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Assortments and prices in online grocery retailing

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ABSTRACT

Grocery retailing is undergoing rapid changes. New store formats and market channels, the entry of additional large players, and increasing multichannel activities on the supply side are accompanied by heterogeneous and changing consumer preferences. Retailers are increasingly competing in both price and variety. The question arises: how do product assortments affect retailers' prices? Larger assortments may be attractive for consumers who derive utility from variety or search for niche products. Retailers with a deeper assortment might be in a position to realize higher prices. Our study is the first to quantify the assortment-depth elasticity of price in online retailing, and the magnitude of assortment depth at which a further expansion of the assortment may no longer allow for a higher average price level. We collect a unique dataset for major online full-assortment grocery retailers in Germany and show that an increasing depth of grocery assortment raises online prices. The depth elasticity of price is below unity, and the influence is nonlinear.

1. Introduction

Pricing plays a major role in grocery retailers' marketing activities (Bolton & Shankar, 2018). Increasing multichannel activities, new suppliers and store formats as well as consumers' heterogeneous and changing preferences (González-Benito, Martos-Partal, & Garrido-Morgado, 2018) make retailers compete in both price and variety. For most households, offering more brands in product assortments has a strong and positive effect on store choice decisions (Briesch, Chintagunta, & Fox, 2009). Consumers increasingly mention variety, trust, and convenience as factors that are comparable or even more important than prices in making their online store decisions (HDE, 2020; Seitz, Pokrivčák, Tóth, & Plevný, 2017). While conventional brick-and-mortar stores may be better off following the efficient-assortment hypothesis (Broniarczyk & Hoyer, 2006), online retailers may be able to exploit the long tails of assortment (Brynjolfsson, Hu, & Smith, 2003; Hoskins, 2020). In Germany, larger and not necessarily cheaper online retailers (Fedoseeva, Herrmann, & Nickolaus, 2017), and specialized stores with deep assortments within a limited number of product categories show the highest sales numbers (EHI, 2018). In the literature on consumers' store choice, retailers' assortments and prices have been identified as very important determinants (see Section 2). Typically, assortment and pricing decisions have been analyzed separately although some exceptions exist. Shankar and Bolton (2004) elaborate on the determinants of retailers' pricing decisions in selected U.S. markets. Beyond the strong impacts of competitor factors, they find that store-level variables such as store size and category assortment significantly affect price-promotion activities and relative brand prices. Optimal prices by retailers have been modeled theoretically and depend on their assortment choices and the resulting search processes by consumers (Sun & Gilbert, 2019) and increase with the number of products available in online stores (Li, Lu, & Talebian, 2015). For online markets, empirical studies on the influence of assortment choices on prices are lacking.

The increasing availability of data for online markets allows for the study of linkages between decisions already made by online retailers regarding their assortment strategies and pricing. This study aims to analyze online prices for grocery retailers' assortments using an empirical model that incorporates variables of the variety provided by retailers. It is of particular interest to examine whether retailers offering a larger assortment of products, which may attract consumers who derive utility from variety, are able to set higher prices and whether this relationship reverses when an excessive number of products is offered. The empirical focus is on Germany, and the analysis is based on a unique dataset for seven of the largest online grocery full-assortment retailers which includes over 100 million daily price quotes.

The remainder of the article is organized as follows. In Section 2, we present a short literature review on assortment strategies in retailing and how we extend this literature. In Section 3, we describe the German

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online market for foods and beverages and the raw data. We explain the empirical modeling strategy in Section 4. New evidence is then provided in Section 5 on the influence of the retailers' product assortments on their prices. In Section 6, we discuss main findings and draw conclusions.

2. Retailers' assortment strategies in the literature

A significant part of the business literature on retailers' product assortments has focused on medium- and long-run assortment decisions. Two major determinants have been identified: (i) retailers' costs of an increasing product assortment and (ii) consumers' preferences for more variety. These factors play an important role in competing theories of an "optimal assortment" based on either the "efficient-assortment" or the "long-tail" hypothesis.

