Online food prices during the COVID-19 pandemic

Judith Hillen

Abstract
During the coronavirus disease-2019 pandemic, online grocery shopping experienced a never seen popularity in many countries. To study how the globally active online grocer Amazon Fresh reacted to this extraordinary demand increase, we analyzed a large dataset of daily price quotes for over 19,000 products for the customer location, Los Angeles. We found that contrary to the US consumer food price index, the overall price level at Amazon Fresh did not increase during the pandemic, but even slightly decreased for several product groups. Amazon seems to follow its low-price strategy also in the grocery sector, even in times of high demand. However, during the lockdown phase, there were more price increases for certain highly demanded product groups such as frozen and prepared foods. Moreover, fewer prices were communicated as promotional prices. Because this change did not influence the general price level, we conclude that such promotional prices are used more as a marketing tool than as a price-setting instrument.

KEYWORDS
coronavirus, e-commerce, online grocery delivery

ECONLIT CITATIONS
E31; L81; Q11; Q13
INTRODUCTION

If there is anything like “winners” in the coronavirus disease-2019 (COVID-19) crisis, online grocers are among them because they have been experiencing a large boost in sales during the pandemic. An analysis of US credit and debit card data showed that in the COVID-19 crisis, spending at online grocers has increased by 79%, which is the highest percentage increase out of all categories, even higher than for gaming and food delivery (Leatherby & Gelles, 2020). An analysis of online search terms showed that the search term “online food shopping” has experienced a 3,500% usage increase during the COVID-19 lockdown in spring 2020, compared with the previous year (Adimo, 2020).

We know at least broadly how consumers behaved in this crisis: with increased at-home food consumption, stockpiling canned foods and pasta, and a sudden preference for online shopping (e.g., Biggs et al., 2020; Lusk & McCluskey, 2020). Yet, little is known about the seller side. How did online grocers react to this extreme surge in demand? Did they use the opportunity to increase prices, especially for highly demanded products? Did they offer fewer sales promotions, because there is less need to attract customers? Or did they continue with business as usual? Also, are there differences in the pricing of highly demanded pantry food products with a long shelf life and fresh produce?

To answer these questions and to better understand the behavior of online food retailers during the COVID-19 pandemic, we analyzed the price setting of the online grocer Amazon Fresh. We chose this player because 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). Amazon Fresh has expanded globally to urban areas in Germany, the United Kingdom, Japan, and India. 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). The fact that grocery expenses make up a large share in total household expenses compensates for the still modest shares of e-commerce in the total grocery revenues (Doplbauer, 2015). The COVID-19 pandemic could be a chance for Amazon to accelerate its development toward a leading role in the food retail sector. Given Amazon’s dominant position in nonfood retail and its reputation for low prices and dynamic prices (Marktwächter, 2018), it is relevant to understand how Amazon Fresh sets food prices in this extraordinary situation.

Using a large dataset with more than 2 million daily price quotes for over 19,000 products, we studied how price levels and sales promotions have evolved before, during, and after the COVID-19-related stay-at-home order in spring 2020. Applying a logit model, we analyzed the drivers of price increases to find out for which types of products and in which phases of the pandemic prices have increased.

ONLINE GROCERY DEMAND DURING THE COVID-19 CRISIS

The changes in lifestyle and measures to reduce the spread of COVID-19 have significantly altered many economic activities across the globe. While many sectors have suffered from the crisis, online food shopping has experienced an unprecedented surge in demand during the pandemic. There are three developments contributing to this surge.

First, there was a shift from out-of-home to at-home food consumption because many restaurants, hotels, and canteens were closed, and most people avoided public places. In recent years, more than half of the US consumer food spending was on out-of-home consumption (Okrent et al., 2018). During the pandemic, and specifically during the stay-at-home order, this spending shifted at least partly to food retail for home consumption (Johansson, 2020).

Second, people stocked up on essential food items. An evaluation of US credit card data showed that spending on grocery products had increased in mid-March 2020 by more than 70%, compared with mid-January (Reeves et al., 2020). This is a clear indication of panic buying, because food consumption is generally quite stable over time.
Even though everywhere in the United States supermarkets remained open and there was at no time a real risk of major supply shortages, grocery hoarding seems to be a human reflex in pandemic periods (Bikhchandani et al., 1998). Also, the US media coverage possibly contributed to panic buying, resulting in local and temporary shortages of certain goods (Lusk & McCluskey, 2020).

Third, due to the lockdown measures and as an attempt to decrease personal physical interactions, many people switched to online shopping channels, also for groceries. In March 2020, first-time users made up 41% of US online grocery shoppers (Biggs et al., 2020).

