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Same DNA, same location, same price? Price differences across distribution e-channels of a single online retailer

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Abstract

Although price dispersion remains a prominent feature of international and domestic markets, the development of e-commerce has been increasingly promoting uniform pricing. Existing studies suggest that online competition, especially from Amazon, reduces price dispersion within individual retailer's chains and among stores in different chains. Although Amazon's effect on the rivals have been analyzed, little is known about its pricing across own distribution channels. Do pricing strategies differ among Amazon's online channels within a single geographical market? We use a large dataset on grocery price quotes from Amazon's main platform and its subsidiary Amazon Fresh in Berlin, Germany, to test whether those (both pure online) channels apply deviating pricing strategies. Our results indicate that Amazon's channels partially set unequal prices for overlapping parts of the assortment, focus on assortments with different average unit values, and vary in their application of price promotions.[EconLit Citations: E31, L11, M31, Q11].

KEYWORDS

e-commerce, e-marketplaces, online food retailing, price dispersion

Abbreviation: DISQ, Deutsches Institut für Service-Qualität.

1 | INTRODUCTION

The pandemics turned the online grocery retailing from a niche market to an extremely important and thriving market segment almost overnight. When high infection numbers and lockdowns kept people in home office and promoted social distancing, the pleasure of visiting an actual store to enjoy the haptic of the produce and an occasional social interaction seemed to have been re-evaluated and turned some supermarket goers into online shoppers (Institut der deutschen Wirtschaft, 2020). When searching for a retailer to stock up the pantry, consumers sometimes made use of a well-known nonfood address—Amazon, which turned up to be the main winner of the pandemics in the food sector (Lebensmittelzeitung, 2021). Amazon is by far the largest online grocery retailer in the country. Besides the main Amazon platform that mostly sells nonperishable products, Amazon operates its Amazon Fresh subsidiary that has been delivering a full assortment of grocery products in a few large German cities from 2017. Unlike its UK and US version, in Germany, Amazon Fresh operates online only. Our study uses this unique setting of the German online grocery retailing to test whether price strategies differ across (pure online) channels of the largest online retailer in the same geolocation.

Price dispersion is a prominent feature of online (Pan et al., 2004; Stylianou et al., 2005) and offline retailing (De Silva et al., 2019) alike. Online markets are not necessarily more integrated than offline markets (Duch-Brown et al., 2021) and costs of price adjustment still exist online (Böheim et al., 2021). As e-commerce matures, however, markets seem to become more efficient, which manifests itself in higher share of uniform prices within retailers (Ater & Rigbi, 2018; DellaVigna & Gentzkow, 2019) as well as in lower price rigidity (Böheim et al., 2021; Gorodnichenko & Talavera, 2017; Gorodnichenko et al., 2014). For multichannel retailers, price differences across the channels are mostly driven by geographical price dispersion in their offline stores, and the share of uniform prices is higher if the product can be found on Amazon (Cavallo, 2017, 2018). Although Amazon's effect on its competitors' pricing have been analyzed, its within-retailer price dispersion remains a puzzle. Existing evidence often comes from studies that focus either on the Amazon.com data (Cavallo, 2018) or on the data from its grocery subsidiary—Amazon Fresh (Aparicio et al., 2021). As a result, it is challenging to disentangle where the existing cross-study differences come from: product basket choices or heterogeneity in pricing strategies between Amazon's distribution channels. Our study aims to solve this puzzle.

Our analysis builds on the earlier price rigidity literature and especially relates to recent large-scale studies by Aparicio et al. (2021), Cavallo (2018), and Hillen and Fedoseeva (2021), who focus on within-retailer price differences. Although those studies emphasize the importance of geographical location and the role of a different DNA (in the context used to describe the retailer origin [online, offline, hybrid], online vs. offline) in price dispersion, we extend the existing discussion by analyzing Amazon's pricing within the same location among its own electronic-only channels.