Conceptually, assortment strategies have been assessed under the assumptions of utility-maximizing consumers and profit-maximizing retailers by Baumol and Ide (1956). These authors developed a model in which consumers maximize expected utility with regard to two important factors: (i) the attractiveness of a retail store that rises with an increased product assortment due to more choice options, and (ii) the transaction costs due to a store visit, which increase with the assortment as a consequence of higher search costs. The consumer will visit the store if the expected net benefit is positive. Empirical results confirm that retailers' assortments matter for the consumer's selection of a grocery store. Shoppers reported that the most important determinants of their store choices are (i) a convenient location, (ii) low prices, and (iii) an attractive assortment (Arnold, Ma, & Tigert, 1978). In modeling store choice decisions as a function of product assortments, Briesch et al. (2009) identify a convenient location as the most important factor and derive that, "in general, assortments are more important than retail prices in store choice decisions" (ibid., p. 178).

Often, attractive assortments for consumers have been equated with large assortments in terms of breadth and depth, as these signal more choice options. An increasing number of products boosts consumer spending and raises the returns to retailers as long as greater product variety matches consumer preferences (Richards & Hamilton, 2006). From the consumers' point of view, however, larger stores with their higher number of brands and product attributes may lead to an information overload that makes rational decisions more difficult and costly (Dörnyei, Krystallis, & Chrysochou, 2017). Thus, consumers may not necessarily view a larger retail assortment as better. They may prefer smaller stores with fewer choices but lower transaction costs if the assortment matches their tastes (Broniarczyk & Hoyer, 2006). Stores with more or less product variety may coexist as consumers' assortment preferences are heterogeneous.

From the retailers' perspective, a broad and deep assortment in brick-and-mortar stores is often associated with high costs due to many low-selling stock-keeping units (Aurier & Mejía, 2020). Several business-management studies have shown that item reduction towards an "efficient assortment" can raise profits of large retailers even without reducing sales or the number of buyers. It is crucial, however, that the assortment reduction is in line with consumer demand, i.e., restricted to the less preferred items (Broniarczyk, Hoyer, & McAlister, 1998). Having consumers' favored brand in the reduced assortment is one of the strongest drivers that inhibit store switching due to assortment reduction (Gázquez-Abad, Martínez-López, & Sethuraman, 2021). Briesch et al. (2009) provide more details on the structure of assortment that are important for store choice for most households: While the number of brands offered has a positive effect, the number of stock-keeping units per brand, sizes per brand, and the proportion of stock-keeping units that are unique to a store affect store choice negatively. The impacts of an assortment reduction seem to be different on online and offline markets. Borle, Boatwright, Kadane, Nunes, and Shmueli (2005) model the impacts of a large-scale assortment reduction for an online grocery retailer and find a negative impact on overall store sales due to reduced shopping frequency. Apparently, there are stronger arguments for a large assortment on online than on offline markets.

Another important branch of the assortment literature focuses on the relative importance of mass and niche markets, or hit or niche products, in online retailing. There is a major discussion on whether the Pareto principle or the long-tail hypothesis better explains recent trends in online markets. According to the Pareto principle, few best-selling products (e.g., 20%) capture a large revenue share (e.g., 80%). Many markets have been characterized by such a pattern of sales concentration. Recently, Kim, Singh, and Winer (2017) confirmed for a wide variety of consumer-packaged goods that consumer purchases followed the 80:20 rule at the brand level. On the other hand, the long-tail hypothesis suggests that the future of online sales is in niche rather than hit products, or, as Anderson (2006) puts it, in "selling less of more" (products). Increases in the assortment size due to the internet are expected to shift consumption towards products that were formerly less available or less discovered in offline markets. The sales distribution has longer tails in many markets, creating new market opportunities for retailers. Drivers of these long tails in online markets can be expected on the demand side, as the demand for variety comes together with a reduction in search cost, and on the supply side with lower marginal costs of supplying more variety (Hinz, Eckert, & Skiera, 2011). It has also been shown that the reduction in search costs on the internet depends strongly on the search algorithms and recommendation systems provided (Fleder & Hosanagar, 2009; Hinz et al., 2011). Some empirical case studies support the long-tail theory; the relative importance of the long tail has increased on various online markets (Brynjolfsson, Hu, & Simester, 2011; Clemons, Gao, & Hitt, 2006; Hinz et al., 2011).

Our research objective is closely related to consumers' perceptions towards variety and brands in store choice: As information search is costly, rational consumers will often not acquire full information prior to making their choice. If consumers value variety (Bauer, Kotouc, & Rudolph, 2012; Fornari, Fornari, Grandi, Iuffmann Ghezzi, & Menegatti, 2021; Hoch, Bradlow, & Wansink, 1999; Kahn & Lehmann, 1991) and the convenience of one-stop shopping (Borle et al., 2005) or have a strong preference for a brand or store (Anania & Nisticò, 2014; Reichheld & Schefter, 2000), retailers might be able to command and consumers may be willing to accept higher prices associated with these features.