As a result, Amazon Fresh experienced an extraordinary demand increase. According to Bain (2020), the estimated year-over-year increase in the number of Amazon Fresh orders jumped from 139% in January to 323% in March 2020 in the United States. Even though Amazon Fresh increased the numbers of orders they can fulfill by 60%, in April they started to deny new customers to satisfy existing customers’ queries (Bain, 2020).

Presumably, this demand increase does not apply equally to all product categories. There is plenty of anecdotal evidence that customers developed a preference for storable products with a long shelf life such as pasta or canned foods. For the United States, this seems to be true at least for the period until mid-March, that is, until the beginning of the lockdown (Reeves et al., 2020). Lusk and McCluskey (2020) reported that sales of processed foods have increased, partly because of missing cooking skills, partly because in times of uncertainty, consumers prefer familiar comfort foods. There are some insights for Asia, which was hit first by the COVID-19 crisis. E-commerce data for the months of January until March found mixed evidence varying between countries. An analysis for Singapore showed that from January until March 2020, bakery products had the highest growth (+712%), followed by dairy and chilled products (+414%) and food staples (+ 397%; BrandIQ, 2020). In Indonesia, demand increased most for breakfast products (+71%), whereas demand for fresh produce decreased (~5%).

Thus, there are some first insights on consumer behavior during the COVID-19 pandemic—but how about the seller side? One can suspect that the overall price level at Amazon Fresh has increased, first because of the heavy demand increase and secondly because food prices generally increased in the first semester of 2020. The US Bureau of Labor Statistics (2020) documented an increase in food prices during the COVID-19 pandemic, particularly in April and May 2020, with the food consumer price index more than 4% higher compared with the previous year (see Figure 1). Between March and April 2020, the grocery store consumer price index increased by 2.7%. This is the highest monthly increase since the 1970s. A main driver of the nationwide price increase is the food category “Meat, Poultry, Fish, & Eggs” with a year-over-year price increase of 10% in May 2020. Due to

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**Figure 1** Year-over-year difference in the US consumer price index

Source: Own representation based on US Bureau of Labor Statistics (2020)
temporary closures of some meatpacking plants, supplies of many meat products have tightened and prices subsequently increased (Tonsor & Schulz, 2020).

The remainder of this article examines how the online grocer Amazon Fresh adjusted its price-setting throughout the pandemic, both for the overall assortment and for different product groups.

3 | DATA AND METHODOLOGY

Our data consist of daily price quotes collected from the Amazon Fresh website for the customer location Los Angeles (ZIP Code 90001). The dataset covers the period from December 2, 2019 to June 18, 2020. During this period, the website was accessed each day using a Python web scraping script¹ to retrieve product and price information for all items available in 12 major product categories: Baby Foods; Beverages; Breads & Bakery; Breakfast Foods; Candy & Chocolate; Dairy, Cheese, & Eggs; Deli & Prepared Foods; Frozen Foods; Meat & Seafood; Pantry Staples; Produce; and Snack Foods. This results in a sample with over 2 million price observations for 19,118 products (Table 1).²

We split our sample into four periods. The first period, "pre-COVID-19," lasts from December 2, 2019 until the day before the lockdown began in Wuhan, China (22 January 2020). The second period (23 January to 18 March) is the "preparation" phase, during which COVID-19 was spreading across the globe and was a very present topic in the news, but there were no official lockdown measures yet. The third period is the "lockdown," starting on the day of the announcement of the statewide stay-at-home order in California (19 March). Finally, there is the "post-lockdown" period, starting on June 6, 2020, when the stay-at-home order was partly repealed, allowing counties to move ahead following a reopening roadmap (California Department of Public Health, 2020).³

To understand Amazon Fresh’s pricing throughout the COVID-19 crisis, we analyzed how the following variables developed over time.

1. The share of promotional sales prices
   a. of the whole sample;
   b. by-product category.

2. Price levels, measured as median prices
   c. of the whole sample;
   d. by-product category.

A first indication of price development and a potential reaction to demand changes can be the use of promotional sales prices, which is a common pricing and marketing tool in food retail (Bogomolova et al., 2015). For products advertised as promotional sales, there is a higher, crossed-out price next to the currently valid price. Products without this attribute were treated as regular prices. For each day, we calculated the relative share of promotional prices among all price observations. We hypothesized that in times of high demand, fewer promotional sales are needed to attract and to retain customers (Van Heerde et al., 2004; Yeshin, 2006).