In the empirical part, we focus on Germany, which is one of the most important markets for Amazon. Up to now, only scattered case-study evidence of Amazon grocery pricing is available for Germany. Although Fedoseeva et al. (2017) show that prices of pure online retailers (including Amazon) are on average higher than prices of pure offline stores or multichannel retailers, Deutsches Institut für Service-Qualität (DISQ; 2018) reports that Amazon (Fresh) prices are among the lowest, outpacing competitors in two-thirds of examined products.

Amazon.de and Amazon Fresh share the online platform but have differential product baskets and orders placed at each market place are treated separately. There is, however, no information regarding price synchronization across those channels available up to date. We use a rich dataset on grocery price quotes from Amazon.de and Amazon Fresh for food and beverages simultaneously collected for over a year for the same location, Berlin, to shed more light into pricing among Amazon's own marketing channels.

2 | DATA

Our data includes prices for grocery items (in stock, no market place) with their product names, store, product, and product category identifiers for Amazon.de and Amazon Fresh. Data were automatically collected for the location Berlin on the last day of each calendar month between September 2019 and September 2020. When we eliminate duplicates within assortments of both distribution channels, product categories only available on one platform and exclude the top and bottom 0.5% of the observations to avoid extreme values, our sample includes 674,559 items with a unique product identifier (Amazon Standard Identification Number) and 3,369,605 corresponding price entries. In the sensitivity analysis, we test robustness of our conclusions to differently specified cutoff values.

The observed promotional (regular) prices vary from 0.35 to 358.99 (642.36) Euros. The average promotional (regular) price at the main platform is 24.51 (24.58) Euros.[1] Roughly 115,000 price quotes are for products sold via Amazon Fresh. The mean promotional (regular) prices here are 4.04 and 4.18 Euros, respectively. Table 1 reports mean (median) promotional prices for various product categories offered by Amazon.de and Amazon Fresh.

The differences in regular and promotional prices in our sample come from price promotions: there are 108,020 price deals in our data. Of those deals, 89,935 are offered on the main platform and 18,085 on the Amazon Fresh platform. The shares of deals in total assortments are 2.8% and 15.7%, respectively; Amazon Fresh seem to be using price discounts more actively than the main platform. Most deals both in absolute and relative terms are observed in alcoholic beverages, snacks and sweets, and cooking ingredients. In absolute terms, an average deal equals 0.91 Euro at Amazon Fresh and 2.34 Euros at the main platform, a rough equivalent of 22% and 10% of respective average regular prices.

3 | EMPIRICAL STRATEGY AND RESULTS

In our sample, 25,140 products were distributed simultaneously via both channels at the same point of time but not necessarily at all times of data collection, rendering 94,004 price quotes. Most products have identical promotional (regular) prices (39,514 vs. 39,506 identical price pairs, respectively). Roughly 15% products have promotional (regular) prices that vary across channels.

To test whether distribution-channel-specific price differences exist, we regress the natural logarithm of Price (regular, *reg*, or promotional, *pro*) of a product *i* from the product group *j* simultaneously available on the day *t* at both channels *s* on the Amazon Fresh variable (binary, with 1 for price of the product at the Amazon Fresh and 0 otherwise) for the whole group of products, including those that are sold at identical prices (47,002 price pairs, 94,004 obs.) or its subgroups with nonidentical promotional (regular) prices (14,976 vs. 14,992 obs.):

$$\ln Price_{ijts} = a + bFresh_i + \mu_j + \omega_t + e_{ijts} \tag{1}$$

The dependent variable is the natural logarithm of the respective price and its elasticity can be calculated as $(e^b - 1) * 100$. We augment each equation with a full set of time- and product-category-specific effects (ω_t and μ_j, respectively) to control for between-category price heterogeneity and all-product related price variation over time, and cluster SEs at an individual product level to account for potential dependency of product-related residuals. The estimation is performed by means of ordinary least squares using the reg command in Stata15.