We will test the implications of retailers' decisions on variety (or assortment depth) for prices in online markets. Empirical studies on this linkage are lacking in the literature. Unlike the surveyed literature, which deals with the determinants of medium- and long-run decisions on assortments as a function of its determinants, we treat assortments as independent variables in the short-run pricing decisions. Based on daily observations of prices and assortment depth in online grocery retailing, we will answer four research questions (RQs): (i) Does assortment depth affect prices in e-commerce and is the effect positive? (RQ1); (ii) How large is the effect? (RQ2); (iii) Are nonlinear influences of the independent on the dependent variable relevant? (RQ3); and (iv) Was the linkage between the assortment depth and prices online weakened or strengthened under the Covid-19 pandemic? (RQ4).

The four research questions are answered by using fixed-effects regression models in which price and assortment depth are entered in natural logarithms. Models with a linear as well as a nonlinear, i.e. polynomial, function between these two variables are applied and compared. RQ1 and RQ2 are initially answered with the linear functional form and its constant assortment-depth elasticity of price. The nonlinear model specification is used to answer RQ3 and to assess the validity of the initial answers to RQ1 and RQ2. Linear and nonlinear model specifications are also applied when deriving implications of the Covid-19 pandemic (RQ4).

3. Online grocery retailing in Germany: Overview and data

German retailing is concentrated and highly competitive, with a few

Table 1
Average price and assortment depth (in []) across retailers and product categories.

	Amazon	Amazon Fresh	Edeka	Gourmondo	MyTime	Real	Rewe
Alcoholic beverages	55.39	15.23	11.72	36.67	8.40	9.32	23.29
	[50,740]	[767]	[1025]	[3707]	[874]	[1147]	[2115]
Baby food	16.10	3.35	3.86	n/a	n/a	2.81	4.03
	[3823]	[315]	[466]			[427]	[291]
Cooking ingredients	14.53	2.79	2.14	7.00	2.45	2.16	4.95
	[50,094]	[1028]	[1143]	[386]	[805]	[1412]	[2270]
Dairy	27.10	1.85	2.92	14.57	2.28	1.61	2.23
	[3449]	[940]	[990]	[123]	[665]	[1074]	[938]
Fresh and chilled	36.77	4.14	6.12	22.48	2.69	2.56	7.30
	[4379]	[721]	[1065]	[610]	[352]	[574]	[616]
Frozen products	9.54	3.36	7.11	n/a	3.89	3.54	4.38
	[1199]	[584]	[1996]		[697]	[640]	[571]
Fruits and vegetables	54.84	3.14	2.41	n/a	2.30	2.44	2.98
	[3832]	[162]	[357]		[168]	[349]	[284]
Instant meals	16.69	2.06	2.08	n/a	1.92	1.84	2.96
	[11,351]	[784]	[1264]		[1106]	[781]	[1383]
Jams and spreads	20.38	2.96	3.10	6.74	3.40	3.08	4.22
	[8422]	[342]	[324]	[107]	[223]	[202]	[483]
Muesli and cereals	17.23	3.61	4.26	5.21	2.78	2.85	6.16
	[2766]	[382]	[388]	[24]	[160]	[169]	[430]
Non-alc. beverages	23.95	5.30	5.39	11.95	2.84	4.04	7.07
	[32,355]	[653]	[625]	[500]	[893]	[1257]	[2270]
Oils and vinegar	20.33	2.97	3.15	8.00	2.25	2.44	5.30
	[22,276]	[627]	[409]	[688]	[388]	[434]	[885]
Pantry products	17.82	2.26	2.23	5.68	2.33	1.94	4.02
	[8562]	[323]	[283]	[247]	[197]	[270]	[644]
Snacks and sweets	18.54	2.32	2.32	7.68	2.81	2.16	3.60
	[51,734]	[1108]	[605]	[560]	[1086]	[1025]	[1608]
Mean sample price	26.81	4.05	4.82	24.77	3.30	3.37	7.22
Average daily grocery assortment	252,991	8736	10,938	6952	7614	9763	14,791