¹For more details on the data collection process, see Hillen (2019).
²Missing observations can occur due to technical issues in the data collection or due to temporal unavailability of some products. To obtain continuous time series, we assume the previous day’s price for missing observations. Hence, price changes for these products might be recorded with some delay. Sensitivity analysis with noncontinued time series led to qualitatively very similar results and showed that this approach does not lead to any systematic bias (results available on request). Moreover, the product assortment is not stable over time, but there is a rather large variation in available products throughout the observation period. Restricting the sample to product which are available on min. 95% of all observation days led to qualitatively similar results (results available on request).
³This analysis is based on data until June 2020, and hence only covers the first wave of the pandemic.
To understand how price levels developed over time, we analyzed median prices. In the first step, we calculated for each phase the price difference to the pre-COVID-19 reference phase. Applying Wilcoxon rank-sum tests with continuity correction (Mann & Whitney, 1947), we tested the null hypothesis of identical distributions for prices in the different phases, without having to assume any specific distribution. This price development can give insights into the pricing decisions made throughout the COVID-19 crisis. However, potential differences between the phases could also simply represent seasonal patterns. Therefore, we additionally computed the year-over-year difference, compared with the same dates in 2018 or 2019, and again tested for significant differences using Wilcoxon rank-sum tests. In this comparison with the previous year, we matched products by their unique Amazon Standard Identification Number and only included products that were available in both years at a given date. Through this direct product matching, we filtered out any effects that resulted from changes in the assortment. Unfortunately, this comparison with the previous year is not possible for the share of promotional prices, because we do not have information on promotional sales for the first semester of 2019.

Furthermore, we investigated what drives price increases. We applied a logit model to assess which factors influence the probability of observing a price increase in our sample. The dependent variable $Y_{it}$ is therefore a binary variable taking the value of 1 for all price $p$ changes greater than zero, and 0 for unchanged or decreasing prices compared with the previous day (Equation 1):

$$Y_{it} = \begin{cases} 0 & \text{if } p_{i,t} - p_{i,t-1} \leq 0 \\ 1 & \text{if } p_{i,t} - p_{i,t-1} > 0 \end{cases}$$

### Table 1

Summary statistics of the sample by product category

| Category                        | Products | (% | Observations | (%) |
|---------------------------------|----------|----|--------------|-----|
| Baby Foods                      | 338      | 1.8| 37,466       | 1.9 |
| Beverages                       | 2,609    | 13.6| 256,781      | 12.7|
| Breads & Bakery                 | 609      | 3.2| 52,331       | 2.6 |
| Breakfast Foods                 | 1,017    | 5.3| 102,112      | 5.1 |
| Candy & Chocolate               | 787      | 4.1| 93,616       | 4.6 |
| Dairy, Cheese, & Eggs           | 2,399    | 12.5| 294,115      | 14.6|
| Deli & Prepared Foods           | 696      | 3.6| 74,244       | 3.7 |
| Frozen Foods                    | 2,415    | 12.6| 204,433      | 10.1|
| Meat & Seafood                  | 824      | 4.3| 82,520       | 4.1 |
| Pantry Staples                  | 4,223    | 22.1| 484,161      | 24.0|
| Produce                         | 757      | 4.0| 87,891       | 4.4 |
| Snack Foods                     | 2,444    | 12.8| 249,946      | 12.4|
| Whole Sample                    | 19,118   | 100| 2,019,616    | 100 |

Note: Based on own data collection from December 2, 2019 to June 18, 2020 for the customer location Los Angeles.

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4We used median prices to be robust to outliers. However, we do not have sales figures and cannot weigh products based on their popularity. To ensure that there is no fat tail of very rarely purchased products influencing our results, we also conducted the whole analysis for a small basket of 25 top-selling products (>200 customer reviews each), including popular items from all product categories. For this small basket of goods, we obtained comparable results in all parts of the analysis (results available on request).
\[ P_{it} = P(Y_{it} = 1|X_{it}) = E(Y_{it} = 1|X_{it}) = \frac{1}{1 + e^{-(\alpha + \beta X_{it})}}. \quad (2) \]

Equation (2) is the logit specification that models the probability \( p \) of observing a price increase for product \( i \) at the time \( t \), depending on \( X_{it} \) (a vector of independent variables) and a constant \( \alpha \) (Wooldridge, 2002). Rewriting Equation (2) as a linear term including \( \varepsilon_{it} \) as an independent error term, we get Equation (3), which is then estimated using maximum likelihood

\[ \ln\left( \frac{P_{it}}{1 - P_{it}} \right) = \alpha + \beta X_{it} + \varepsilon_{it}. \quad (3) \]

As independent variables, we included the four phases of the COVID-19 pandemic (pre-COVID-19, preparation, lockdown, postlockdown) as dummy variables. Furthermore, we formed five broad product categories (cat,):

1. Frozen Foods;
2. Pantry Staples;
3. Produce;
4. Perishables (Breads & Bakery; Dairy, Cheese, & Eggs; Meat & Seafood; Deli & Prepared Foods);
5. Other (Baby Foods, Beverages, Breakfast Foods, Candy & Chocolate, Snack Foods).