[1]Promotional price is the price that a consumer would pay for an item if she would immediately check out (free from eventual delivery costs). Regular price is the price that is usually charged for the item. Unless a promotional price applies (in which case the canceled regular price is given in parenthesis next to promotional price), promotional and regular prices are identical, and are shown as one price on the product homepage (see Hillen, 2021; for a graphical example).

TABLE 1 Mean and median promotional prices at Amazon.de and Amazon Fresh across product categories

	Amazon.de		Amazon Fresh	
	Mean (1)	Median (2)	Mean (3)	Median (4)
Baby food	15.40	9.29	3.13	1.25
Nonalcoholic beverages	23.60	15.86	5.31	2.99
Alcoholic beverages	46.27	31.85	15.30	8.99
Instant meals and conserves	16.71	10.05	2.04	1.76
Cooking ingredients	14.06	8.90	4.39	1.99
Jams and spreads	20.42	12.75	2.96	2.29
Müsli and cereals	17.13	12.68	3.72	2.99
Pantry	17.53	11.94	2.22	1.89
Oil, vinegar, and dips	19.81	12.40	2.92	1.99
Snacks and sweets	17.69	10.12	2.33	1.79
Dairy	25.13	14.99	1.85	1.49
Fruits and vegetables	55.39	44.07	2.97	2.11
Fresh and chilled	32.80	13.97	3.99	2.85
Frozen	12.79	6.95	3.50	2.93
All products	24.51	13.89	4.04	2.19

TABLE 2 Regression results: Amazon-Fresh effect for overlapping and nonoverlapping parts of assortment

	Overlapping assortment					
	At any price		At different prices		Nonoverlapping assortment	
	ln(prom) (1)	*ln(reg)* (2)	*ln(pro)* (3)	*ln(reg)* (4)	*ln(pro)* (5)	*ln(reg)* (6)
Fresh	−0.05***	−0.05***	−0.31***	−0.29***	−1.80***	−1.78***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Constant	0.73***	0.74***	1.04***	1.06***	2.29***	2.29***
	(0.03)	(0.03)	(0.07)	(0.08)	(0.01)	(0.01)
Adj. R^2	0.45	0.45	0.46	0.41	0.24	0.24
Obs.	94,004	94,004	14,976	14,992	3,275,601	3,275,601

Note: Robust SEs clustered at a product level are reported in parentheses. Each model includes a full set of time- and product-category fixed effects (September 2019 and Baby Foods are reference categories).
***$p < 0.001$; **$p < 0.01$; *$p < 0.1$.

For all products simultaneously offered via the main platform and Amazon Fresh (overlapping assortment), irrespective of uniformity of their prices, the Amazon Fresh prices are on average about 4.5% cheaper than those of Amazon.de (Table 2, Columns 1 and 2). Once products with identical prices (zero price difference between Amazon.de and Amazon Fresh) are removed from the sample, the Fresh effect is expectedly larger: the products sold via Amazon Fresh are roughly 26% cheaper than identical products sold on the main platform (Column 3). For regular prices (Column 4), the difference is only slightly smaller, suggesting that only a minor part of price discrepancies across channels is due to the use of deals by the Amazon Fresh. Given that Amazon is known for its dynamic pricing strategies (Chen et al., 2016), it could be possible that the observed price discrepancies in promotional prices are due to such adjustments that took place during the data collection. The deviations that exist for regular prices as well as persistence of such discrepancies over time, however, are more difficult to attribute to data collection issues.

The average unit values of products offered at Amazon Fresh are lower also for nonoverlapping parts of grocery assortments of both distribution channels (Columns 5 and 6). This effect is driven by both Amazon's focus on relatively more expensive product groups in its assortment and offering on average more expensive items within each product category. The average within-product group Fresh effect =− 1.78 (roughly 83% lower unit values than non-Fresh products) and it is virtually the same for promotional and regular prices.

