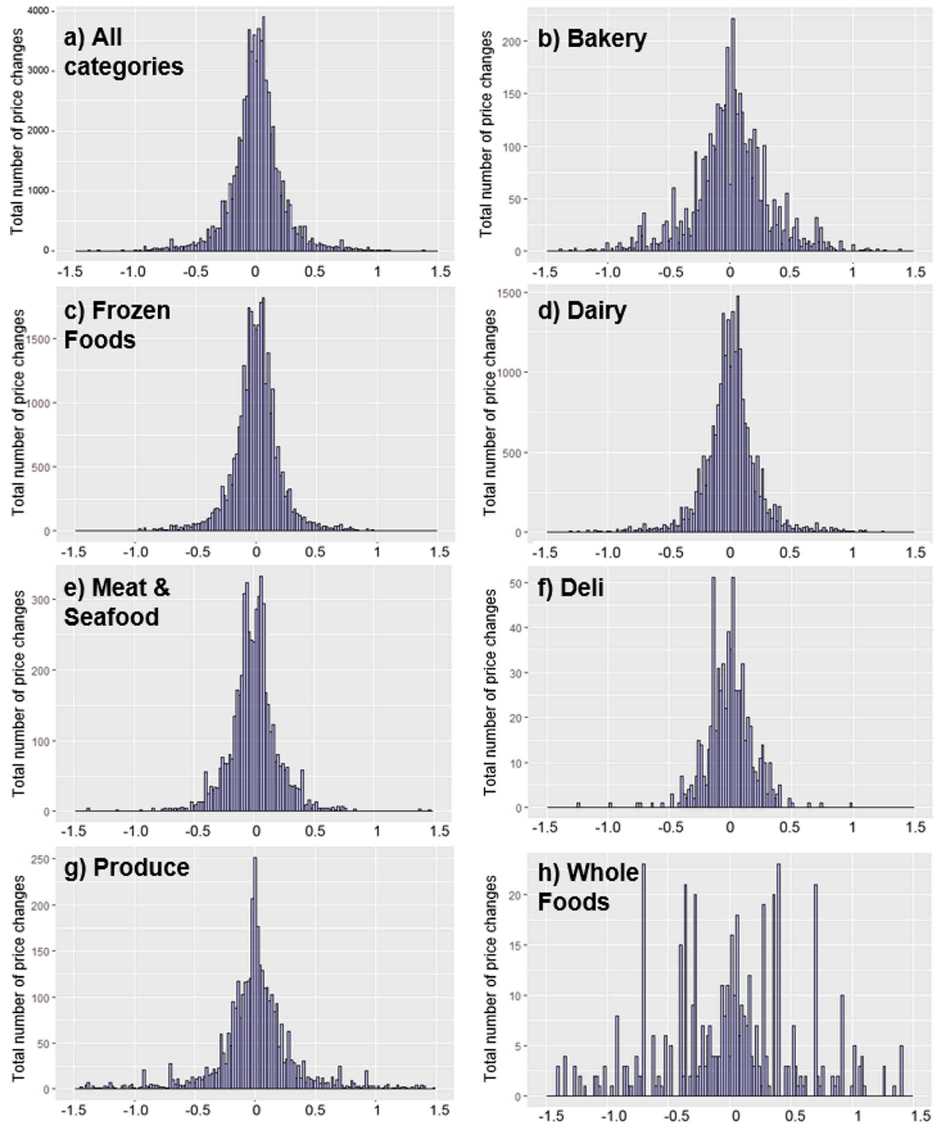

Fig. 2. Histogram for non-zero price changes by product category (log returns).

and Table 4). The price level of the products subject to temporary sales is only slightly below the price level of products subject to other price changes (mean 4.22 USD compared with 4.48 USD, median 3.99 USD compared with 4.19 USD).

To analyze whether these temporary sales influence our results, we filter them out and conduct the above analysis for non-temporary sales only.[12] This filtering does not change our results qualitatively. In fact, with this reduced sample, we find that Whole Foods prices are even more rigid compared with all other categories.

5. Discussion and conclusion

We find that the price setting of Amazon Fresh is characterized by frequent and small price adjustments. On average, there are 20.4 price

Table 4
Price change magnitude per product category (absolute price changes, in log returns).