Moreover, we created a convenience variable, applicable if a product name included one or more of the following words: "canned," "microwave," "minute," "pasta," "quick," or "ready." This variable captured 9.68% of all products and is an attempt to capture convenience products with particularly high demand according to news coverage and anecdotal evidence. To account for interdependencies with the different time phases, we included the two interaction terms \( c \times \text{phase}_{it} \) and \( c \times \text{convenience}_{it} \). These terms would indicate specific scenarios such as, for instance, more price increases for frozen products during the lockdown phase. Equation (4) summarizes the model

\[ \text{logit(price increase}_{it} = \alpha + \beta_1 \text{phase}_{it} + \beta_2 \text{cat}_{it} + \beta_3 \text{convenience}_{it} + \beta_4 \sum (\text{cat}, \times \text{phase})_i + \beta_5 \sum (\text{convenience}, \times \text{phase}) + \varepsilon_{it}. \quad (4) \]

Seeking robustness, we applied clustered standard errors (Petersen, 2009; Rogers, 1993).5

4 | RESULTS

4.1 | Promotional sales development

To obtain a first indicator of the price development at Amazon Fresh, we analyzed how the share of promotional prices developed throughout the pandemic. Figure 2 and Table 2 show that in the pre-COVID-19 phase, around 30% of all prices were advertised as promotional sales. Starting at the end of February, this share rapidly decreased to 23.55% in the lockdown phase in April and May 2020. Even after the end of the official lockdown, this downward trend continued, with now 20.29% promotional prices. This downward trend was more or less pronounced but strongly significant for all

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5As demonstrated by Petersen (2009), clustered standard errors produce unbiased results and are the preferred method to control for heteroscedasticity across individual products. For our panel structure with a very large number of products (clusters), this method has proven more appropriate than fixed-effects models, especially because we do not need to assume that the fixed effects are permanent. In our case, it could for instance be that there are different product fixed effects before and during the COVID-19 lockdown. A potential time effect is addressed parametrically by building phase dummies for the different pandemic phases.
product categories except for Produce. For fresh fruits and vegetables, the share of promotional prices initially had been quite low (17.82%) and temporarily increased during the lockdown phase to 20.11%.

4.2 | Price level development

First, we analyzed how the overall price level developed throughout the different phases of the pandemic. For the whole sample (Figure 3 and Table 3), we found that compared with the pre-COVID-19 phase (median 3.59 USD),
### TABLE 2  Share of promotional sales prices by pandemic phase and product category in percent (%)

| Category                      | Pre-COVID-19 Promo. (%) | Preparation Promo. (%) | Diff. to Pre-COVID-19 | Wilcox. | Lockdown Promo. (%) | Diff. to Pre-COVID-19 | Wilcox. | Postlockdown Promo. (%) | Diff. to Pre-COVID-19 | Wilcox. |
|-------------------------------|-------------------------|------------------------|-----------------------|---------|---------------------|-----------------------|---------|-------------------------|-----------------------|---------|
| Whole Sample                  | 30.26                   | 28.22                  | −2.04                 | ***     | 23.55               | −6.71                 | ***     | 20.29                   | −9.97                 | ***     |
| Baby Foods                    | 33.01                   | 21.30                  | −11.71                | ***     | 20.22               | −12.79                | ***     | 18.44                   | −14.57                | ***     |
| Beverages                     | 33.22                   | 30.79                  | −2.43                 | **      | 25.94               | −7.29                 | ***     | 24.61                   | −8.61                 | ***     |
| Breads & Bakery               | 35.51                   | 36.09                  | 0.58                  |         | 19.62               | −15.89                | ***     | 20.09                   | −15.42                | ***     |
| Breakfast Foods               | 31.03                   | 30.78                  | −0.24                 |         | 27.38               | −3.64                 | ***     | 25.43                   | −5.60                 | *       |
| Candy & Chocolate             | 32.45                   | 29.25                  | −3.21                 | ***     | 21.48               | −10.97                | ***     | 24.31                   | −8.15                 | ***     |
| Dairy, Cheese, & Eggs         | 31.99                   | 30.79                  | −1.20                 |         | 21.24               | −10.75                | ***     | 22.61                   | −9.38                 | ***     |
| Deli & Prepared Foods         | 29.02                   | 26.36                  | −2.66                 | ***     | 23.16               | −5.86                 | ***     | 18.35                   | −10.68                | ***     |
| Frozen Foods                  | 36.04                   | 35.31                  | −0.73                 |         | 27.76               | −8.29                 | ***     | 25.75                   | −10.29                | ***     |
| Meat & Seafood                | 31.22                   | 20.30                  | −10.92                | **      | 18.36               | −12.86                | ***     | 16.18                   | −15.04                | ***     |
| Pantry Staples                | 25.99                   | 24.40                  | −1.59                 | ***     | 19.62               | −6.37                 | ***     | 16.94                   | −9.06                 | ***     |
| Produce                       | 17.82                   | 17.53                  | −0.29                 |         | 20.11               | 2.29                  | ***     | 9.41                    | −8.42                 | ***     |
| Snack Foods                   | 28.51                   | 26.85                  | −1.66                 | ***     | 24.95               | −3.56                 | ***     | 20.69                   | −7.82                 | ***     |