The price gap between the two distribution channels has been increasing over time. Although for nonoverlapping assortment the average Fresh affect increased by about 1 pp (Table 3, Columns 5 and 6), for identical products offered at different promotional (regular) prices the difference in prices increased by roughly 11 (15) pp between September 2019 and 2020 (Columns 3 and 4). Although the magnitude of the price gap for differently priced items of the overlapping assortment rather increased over time, the share nonuniform prices at Amazon.de and Amazon Fresh declined. As a result, the Fresh coefficient becomes both economically and statistically insignificant at the end of the sample period when all identical products distributed via both channels are considered (Columns 1 and 2).

Table 4 illustrates how Fresh-effect differs across individual product groups. The effects are obtained similar to time-specific effects, by interacting the Fresh variable with the set of product-category effects. For nonoverlapping parts of assortment, the negative Fresh-effect is the largest for perishable fresh and chilled products (e.g., fruits and vegetables, and dairy products): here, the difference in the average unit values can be as large as 94% (Columns 5 and 6). As the main platform focuses mostly on storable items and only sells a small selection of fresh products in the long-tail of price distribution, whereas Amazon Fresh covers the basic grocery assortment, such result is plausible. The smallest Fresh effects (77%–80% lower unit values) are observed for alcoholic and nonalcoholic beverages. For overlapping parts of assortment, however, the highest Fresh-related discounts are associated with storable pantry products: jams and spreads, oils, vinegar, and dips, snacks and sweets, whereas little difference can be detected for fresh and perishable products (Columns 3 and 4).

4 | SENSITIVITY ANALYSIS

In the main analysis, we eliminated the top and bottom 0.5% of observations. This has been done to minimize the impact of extreme price quotes and reduce the number of nonfood products that sometimes find their way to Amazon's grocery data. Given that eliminating extreme values and the cutoff value selection has sometimes been criticized as delivering not robust results, we repeat the analysis with other cutoff values as well as with the full sample. Table 5 summarizes the results from our models for identical and nonidentical products when we eliminate 1%, 2.5%, and 5% at the top and bottom of the sample (2%, 5% and 10% observations, respectively) or use all the data available (zero cutoff).

With the higher magnitude of the cutoff value, the Fresh coefficient becomes smaller, as price differences between platforms diminish, but it remains consistently negative and statistically significant. Most discrepancies in results are observed for nonoverlapping parts of assortment. For instance, the magnitude of the Fresh-effect estimated in the Model 5 (nonidentical products, promotional prices), which we discuss in the previous section, is −1.80, which implies that on the average the products sold via Fresh are 83% cheaper than those on the main platform. When the cutoff value increases to 2 (5 and 10)%, the coefficient changes to −1.65, −1.46, and −1.19, respectively. These values suggest that in the adjusted sample, the products in the Amazon Fresh assortment are on the average 81%, 77%, and 70% cheaper than groceries sold at the main platform.

TABLE 3 Time-specific Amazon-Fresh effects for overlapping and nonoverlapping parts of assortment