retailers controlling the majority of sales. Offline retailing is dominated by discounters and supermarkets, with Edeka and Rewe generating almost 90% of sales. Grocery retailing is one of the fastest-growing online market segments. Most of the grocery sector's sales growth in recent years has been achieved by e-commerce, either by pure online retailers or by marketplaces and online channels of multichannel retailers. 15% of consumers buy a part of their groceries online at least every second week (HDE, 2021), and online channels are increasingly used to stock up on a pantry, manage regular weekly grocery shopping, or search for items that are not easily attainable in offline grocery stores. The Covid-19 pandemic amplified the growth of online retailing: the number of online consumers and their online expenditures increased. In the online grocery sector, revenues increased by almost 60% in 2020 compared to 2019, while the growth in stationary grocery retailing was at 9.5% (HDE, 2021). Most online consumers reported spending considerably more online in 2020 than in previous years and did not foresee a decline in online expenses in the coming years: a trend that was amplified by the pandemic and is likely to outlast it (Jung, Rürup, & Schrinner, 2020; UNCTAD, 2020).

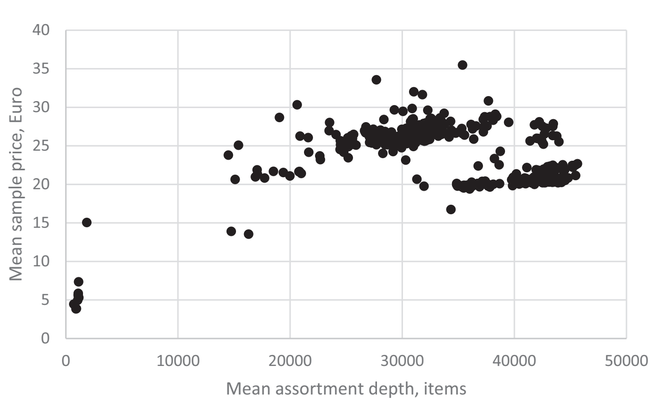

Fig. 1. Mean sample price plotted against average assortment depth.

The market shares in online retailing are split differently from those in offline retailing. Most discounters show little interest in grocery e-commerce, fearing to cannibalize their own store sales (Kantar, 2018). Lidl, the only discounter among the top-15 online retailers for foods and beverages (EHI, 2018), only sells alcoholic beverages besides non-food items in its online shop. In addition to narrowly specialized retailers (vinos.de, hawesko.de, delinat.de, http://mymuesli.com, bofrost.de, whisky.de, wine-in-black.de, worldofsweets.de), multichannel grocery retailers such as MyTime, Rewe and Edeka have been successful in embracing the digital market. The top positions in online grocery retailing, however, are occupied by pure onliners that do not quite resemble a traditional grocery store. While HelloFresh only sells cooking boxes, Amazon.de is mostly associated with non-food products. Yet, it generates the highest sales in German online retailing (EHI, 2018) and has a high household penetration, with almost 20 million Prime members in Germany and 90% of online shoppers buying occasionally at the platform (Schamberg, 2016).

Our data include information on prices and grocery assortments of major German online full-assortment grocery stores. Amazon includes, in addition to its own distributing channel and its pure grocery delivery subsidiary Amazon Fresh, a marketplace that hosts external sellers. In our data, we only include the products that are offered by Amazon itself; no marketplace items are covered. Amazon Fresh has a separate basket and is counted as individual retailer. Gourmondo is another pure online player that focuses on specialties, while other retailers (Edeka's Bringmeister, MyTime, Real and Rewe) belong to multichannel retailers who operate both online and offline.

The data collection took place daily at the same time of the day and for the same zip code in Berlin in order to minimize cross-retailer price differences that are only due to price adjustments within the day or across geographical locations. For each retailer, the number of items in stock available in each product category was calculated. The number of items available in each product category (quantified by the number of unique product IDs) was used as the measure of assortment depth. All data are freely available online and accessible without login. The data collection took place from September 2019 to September 2020, resulting in over 118 million price quotes. Prices are measured in Euro per sales unit. Table 1 reports average assortment depth and mean sample prices across retailers and product categories.

Amazon had the highest depth of assortment across all products and, with the exception of frozen products, in each group. It also had higher average unit values in all product categories. Gourmondo, which specialized on fine foods and beverages, had the second largest unit values across all products and in all but one of their product groups. Gourmondo also ranked second in the assortment depth of the category of alcoholic beverages. The remaining retailers ranked clearly lower in terms of average prices but provided a larger overall assortment than Gourmondo. Fig. 1 depicts average sample prices plotted against assortment depth, hinting at a positive and possibly non-linear (inverse U-shape) relation between the two variables.