Category	All price changes		Price increases		Price decreases	
	Median	Mean	Median	Mean	Median	Mean
Bakery	0.1599	0.2402	0.1616	0.2371	0.1580	0.2435
Dairy	0.0991	0.1627	0.0956	0.1605	0.1027	0.1649
Deli	0.1097	0.1571	0.1035	0.1519	0.1154	0.1619
Frozen Foods	0.0969	0.1438	0.0983	0.1425	0.0955	0.1451
Meat & Seafood	0.0954	0.1665	0.0874	0.1635	0.1034	0.1696
Produce	0.1339	0.2400	0.1339	0.2403	0.1339	0.2396
Whole Foods	0.3574	0.4825	0.3573	0.4614	0.3576	0.5058
All categories	0.1056	0.1660	0.1045	0.1641	0.1068	0.1681

Source: Own calculation. Note: All values represent absolute price changes, expressed in log returns: $|\ln(p_t/p_{t-1})|$.

Table 5
Testing positive against negative price change distributions.

Category	Wilcoxon rank sum test		Two-sample Kolmogorov–Smirnov test	
	W	*p*-value	*D*	*p*-value
Bakery	2,235,700	0.658	0.021	0.985
Dairy	69,509,000	0.017	0.030	0.058
Deli	60,979	0.160	0.075	0.537
Frozen Foods	109,490,000	0.434	0.029	0.026
Meat & Seafood	3,830,500	0.001	0.071	0.001
Produce	1,608,200	0.404	0.027	0.747
Whole Foods	35,962	0.121	0.112	0.467
All categories	576,040,000	0.144	0.007	0.965

Source: Own calculation with absolute logarithmic returns, based on Conover (1971), Mann and Whitney (1947) and Smirnov (1939). H_0 in both tests assumes equal distribution of the different product category populations.

Table 6
Proportion of temporary sales in overall price changes per category.

Category	Share of temporary sales
Bakery	5.50%
Dairy	4.72%
Deli	5.49%
Frozen Foods	3.46%
Meat & Seafood	4.58%
Produce	3.09%
Whole Foods	7.75%
All categories	4.24%

Note: Temporary sales are defined as price decreases reversed within max. 14 days.

Table 7
Properties of temporary sales prices.

Variable	Temporary sales		Other price changes	
Number of observations	2864	(4.24%)	64,730	(95.76%)
Δp^{mean}	0.327		0.157	
Δp^{median}	0.255		0.097	
p^{mean}	4.22 USD		4.48 USD	
p^{median}	3.99 USD		4.19 USD	

Note: Temporary sales are defined as price decreases reversed within max. 14 days.
Δp refers to absolute price changes measured as log return, p refers to the price level before a price decrease.

changes per product and year, implying an average price spell of less than 18 days. This finding shows that overall, Amazon Fresh product prices are less rigid than prices in traditional (offline) grocery stores (Herrmann et al., 2005; Nakamura & Steinsson, 2008) or even in online markets for earlier periods (Cavallo, 2018). Our study confirms that price rigidity decreases over time as earlier empirical studies postulate. Our results even suggest that the speed of this development has increased. In fact, no previous empirical study has found such frequent price changes for food items. Because we collect data once a day, we potentially even underestimate the frequency of price changes for some products, and we can make no statements regarding intra-day price adjustments. Most of these price changes are small adjustments (median magnitude of 10%). Large price changes and temporary promotional sales, as known from offline retail, only play a minor role. Our study cannot identify how these prices are set. Yet, such frequent and small adjustments hint at the use of automated algorithms, rather than manual price reviews. Previous academic studies have proven the use of such algorithmic or dynamic pricing for various online sellers, including Amazon Marketplace (Chen, Mislove, & Wilson, 2016). Such dynamic pricing can be based on but is not limited to information about customers and demand, inventory, and suppliers' and competitors' prices in real time. Understanding the use of dynamic pricing in food retail in general, and particularly for Amazon, is a relevant field for future research. Given the high concentration in food retail, the large players' pricing strategies could become highly interconnected, responding in real time to each other's price changes, and hence changing the price setting in the whole industry.