	Overlapping assortment					
	At any price		At different prices		Nonoverlapping assortment	
	ln(pro) (1)	*ln(reg)* (2)	*ln(pro)* (3)	*ln(reg)* (4)	*ln(pro)* (5)	*ln(reg)* (6)
Sep-2019	−0.10***	−0.10***	−0.25***	−0.24***	−1.79***	−1.78***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Oct-2019	−0.09***	−0.09***	−0.30***	−0.25***	−1.77***	−1.76***
	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)	(0.01)
Nov-2019	−0.11***	−0.10***	−0.35***	−0.31***	−1.77***	−1.76***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.01)	(0.01)
Dec-2019	−0.09***	−0.08***	−0.26***	−0.24***	−1.79***	−1.77***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Jan-2020	−0.12***	−0.11***	−0.32***	−0.29***	−1.80***	−1.77***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Feb-2020	−0.11***	−0.10***	−0.35***	−0.30***	−1.80***	−1.79***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.01)	(0.01)
Mar-2020	−0.02	−0.01	−0.29***	−0.30***	−1.83***	−1.82***
	(0.01)	(0.01)	(0.06)	(0.07)	(0.01)	(0.01)
Apr-2020	−0.02	−0.02	−0.35***	−0.39***	−1.80***	−1.79***
	(0.02)	(0.02)	(0.07)	(0.07)	(0.01)	(0.01)
May-2020	−0.01	−0.01	−0.24*	−0.27*	−1.71***	−1.69***
	(0.02)	(0.02)	(0.11)	(0.11)	(0.02)	(0.02)
June-2020	−0.02	−0.02	−0.32***	−0.34***	−1.83***	−1.82***
	(0.01)	(0.01)	(0.07)	(0.07)	(0.01)	(0.01)
July-2020	−0.01	−0.02	−0.38***	−0.43***	−1.84***	−1.83***
	(0.02)	(0.02)	(0.08)	(0.09)	(0.01)	(0.01)
Aug-2020	−0.02	−0.02	−0.41***	−0.44***	−1.83***	−1.82***
	(0.02)	(0.02)	(0.08)	(0.08)	(0.01)	(0.01)
Sep-2020	−0.02	−0.02	−0.41***	−0.45***	−1.87***	−1.86***
	(0.01)	(0.01)	(0.07)	(0.08)	(0.01)	(0.01)
Constant	0.75***	0.77***	1.01***	1.03***	2.29***	2.29***
	(0.03)	(0.03)	(0.08)	(0.08)	(0.01)	(0.01)
Adj. R^2	0.45	0.45	0.46	0.41	0.24	0.24
Obs.	94,004	94,004	14,976	14,992	3,275,601	3,275,601

Note: Robust SEs clustered at a product level are reported in parentheses. Each model includes a full set of time- and product-category fixed effect. The reported coefficients refer to the product of multiplication between the Amazon Fresh variable and individual time effects.

**$p < 0.01$.; ***$p < 0.001$.; *$p < 0.1$.

TABLE 4 Product-category-specific Amazon Fresh effects for overlapping and nonoverlapping parts of assortment

	Overlapping assortment					
	At any price		At different prices		Nonoverlapping assortment	
	ln(pro) (1)	*ln(reg)* (2)	*ln(pro)* (3)	*ln(reg)* (4)	*ln(pro)* (5)	*ln(reg)* (6)
Baby food	−0.02	−0.02	−0.17	−0.15	−1.67***	−1.66***
	(0.06)	(0.06)	(0.15)	(0.15)	(0.05)	(0.05)
Nonalcoholic beverages	−0.07*	−0.07	−0.34***	−0.33***	−1.48***	−1.46***
	(0.04)	(0.04)	(0.07)	(0.07)	(0.03)	(0.03)
Alcoholic beverages	−0.04	−0.04	−0.18*	−0.22*	−1.61***	−1.59***
	(0.04)	(0.05)	(0.08)	(0.09)	(0.03)	(0.03)
Instant meals	−0.04	−0.04	−0.31***	−0.27***	−1.79***	−1.78***
	(0.03)	(0.03)	(0.08)	(0.07)	(0.02)	(0.02)
Cooking ingredients	−0.05	−0.05	−0.26***	−0.24***	−1.55***	−1.53***
	(0.03)	(0.03)	(0.06)	(0.06)	(0.02)	(0.02)
Jams and spreads	−0.08	−0.07	−0.46***	−0.42**	−1.71***	−1.70***
	(0.04)	(0.04)	(0.12)	(0.12)	(0.03)	(0.03)
Müsli and cereals	−0.02	−0.02	−0.14*	−0.14*	−1.69***	−1.68***
	(0.03)	(0.03)	(0.07)	(0.06)	(0.03)	(0.03)
Pantry	−0.04	−0.03	−0.26**	−0.20*	−1.81***	−1.80***
	(0.03)	(0.03)	(0.08)	(0.08)	(0.03)	(0.03)
Oil, vinegar, and dips	−0.09*	−0.08*	−0.44***	−0.39***	−1.82***	−1.81***
	(0.04)	(0.04)	(0.07)	(0.07)	(0.02)	(0.02)
Snacks and sweets	−0.08***	−0.08**	−0.40***	−0.36***	−1.85***	−1.84***
	(0.02)	(0.02)	(0.05)	(0.05)	(0.02)	(0.02)
Dairy	−0.00	−0.00	−0.15	−0.04	−2.34***	−2.33***
	(0.04)	(0.04)	(0.35)	(0.31)	(0.03)	(0.02)
Fruits and vegetables	−0.01	−0.01	−0.24	−0.26	−2.79***	−2.78***
	(0.15)	(0.15)	(0.46)	(0.46)	(0.03)	(0.03)
Fresh and chilled	−0.01	−0.00	−0.29	−0.09	−1.71***	−1.70***
	(0.06)	(0.06)	(0.25)	(0.23)	(0.02)	(0.02)
Frozen	0.00	0.00	0.01	0.00	−1.39***	−1.38***
	(0.03)	(0.03)	(0.19)	(0.30)	(0.03)	(0.03)
Constant	0.71***	0.73***	0.97***	0.99***	2.28***	2.28***
	(0.04)	(0.05)	(0.11)	(0.11)	(0.01)	(0.01)