4. Empirical strategy

In the empirical part, we randomly draw 10% of the sample observations to investigate the effects of assortment depth on prices with Eq. (1) and to model the potential nonlinearity of the assortment-price relation with Eq. (2) while controlling for unobservable factors by fixed effects:

$$lnPrice_{i,j,k,t} = \alpha + \beta lnDepth_{j,k,t} + \mu_j + \omega_t + \psi_k + e_{i,j,k,t} \quad (1)$$

and

$$lnPrice_{i,j,k,t} = \alpha + \beta lnDepth_{j,k,t} + \gamma (lnDepth)^2_{j,k,t} + \mu_j + \omega_t + \psi_k + e_{i,j,k,t}. \quad (2)$$

Subscripts ***i, j, k*** and ***t*** refer to product, category, retailer and period, respectively. Prices and the depth of assortment enter the regression in natural logarithms, which facilitates the interpretation of results for retailers of very different sizes. Moreover, the linear relation between the (natural logarithm of the) assortment depth and the (natural logarithm of the) price in Eq. (1) will provide us with unitary assortment-depth elasticities of price that amount to the regression coefficient β. This is a convenient feature, but Eq. (1) does not capture possible nonlinearities in the effect of *lnDepth* on *lnPrice*. Eq. (2) allows us to test for nonlinearities in this relation and to estimate the inflection point of the quadratic function.

Other factors besides assortment also influence prices. At the retailer level, store DNA matters as online and hybrid retailers face different costs (Aurier & Mejía, 2020; Bhatnagar & Syam, 2014), while consumer loyalty and trust affect willingness to pay and price sensitivity in e-commerce (Grover, Lim, & Ayyagari, 2006). Over time, both price levels and retailer assortments may be affected by global shocks such as the Covid-19 pandemic (Engemann & Jafari, 2022). Unless we control for retailer-specific and temporal heterogeneity that may affect both prices and assortments in our regression analysis, omitted variable bias remains an issue.

We include product-category fixed effects, μ_j, to isolate differences in price levels between various product categories, daily time effects, ω_t, to control for price changes relevant to all products in the sample, and retailer-specific fixed effects, ψ_k, to account for non-observable retailer heterogeneity (non-food assortment, reputation, business model etc.). In an alternative specification, we use product-category-time fixed effects, $\mu_j \times \omega_t$, to better pinpoint product-category specific price changes over time. The econometric analysis is conducted in Stata15. We use the ***reghdfe*** estimator (Correia, 2017) to deal with the large number of observations and fixed effects. In all specifications, we cluster standard errors at the product level to account for possible within-cluster correlation. We start our analysis with estimations for the grocery assortment over the whole sample period and then assess how the relation between assortment depth and price changed due to the Covid-19 pandemic.

Table 2
The impact of assortment depth on prices.

	lnPrice	*lnPrice*	*lnPrice*	*lnPrice*
lnDepth	0.08***	0.07***	0.48***	0.57***
	(0.00)	(0.00)	(0.01)	(0.01)
lnDepth²			−0.02***	−0.03***
			(0.00)	(0.00)
Const	1.60***	1.67***	−0.24***	−0.52***
	(0.03)	(0.03)	(0.06)	(0.07)
Category fixed effects (FE)	Yes	No	Yes	No
Time FE	Yes	No	Yes	No
Category x Time FE	No	Yes	No	Yes
Retailer FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.39	0.39	0.39	0.40
Observations	11,899,959	11,899,959	11,899,959	11,899,959
Products	772,492	772,492	772,492	772,492
Inflection point			93,501	34,007

Notes: ***, **, * refer to statistical significance at 1, 5 and 10%, respectively. Robust standard errors clustered at the product level to account for possible within-cluster correlation are reported in parentheses.

5. Results

There is a very clear result from the two linear models in Table 2 on RQ1 and RQ2. The effect of retailers` depth of assortment on prices is statistically significant and positive. A 1% increase in assortment depth leads to a 0.07–0.08% increase in prices.

The results from the nonlinear models in Table 2 are more differentiated. Both the regression coefficient of ***lnDepth*** and (***lnDepth)²*** are statistically significant. With regard to RQ3, this suggests a nonlinear influence of ***lnDepth*** on ***lnPrice***. Apparently, the expected percentage change in price depends on the current depth of assortment. It decreases as the depth of assortment increases and eventually becomes negative. The signs of the coefficients indicate an inverse-U functional form.