Note: All values are median percentage terms per category and phase. "Wilcox." summarizes the Wilcoxon rank-sum test with continuity correction (H0: median shares in both populations are equal). Significance codes: "***" 0.001; "**" 0.01; "*" 0.05; "." 0.1; "" 1.

Abbreviations: Diff., difference; Promo., promotions.
median prices decreased in the preparation phase to 3.51 USD and then temporarily increased during the lockdown phase (3.64 USD). After the lockdown, prices decreased again (3.50 USD). Although there were significant differences between the different phases (see Wilcoxon rank-sum tests in Table 3), it is difficult to see a clear trend for the whole sample.

Studying the price development in the individual product groups, we found differences between the different product types. For the following categories, prices in the lockdown period significantly increased, compared with the pre-COVID-19 period: Breads & Bakery (+0.25 USD), Deli & Prepared Foods (+0.19 USD), Breakfast Foods (+0.14 USD), Snack Foods (+0.06 USD), and Dairy, Cheese, & Eggs (+0.05 USD). For other product categories, prices in the lockdown period significantly decreased: Meat & Seafood (−0.49 USD),

FIGURE 3 Median price level development throughout the COVID-19 pandemic in USD. Note: Based on own data collection from December 2, 2019 to June 18, 2020 for food prices at Amazon Fresh, customer location Los Angeles. For illustrative purpose, weekly averages are shown.
| Category                  | Pre-COVID-19 | Preparation | Diff. to Pre-COVID-19 | Wilcox. | Lockdown | Diff. to Pre-COVID-19 | Wilcox. | Postlockdown | Diff. to Pre-COVID-19 | Wilcox. |
|--------------------------|--------------|-------------|-----------------------|---------|----------|-----------------------|---------|--------------|-----------------------|---------|
|                          | $p_{\text{median}}$ | $p_{\text{median}}$ | $p_{\text{median}}$ | Wilcox. | $p_{\text{median}}$ | $p_{\text{median}}$ | Wilcox. | $p_{\text{median}}$ | $p_{\text{median}}$ | Wilcox. |
| Whole Sample             | 3.59         | 3.51        | -0.08                 | ***     | 3.64     | 0.05                  | ***     | 3.50         | -0.09                 | ***     |
| Baby Foods               | 1.98         | 1.96        | -0.02                 | ***     | 1.89     | -0.09                 | ***     | 1.74         | -0.24                 | ***     |
| Beverages                | 3.94         | 3.79        | -0.15                 | ***     | 3.69     | -0.25                 | ***     | 3.69         | -0.25                 | ***     |
| Breads & Bakery          | 3.24         | 2.99        | -0.25                 | ***     | 3.49     | 0.25                  | ***     | 3.28         | 0.04                  |         |
| Breakfast Foods          | 3.84         | 3.69        | -0.15                 | ***     | 3.98     | 0.14                  | ***     | 3.65         | -0.19                 | ***     |
| Candy & Chocolate        | 3.35         | 3.18        | -0.17                 | ***     | 3.28     | -0.07                 | ***     | 3.19         | -0.16                 | ***     |
| Dairy, Cheese, & Eggs    | 3.83         | 3.55        | -0.28                 | ***     | 3.88     | 0.05                  | **       | 3.82         | -0.01                 |         |
| Deli & Prepared Foods    | 4.74         | 4.78        | 0.04                  | ***     | 4.93     | 0.19                  | ***     | 4.99         | 0.25                  | ***     |
| Frozen Foods             | 4.10         | 3.99        | -0.11                 | ***     | 4.03     | -0.07                 | *        | 4.13         | 0.03                  |         |
| Meat & Seafood           | 6.49         | 6.41        | -0.08                 | ***     | 6.00     | -0.49                 | ***     | 6.44         | -0.06                 |         |
| Pantry Staples           | 2.90         | 2.94        | 0.04                  | ***     | 2.99     | 0.09                  | ***     | 2.98         | 0.08                  | ***     |
| Produce                  | 3.79         | 3.69        | -0.10                 | ***     | 3.69     | -0.10                 | ***     | 3.49         | -0.30                 | ***     |
| Snack Foods              | 3.48         | 3.36        | -0.12                 | ***     | 3.55     | 0.06                  | ***     | 3.29         | -0.19                 | ***     |