(Continues)

TABLE 4 (Continued)

	Overlapping assortment					
	At any price		At different prices		Nonoverlapping assortment	
	ln(pro) (1)	*ln(reg)* (2)	*ln(pro)* (3)	*ln(reg)* (4)	*ln(pro)* (5)	*ln(reg)* (6)
Adj. R^2	0.45	0.45	0.46	0.41	0.24	0.24
Obs.	94,004	94,004	14,976	14,992	3,275,601	3,275,601

Note: Robust SEs clustered at a product level are reported in parentheses. Each model includes a full set of time- and product-category fixed effects. The reported coefficients refer to the product of multiplication between the Amazon Fresh variable and individual product category effects.

***$p < 0.001$; **$p < 0.01$; *$p < 0.1$.

TABLE 5 Amazon Fresh coefficients in all models at different cutoff values

	Overlapping assortment					
	At any price		At different prices		Nonoverlapping assortment	
Cut-off	*ln(prom)* (1)	*ln(reg)* (2)	*ln(pro)* (3)	*ln(reg)* (4)	*ln(pro)* (5)	*ln(reg)* (6)
0%	−0.05***	−0.05***	−0.31***	−0.29***	−1.82***	−1.80***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
0.5%	−0.05***	−0.05***	−0.31***	−0.29***	−1.80***	−1.79***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
1%	−0.05***	−0.05***	−0.30***	−0.29***	−1.65***	−1.64***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
2.5%	−0.05***	−0.05***	−0.28***	−0.28***	−1.46***	−1.45***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
5%	−0.05***	−0.05***	−0.27***	−0.27***	−1.19***	−1.18***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)

Note: Robust SEs clustered at a product level are reported in parentheses. Each model includes a full set of time- and product-category fixed effects and a constant (not reported in the table). Here, 0.5% cutoff is used in the main body of the paper.

$p < 0.1$; **$p < 0.01$; ***$p < 0.001$.

5 | DISCUSSION AND CONCLUSIONS

Media often suggested that the German grocery market would be extremely hard to penetrate for Amazon, citing the low willingness to pay for food and delivery, the high density of supermarkets and discounters, and the wish to inspect the produce before buying it. The pandemic has changed the importance of some those traits and Amazon seems to have noticed it and put the knowledge into building its client base and its loyalty. In the United States, the Amazon Fresh fees were abolished in early 2020 and no increase in grocery prices could be detected even when demand was surging and the food consumer price index went up during the first Covid-19 wave (Hillen, 2020). In the following months, Amazon has launched Amazon Fresh services in Spain and Italy, entered the market of

Poland, and eliminated Amazon Fresh fees in Germany at the end of 2020. Amazon also works on expanding its private label food brands, adding Aplenty to already existing Happy Belly (Silverstein, 2021), and consolidates a number of its services, including Prime Now and Amazon Go under Amazon Fresh (Schader, 2021).