We find that the product category has the largest influence on how frequently prices change. This finding underlines the importance of disaggregating groceries into more detailed product categories. Other factors such as weekdays, months, or special events such as cyberweek or federal holidays only play a subordinate role. Produce and Dairy products show most price changes, with an average price spell of only two weeks. This finding could be an indicator that pricing is also used as an inventory management tool, particularly for unprocessed and perishable food products. Meat & Seafood, which includes a large share of packaged products with a long shelf-life, is the online-only category with the stickiest prices, with an average price spell of 39 days. This is still very frequent compared with price change frequencies reported by several offline studies for grocery products. Also, the fact that our sample includes many fresh products could partly explain why we observe less price stickiness than the online study by Cavallo (2018), who only analyzed non-perishable pantry staples and found that prices remain unchanged for about six months.

Our study also analyzed the price behavior of Whole Foods products sold via Amazon Fresh after the acquisition by Amazon. Once Whole Foods is considered as a separate product group, the difference in price adjustment patterns compared with all other categories is striking. In the Whole Foods category, price changes are significantly less frequent and larger than in the online-only categories. Despite the acquisition by Amazon in 2017 and the online distribution via Amazon Fresh, Whole Foods products continue to follow the known offline pricing schemes: First, prices continue to be rigid with on average less than one price change per product and year. Second, when those seldom price changes occur, they are large (median change 35.7%). Third and finally, temporary sales promotions continue to play a role, accounting for 7.75% of all price changes (compared with 4.24% for the whole sample). The dynamic pricing with frequent, small price adjustments observed for all other Amazon Fresh product categories does not seem to transmit to Whole Foods prices. If anything, discrepancies between the two channels seem to grow over time[13], mostly due to a rapidly increasing frequency of price adjustments by Amazon Fresh (excluding Whole Foods).

So why does Amazon stick to this traditional pricing for Whole Foods? With electronic shelf labels, it would technically be feasible to adopt a more dynamic pricing in the stores (Garaus, Wolfsteiner, & Wagner, 2016). However, consumer acceptance may be an issue, because price changes within very short time are perceived as unfair by many consumers (Haws & Bearden, 2006). Whereas in e-commerce and transportation sectors, consumers are already habituated to dynamic pricing (Bugden & Stedman, 2019; Priester, Robbert, & Roth, 2020), customers visiting a Whole Foods Market store are used to stable retail prices and could be unsettled by frequent price changes. To avoid this customer dissatisfaction, Amazon could apply a dynamic pricing approach only to Whole Foods products sold online. However, previous research has shown that consumers perceive such a price discrepancy between online and offline distribution channels also as unfair (Fassnacht & Unterhuber, 2016). For the online-only categories, customers seem to find the frequent price changes acceptable. Especially for relatively cheap items such as groceries, shoppers generally do not evaluate prices for each single item, but rather for a whole basket of goods (Desai & Talukdar, 2003). The Amazon Fresh website offers tools such as shopping lists and past purchase sections to save and re-buy frequently purchased items, without having to search for them again or to look for prices. Without being exposed to each price tag at every purchase, even regular customers presumably do not notice most price changes of a few cents, especially if price increases and decreases are balanced across the overall shopping basket, as it is the case in our sample. However, consumer price perception and acceptance on- and offline is the topic of a different strand of literature (e.g., Jiang & Rosenbloom, 2005; Lii & Sy, 2009). The herein identified price setting behavior might be only a transitory stage, and the situation might change in the future. Nonetheless, at this point we ought to conclude that it is too early to call it the end of price rigidity for Whole Foods and other stationary retailers. Although Amazon certainly has introduced a new way of more dynamic food retail pricing, this strategy is currently only applied to its online-only food segment, but it has not yet spread to its multi-channel subsidiary Whole Foods.

We do not know at which intensity and speed Amazon will increase its presence in the food market through its Amazon Fresh service, the Whole Foods acquisition, or the new convenience store concept Amazon

[13] Detailed results of a convergence analysis over the observed time span are available on request.

Go. Hence, it remains to be seen if and how this development will change the price setting in the overall food retail landscape in the long run.

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Appendix

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2020.11.052.

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