Note: "Wilcox." summarizes the Wilcoxon rank sum test with continuity correction (H0: median prices in both populations are equal). Significance codes: "**** 0.001, "*** 0.01, "** 0.05, "* 0.1," 1. $p_{\text{median}}$, median price, diff., difference.
Beverages (−0.25 USD), Produce (−0.10 USD), Baby Foods (−0.09 USD), Candy & Chocolate (−0.07 USD), and Frozen Foods (−0.07 USD).

Additionally, we computed year-over-year median price differences to see how the price level had developed compared with the same dates in the previous year. Here, we compared only prices of products that were available in both years at a given date. During the pre-COVID-19 phase, the median year-over-year price difference was almost constantly zero. So, there was no general shift in the price level, as Figure 4 and Table 4 show. In the preparation and lockdown phases, there was a small median price decrease of −0.01 USD for the whole sample, indicating that the

FIGURE 4 Year-over-year median price differences matched by-product identification number in USD. Note: Based on own data collection from December 2, 2019 to June 18, 2020 for food prices at Amazon Fresh, customer location Los Angeles. For illustrative purpose, weekly averages are shown.
overall price level had slightly decreased compared with the previous year. At the end of the lockdown phase and throughout the postlockdown phase, we found a rather large drop in the price level of \(-0.20\) USD for the whole sample. Hence, despite the booming demand in the COVID-19 crisis, and despite a rising US food price index, Amazon did not increase the price level but even decreased prices compared with the previous year.

However, there may be differences among the different product categories. Figure 4 illustrates the median year-over-year price difference for the single product groups. It shows that the products in most categories became slightly cheaper during the lockdown phase in 2020 compared with 2019 (Breads & Bakery, Breakfast Foods, Deli & Prepared Foods, Frozen Foods, Meat & Seafood, Pantry Staples, and Snack Foods). For products in other categories, prices remained unchanged (Beverages; Dairy, Cheese, & Eggs; Produce). The two relatively small product categories Baby Foods and Candy & Chocolate experienced large up- and downward price differences without a clear trend and with low statistical significance because of the small number of observations. Overall, these yearly price differences are a lot less pronounced than the differences throughout the different pandemic phases (Figure 3 and Table 3). This is at least partly because here we only compare identical products and have no effects due to assortment changes.

### 4.3 Drivers of price increases

To determine if there were price increases under certain circumstances, we estimated the probability of a price increase, applying a logit model with the pandemic phases and different broad product categories as independent variables. Table 5 summarizes the logit model estimation results. In an alternative model specification, we include the previous week’s number of confirmed COVID-19 cases in Los Angeles county instead of the pandemic phases. The results are qualitatively similar to the results presented in this article and are available on request.
that the pseudo $R^2$ value is quite low with 0.025. This is not surprising because we only included dummies as explanatory variables (Shtatland et al., 2002). The Brier score of 0.018 testifies a reasonably good model fit. This score measures the accuracy of probabilistic predictions for discrete binary outcomes (Brier, 1950; Rufibach, 2010).

The coefficients of the different phases tell us that overall, a price increase was more likely to occur during the preparation (0.545) and the postlockdown phase (1.098) than during the pre-COVID-19 and the lockdown phase.

| Variable                        | Estimate | SE   | z value | AME |
|---------------------------------|----------|------|---------|-----|
| (Intercept)                     | -4.201   | 0.106| -39.628 | ***|
| Preparation                     | 0.545    | 0.196| 2.775   | ** |
| Lockdown                        | 0.059    | 0.259| 0.230   |    |
| Post-Lockdown                   | 1.098    | 0.198| 5.549   | ***|
| Perishables                     | -0.397   | 0.093| -4.286  | ***|
| Produce                         | 0.055    | 0.141| 0.389   |    |
| Pantry Staples                  | -0.123   | 0.051| -1.196  |    |
| Frozen Foods                    | -0.298   | 0.137| -2.172  |    |
| Convenience                     | 0.135    | 0.049| 2.754   | ** |
| Preparation × Perishables       | 0.295    | 0.113| 2.623   | ** |
| Preparation × Produce           | -0.585   | 0.201| -2.913  | ** |
| Preparation × Pantry Staples    | 0.043    | 0.145| 0.296   |    |
| Preparation × Frozen Foods      | 0.190    | 0.178| 1.068   |    |
| Preparation × Convenience       | 0.046    | 0.059| 0.785   |    |
| Lockdown × Perishables          | 0.480    | 0.108| 4.430   | ***|
| Lockdown × Produce              | -0.665   | 0.169| -3.940  | ***|
| Lockdown × Pantry Staples       | 0.276    | 0.136| 2.022   |    |
| Lockdown × Frozen Foods         | 0.871    | 0.296| 2.945   | ** |
| Lockdown × Convenience          | 0.133    | 0.078| 1.704   |    |
| Postlockdown × Perishables      | 0.245    | 0.126| 1.941   |    |
| Postlockdown × Produce          | -1.178   | 0.307| -3.836  | ***|
| Postlockdown × Pantry Staples   | 0.106    | 0.211| 0.501   |    |
| Postlockdown × Frozen Foods     | 0.625    | 0.237| 2.639   | ** |
| Postlockdown × Convenience      | 0.085    | 0.079| 1.082   |    |