Amazon is the online grocery market leader on the both sides of the Atlantic. In the online and offline grocery retailing combined, Amazon's importance also continues to grow. Already today, Amazon is the second largest grocery retailer in the United States (Progressive Grocer, 2021) and it belongs to the Top-6 grocery retailers in Germany (Hölting, 2017). Amazon's food pricing, however, largely remains terra incognita. Although evidence on nonfood products is abundant, groceries sold by large tech firms have seldomly been in focus of empirical research. The few analyses that exist mostly focus on price rigidity or compare Amazon's prices with competitors' (e.g., see Cavallo, 2018, for the United States), often limiting the data to a relatively small basket of products (e.g., DISQ, 2018, for Germany).

Our paper is an attempt to provide more insights into price differences and their developments between and within Amazon's grocery (online) distribution channels in Germany. Using price quotes for food and beverages from Amazon.de and Amazon Fresh, we show that conclusions from studies that use Amazon's different distribution channels as their data sources are not easily comparable.

Products sold via Amazon Fresh have lower unit values than the products sold via the main platform. There is little overlapping between the products that are simultaneously available in both channels. In line with earlier findings for multichannel retailers, the majority of the prices for identical goods are the same. However, although Cavallo (2017) suggests that the existing price dispersion comes from price variation in the retailers' physical stores with mostly uniform price online regardless of the location of the buyer, our results suggest existence of online price deviations even in the same location. In line with information economics predictions, maturing e-commerce results in lower price dispersion: The proportion of identical prices among goods that are sold via both channels increases over time. When prices of identical goods do not match across the channels, chances are high that the product is offered at a lower price at Amazon Fresh.

For nonidentical products, grocery prices at the Amazon Fresh are on average lower than prices at the main platform. This discrepancy persists also within individual product groups and becomes more pronounced during the sample period. Such low overlapping of assortments and substantial price discrepancies across the channels is consistent with the idea of departing from each other in the product space to avoid cannibalization and reduce cross-channel competition (Gandhi et al., 2008; Sweeting, 2010).

Price promotions are more frequently used at Amazon Fresh when adjusted for the difference in the assortment size. The relative discount offered by Fresh is on average about twice higher than that of the Amazon, although in absolute values the deals are larger at the latter. Over time, the use of deals intensified, but the size of discounts declined.

According to recent research, good quality, timely delivery, an easy online shop navigation, and a strong focus on customer service are essential to pave the path for a strong competitive position in the online grocery market space (Singh & Rosengren, 2020). With its competitive prices and active use of price reductions, paired with the high quality of service, large assortment, and own transport fleet that allows to deliver in time, Amazon Fresh seem to be investing in its reputation. Amazon.de has already found its way to many households: over 44% of the country's population have already ordered at the platform and roughly 17 million have a Prime subscription in Germany (Schamberg, 2016). Making Amazon a viable option when it comes to online food shopping could be another part of becoming a true all-rounder. Dropping the Fresh fee, developing own food brands and keeping a competitive price level with many attractive offers all might be signs that Amazon is on its expansion course in the grocery sector. Furthermore, although increasing the density of the Amazon hubs might take time, an increased awareness of consumers about Amazon's subsidiary as a cheap, reliable, and high-quality provider might also foster Prime memberships and positively spill over to the main platform, which sells even more food and beverages than Fresh and delivers across the whole country.

For research purposes, our results imply that a great caution is needed when comparing results from studies that focus on particular Amazon's branches, as those do not seem to follow similar assortment and pricing strategies.

AUTHOR CONTRIBUTIONS

Authors contributed equally to this manuscript. The order of authorship is alphabetical.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data and code will be made available upon reasonable request.

ETHIC STATEMENT

Not applicable.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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