To illustrate the results from the quadratic equation, Fig. 2 depicts the expected price changes with the depth of grocery assortment under ceteris-paribus conditions of the respective empirical specification (left). The right-hand panel plots the assortment-depth elasticity of price – the expected percentage change of the price level due to a one-percent change in the depth of grocery assortment depending on the existing level of assortment depth.

The inflection point shows the depth of assortment at which the expected change in price becomes negative. The magnitude of the inflection point is high and larger than total grocery assortment of most retailers in our sample, even at its conservative estimate (roughly 34,000 items per product category). This is a depth of grocery assortment that is only relevant for a few product categories of the largest retailer in our sample. In the relevant value range for assortment depth in our sample, which rarely includes assortments with less than 200 and more than 50,000 products per product category (roughly *lnDepth* values between 5 and 11), the predicted assortment-depth elasticity of price varies between 0 and 0.3 (see Fig. 2).

One may question the validity of our answers to RQs 1 and 2, given that Eqs. (1) and (2) represent alternative functional forms and only Eq. (2) allows for a reversal in the sign in the relationship between assortment depth and price. However, the analysis shows that the major conclusions remain valid with nonlinear effects. In the relevant value range, assortment depth affects the price level positively, and the assortment-depth elasticity of price remains clearly below unity. The answers to RQ1 and RQ2 are basically unaffected by the choice of the functional form. As the explanatory power of the nonlinear models is somewhat higher, an argument for Eq. (2) rather than (1) is that it seems better compatible with hypotheses of an inverse U-type functional form from the "more ≠ better" literature on information load and information processing (e. g. Eppler & Mengis, 2004; Guo, 2001).

Splitting the sample into pre-pandemic and pandemic periods

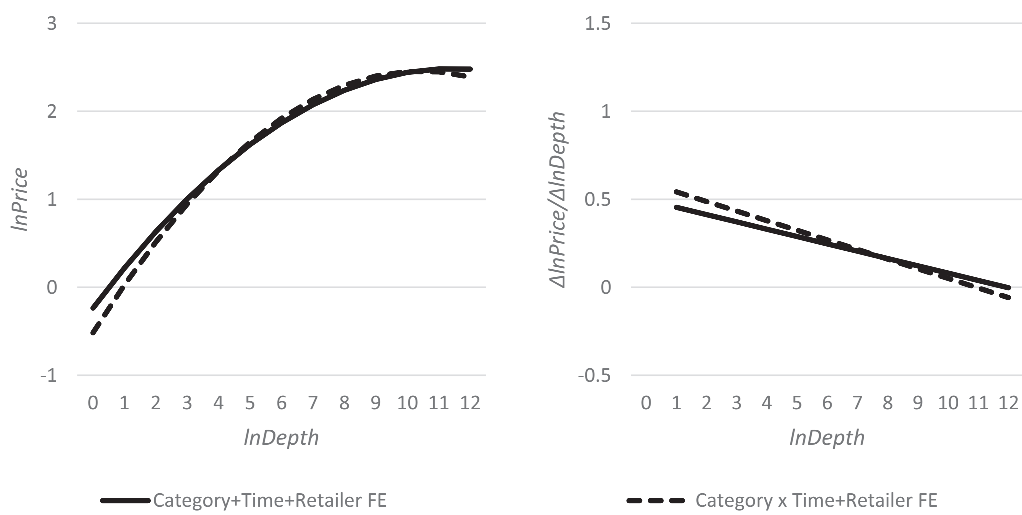

Fig. 2. Predicted values of *lnPrice* (left) and predicted assortment-depth elasticity of price (right) from models with differently specified fixed effects (Eq. (2)).
Notes: Margin plots (left panel) depict how the expected (natural logarithm of) price changes with the (natural logarithm of) depth of grocery assortment under ceteris-paribus conditions of the respective model. Plots of the assortment-depth elasticity of price (right panel) depict the expected percentage change of the price level due to a one-percent change in the depth of grocery assortment depending on the existing level of assortment depth under the ceteris-paribus assumption.