Model: Likelihood ratio test: $\chi^2$: 513,361 with $df = 23$; $Pr(>\chi^2) < .0001$

Pseudo $R^2$: 0.025 Brier score: 0.018

Note: Significance codes: "****" 0.001; "***" 0.01; "**" 0.05; "*" 0.1; "." 1. AME, average marginal effect. Robust clustered standard errors are applied. For the phases, pre-COVID-19 (December 2, 2019 to January 22, 2020) serves as reference. For product categories, "Other" (Baby Foods, Beverages, Breakfast Foods, Candy & Chocolate, Snack Foods) serves as reference. Convenience applies to product names with the following keywords: canned, microwave, minute, pasta, quick, ready.
The corresponding average marginal effects (AME, last column) state that on average, the chance of a price increase were 1.0% higher in the preparation phase, and 3.2% higher in the postlockdown phase, compared to the pre-COVID-19 period. The coefficients for the product categories alone state that there was a lower likelihood of price increases for Perishables (AME −0.6%) and Frozen Foods (AME −0.5%) than for the other analyzed broad product categories. The interaction terms between product category and pandemic phase show that during lockdown, there were significantly more price increases for Frozen Foods (AME +2.3%), Perishables (AME +1.0%), and Pantry Staples (AME 0.5%) than before the pandemic. For Frozen Foods and Perishables, this remains valid in the postlockdown period. For Produce, price increases were less likely in all three phases of the pandemic than in the pre-COVID phase (AME preparation: −0.8%, lockdown: −0.9%, and postlockdown: −1.2%). For potentially highly demanded convenience products with one of the keywords (can, microwave, minute, pasta, quick, ready) in the product name, there was overall a slightly higher probability of price increases (AME +0.2%). The interaction terms with the different phases were not significant on a 5% confidence level. So, prices of these products did not increase more often than in the pre-COVID-19 phase. Overall, the marginal effects are very small (<4%) for all individual variables and interaction terms. This indicates that whereas there are some statistically significant differences between product groups and the different pandemic phases, Amazon Fresh did not massively increase prices during some phase or for some product types.

5 | DISCUSSION

We found that the overall food price level at Amazon Fresh for the customer location Los Angeles did not increase during the COVID-19 crisis. Compared with the previous year, the overall price level even slightly decreased. This is particularly surprising because in the rest of the United States, food prices did increase during the pandemic. Nationwide, particularly meat became a lot more expensive, with a year-over-year price increase of 10% in May 2020. In contrast, Amazon Fresh’s meat & seafood prices decreased compared with 2019, most strongly in the lockdown phase in April and May, with median prices 2.5% lower than in the previous year. This finding suggests that Amazon Fresh’s pricing decisions must depend on other factors than general US price trends and the supply situation. Amazon seems to apply its low-price strategy, for which the company is known in other sectors, also to its grocery business and in unusual times of high demand.

Even though there was no general price increase, there were less promotional sales prices during the lockdown period (from 30.3% before COVID-19 to 23.55% during lockdown). It is possible that the heavy demand increase made such measures less necessary to attract and to retain customers. Yet, it is surprising that there is no correlation between the price level and the use of promotional sales prices. This makes us suspect that promotional prices are used more as a marketing and communication instrument than an actual price setting tool.