Table 3
Covid-19 effects: Regression results for subsamples before and after March 22, 2019.

	lnPrice		*lnPrice*	
	Pre-pandemic	*Pandemic*	*Pre-pandemic*	*Pandemic*
lnDepth	0.08***	0.06***	0.54***	0.67***
	(0.00)	(0.00)	(0.01)	(0.02)
lnDepth^2			−0.02***	−0.03***
			(0.00)	(0.00)
Const	1.55***	1.89***	−0.47***	−0.76***
	(0.04)	(0.04)	(0.07)	(0.08)
Category x Time FE	Yes	Yes	Yes	Yes
Retailer FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.35	0.46	0.35	0.46
Observations	7,564,482	4,335,477	7,564,482	4,335,477
Products	647,600	486,260	647,600	486,260
Inflection point			47,605	18,087

Notes: ***, **, * refer to statistical significance at 1, 5 and 10%, respectively. Robust standard errors clustered at the product level to account for possible within-cluster correlation are reported in parentheses.

(Table 3) reveals that the unitary elasticity declined from roughly 0.08 in the pre-Covid period to about 0.06 in the linear model during the first wave of Covid-19. We can conclude with regard to RQ4, that the link between assortment depth and price weakened during the pandemic.

To facilitate the interpretation of coefficients from the quadratic model, Fig. 3 plots predicted values of the (logarithm of) price and the predicted assortment-depth elasticity of price using the specification that includes both category-time and retailer-specific fixed effects for two subperiods.

The inflection points in the assortment-price association have shifted to the left during the Covid-19 outbreak, from roughly 48,000 products per category to about 18,000 products between the two subperiods. The magnitude of assortment depth, at which an additional increase in the number of items per product category starts to lower prices, apparently declined with the pandemic.

Even at that lower threshold, the turning point remains solely relevant for the largest retailer in the sample. Using alternative dates for splitting the sample (e.g. January 27, the day when the first Covid-19 case was reported for Germany) does not change our conclusions.

Finally, we use the blocked adaptive computationally efficient outlier nominators (BACON) algorithm proposed by Billor, Hadi, and

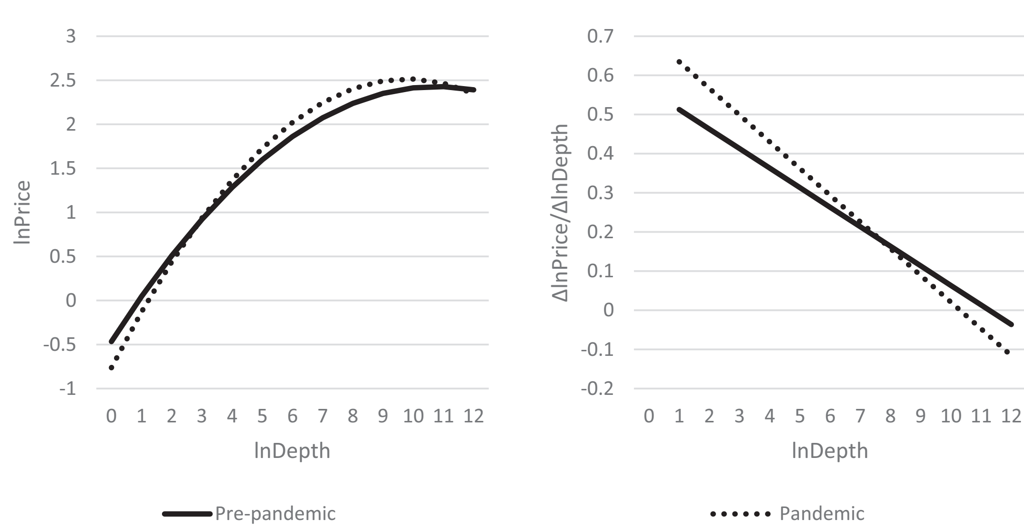

Fig. 3. Predicted values of *lnPrice* (left) and predicted assortment-depth elasticity of price (right) before and after the nationwide lockdown was announced.
Note: The predicted values are derived by estimating Eq. (2) with product-category-time and retailer-specific fixed effects for two sub-samples of data split on March 22, 2020, when the nationwide lockdown was announced.