An analysis of different product categories revealed that during the COVID-19 pandemic, no product group became significantly more expensive compared with the previous year, not even highly demanded pantry staples or convenience products. However, looking at short-term price adjustments during the pandemic, we see that during lockdown, price levels did increase for Breads & Bakery, Deli & Prepared Foods, Breakfast Foods, Pantry Staples, Snack Foods, and Dairy, Cheese, & Eggs. We cannot judge whether the observed price changes for these goods are directly driven by increased demand, and potentially higher willingness to pay, or if they are a result of increased costs such as higher wholesale prices. However, these temporary price increases do not result in year-over-year price increases when we control for changes in the product assortment. Hence, part of these price increases are probably attributable to changes in the assortment. Considering how Amazon Fresh was struggling to satisfy the increased demand, one plausible explanation is that popular low-price products were sold out temporarily. Also, convenience products with presumably particularly high demand during the crisis did not undergo significantly more price increases during the COVID-19 lockdown. Amazon does not seem to consciously increase prices for products with high demand.

For fresh produce, there were fewer price increases during lockdown than for other product groups, and the overall median price level decreased from 3.79 USD in the pre-COVID-19 period to 3.69 USD during lockdown.
One explanation could be that the demand relative to other product groups decreased, because many first-time online grocery customers may have concerns about the quality of fresh produce, without being able to see, feel, and smell it (Wei et al., 2018). Given the short shelf life of produce, a reduced demand may have resulted in decreasing prices. Amazon could use price setting as part of an inventory management strategy, aiming to reduce the total costs of servicing the market (Gallego & Hu, 2014; Herbon et al., 2014).

Some limitations of this study should be mentioned. Because we do not have sales data, we can only make assumptions based on product category or product name, but we do not know which products experienced particularly high demand and how this demand affects the price setting. Furthermore, we do not have data on the inventory or on wholesale prices. It has been shown that Amazon, like many other large online sellers, uses algorithmic pricing (Chen et al., 2016). Such algorithmic pricing can be based on but is not limited to information about customers and demand, inventory, and suppliers’ and competitors’ prices in real time. Because we only have price data, we cannot draw any conclusion on which of these factors contribute to what extent to Amazon Fresh’s price setting. Moreover, we are not able to analyze how the product assortment has evolved over time. When there are missing price observations for some products, we cannot be sure whether this gap is due to technical issues in the data collection process or because the product is sold out or has been taken out of the assortment.

6 | CONCLUSION

We studied the food price setting of Amazon Fresh during the COVID-19 pandemic for the customer location Los Angeles. Our results allow us to draw three main conclusions: First, despite rising food price indices and a strong demand increase, Amazon Fresh’s overall price level did not increase during the COVID-19 pandemic. The company does not seem to take advantage of the sudden surge in demand to increase prices. Our results suggest that also for the grocery sector, Amazon follows its corporate strategy of a strong customer-orientation and its long-term goal to get large market shares, rather than trying to generate short-term profits (Grundy, 2015; Tou et al., 2019). According to the American Customer Satisfaction Index (ACSI) by the University of Michigan, Amazon has repeatedly led the online retailing category and regularly reaches top scores among all companies (ACSI, 2020). It is yet to be seen if this “customer obsession” (Tou et al., 2019) and the demand surge during the COVID-19 pandemic will push Amazon into a leading position in the food retail sector. If they succeed, Amazon Fresh with its low prices will become a challenging competitor to other retailers both online and offline. This is especially true because unlike pure grocery retailers, Amazon can cross-subsidize its low-margin grocery business with profits from the high-margin Amazon Web Services business unit (Aversa et al., 2017).

Second, although there were some differences between product categories, we did not find that products with particularly high demand during the COVID-19 crisis, such as pasta, canned food, frozen foods, and convenience products, became significantly more expensive. For some of these product groups, there were temporary price level increases and more frequent price increases before and/or during lockdown. However, when controlling for assortment changes, these changes did not result in significant price increases compared with the previous year. Although increased demand, a higher willingness to pay, and increased procurement costs may be factors for the price setting at Amazon Fresh, we cannot conclude that there is a general difference in the price setting of storable compared with perishable, or highly demanded compared with less demanded products. However, further research is needed to understand what drives online grocery prices in general and to understand the role of algorithmic pricing in particular.

Finally, we found that the share of prices declared as sales promotions decreased from about 30% in the pre-COVID-19 phase to about 23% during the lockdown phase. However, this reduction in sales promotions did not result in higher price levels. We hence conclude that sales promotions are used more as a marketing and a communication tool than as an actual price setting instrument. In times of heavy demand, such measures may be less necessary to attract and to retain customers.
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DATA AVAILABILITY STATEMENT

Data available on request from the authors.

ORCID

Judith Hillen  http://orcid.org/0000-0001-7216-5531

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**AUTHOR BIOGRAPHY**

Judith Hillen is an agricultural economist and market analyst at the Swiss Federal Research Institute Agroscope. She received her PhD degree in agricultural economics from Göttingen University (Germany) in 2019. Her research focuses on food prices, e-commerce, and international trade.

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