Table 4
Robustness check: Regression results with BACON outliers (p = 0.20) eliminated.

	lnPrice	*lnPrice*	*lnPrice*		*lnPrice*	
			Pre-pandemic	*Pandemic*	*Pre-pandemic*	*Pandemic*
lnDepth	0.10***	0.66***	0.10***	0.08***	0.61***	0.80***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)
lnDepth^2		−0.03***			−0.03***	−0.04***
		(0.00)			(0.00)	(0.00)
Const	1.42***	−1.09***	1.35***	1.59***	−0.92***	−1.55***
	(0.03)	(0.07)	(0.04)	(0.04)	(0.08)	(0.09)
Category x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Retailer FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.41	0.41	0.36	0.48	0.36	0.48
Observations	11,809,164	11,809,164	7,519,155	4,290,009	7,519,155	4,290,009
Products	767,050	767,050	643,655	481,763	643,655	481,763
Inflection point		47,946			64,271	26,003

Notes: ***, **, * refer to statistical significance at 1, 5 and 10%, respectively. Robust standard errors clustered at the product level to account for possible within-cluster correlation are reported in parentheses.

Velleman (2000) to identify outliers in the data and test the robustness of our conclusions. There are 2,980 BACON outliers at the $p = 0.10$. The outcomes largely remain the same when we adjust the sample so that we do not report them here. Instead, we show results of estimating Eqs. (1) and (2) with product-category-time and retailer-specific fixed effects, including their (pre)pandemic modifications with eliminated outliers at a higher percentile level ($p = 0.20$, with 90,795 BACON outliers) in Table 4.

The explanatory power in the models with eliminated outliers is somewhat higher than in models estimated with all available data points. The estimated coefficients and inflection points have higher magnitudes as well. Our results and conclusions, however, remain confirmed: The impact of assortment depth on price is inelastic, nonlinear, and predominantly positive for the relevant value range.

6. Discussion and conclusion

Our results generally support the price-raising impact of a growing assortment. In the linear model, a 1% increase in the assortment depth results in 0.07–0.08% higher prices. The impact of an increasing assortment depth on prices, however, is not constant, and the price elasticity depends on the status quo of the assortment depth. The assortment-depth elasticity of price is rather small and ranges between 0 and 0.3 for the relevant data space.

The positive link between assortment depth and price reverses at a certain depth of assortment: the influence of assortment depth on price becomes negative at about 34,000 products when all data are included. This threshold was higher before the Covid-19 outbreak and was unreachable for most retailers in the market. After the Covid-19-related lockdown was introduced, the inflection point shifted to about 19,000 items in a product category. This still is a value that is above the total grocery assortment of most retailers in our sample, and it only is relevant for the largest market participant, Amazon, in some of its product categories. From that, we conclude that the relationship between assortment depth and price is nonlinear (as many other relations related to consumer choices), but clearly positive for the data space relevant to all retailers in our sample.

The nonlinearity of the assortment-price link further supports the "more-is-not-always-better" literature even for the case of online retailers. Further, we show that the link between the depth of assortment and prices weakens under crisis circumstances, when logistical challenges outweigh possible benefits of a large assortment. During the first wave of Covid-19, many retailers reported delivery delays or even announced a temporary stop of accepting new clients. Managerial costs in times of excess demand and bottlenecks in the supply chain clearly increase with the size of assortment to be maintained.

Although the inflection points which our analysis reveals are only relevant for a single player in German grocery e-commerce, one needs to remember that Amazon is the leading online food retailer in many countries on both sides of the Atlantic. Consequently, our findings might be relevant also for global markets, at least those where Amazon currently expands its e-grocery business.

To the best of our knowledge, our study is the first one to quantify the assortment-depth elasticity of price in online retailing and the magnitude of assortment depth at which a further expansion of the assortment might no longer allow to realize a higher average price level.

A few words of caution are due here. We look at the impact of assortment depth on the price level in a unidirectional way. This is based on the idea that decisions on the product assortment are predetermined by longer-run strategies and firm size when daily price decisions are made. At least in the medium and longer run, prices and assortment may be jointly optimized. The related literature on joint optimization is, however, concentrated more on analytical concepts than on empirical applications (Chen & Simchi-Levi, 2012).

It is also important to note that the impact of assortment depth on price level was quantified at a highly aggregate level. Prices were measured for online grocery retailers by unit values based on all products and product groups offered. This raises new questions regarding the specific channels that are responsible for the positive effect of assortment depth on prices. It would be particularly interesting to conduct additional case studies on the long tails of the assortment and to determine whether higher prices reflect competitive discoveries of market niches or some degree of market power. This issue is left for future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. This work was supported by the German Research Foundation [FE 1830/1-1].

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