Co-location, good, bad or both: How does new entry of discount variety stores affect local grocery business?

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Abstract

We analyze 69 entries and relocations by the Norwegian discount variety chain Europris during the period 2016 to 2019. We measure how its location choices affect local grocery stores' performance, using a diff-in-diff strategy and data from a large Norwegian grocery chain. We combine detailed data on local grocery stores' sales, traffic and travelling distance to new or relocated Europris stores. We find that entries and relocations have significant effects, suggesting an S-shaped relationship; sufficiently close entries increase local demand since more customers are attracted to the market, but, as the distance increases, the competitive effect of a new discount variety store dominates, and local grocery sales and traffic are reduced. As we move further away, the entry effect is gradually reduced to zero. We show that this empirical finding can be squared with a simple theoretical model. Our results confirm theoretical conjectures on agglomeration forces and competitive effects from local competition.

Keywords: Retail economics, local competition effects, positive agglomeration forces, grocery markets

1 Introduction

In this paper, we explore the rise of discount variety retail and how this has changed the competition towards grocery stores. Over time, grocery stores have broadened their product range into everything from books to consumer electronics. Likewise, we see a growing trend where earlier specialized retailers like "dollar stores" and general hardware stores add groceries to their product range. In 2019, the American discount variety chain Dollar General expanded its product range to also include fresh grocery products, and since 2003 they have offered food products in a number of stores.[1] Today, Dollar General delivers grocery products to more than 9,000 of its total 16,500 locations.

We have also seen a strong trend in retail towards stores co-locating in malls and business areas. In this new retail landscape where different chains may both compete and complement each other, store location choices become less obvious. On one hand, differences in product range might lead to increased traffic and number of customers when stores locate very close to one another. On the other hand, increased local competition for the products that are offered by both chains reduces incentives to co-locate.

To understand how this new mix of product ranges and reduced retail chain specialization affect store localization, we analyze the location behavior of the biggest discount variety chain in Norway, Europris. In particular, we analyze how its location choices affect one of the largest grocery chains in Norway. Europris has been one of the most successful retail chains in Norway, establishing a number of new stores across the country. The grocery chain is among the leading discount grocery players in Norway. It serves more than 20% of the national market alone, and is represented across all major regions in Norway. More than one third of the grocery chain's product categories are also offered by Europris, and in terms of sales, as much as one fourth of the grocery chain's turnover is stemming from these product categories.

Benefiting from a very detailed grocery data set covering all transactions before and after the arrival of competing discount variety stores, we use a diff-in-diff approach to estimate the effect of entry. More specifically, we analyze how sales and customer traffic in local stores within the grocery chain is affected by Europris establishments and relocations as compared to a large control group of grocery stores that are not affected by changes in Europris locations. In all models, we control for local competition and local demographics, including separate detailed control variables varying on the municipal level. We also have detailed information on the product overlap between Europris and the grocery chain, allowing us to estimate separate effects for products that are offered by both chains and products that are only offered by the grocery chain.

In the case we consider, an incumbent grocery store may be affected by the estab-

[1]The first store appeared in 1939, and in 1955 they took the name Dollar General. Hence, only after 64 years did they expand into food items.

lishment of a discount variety store with partially overlapping product ranges in two ways. On the one hand, because the stores only compete on a subset of their product categories, the grocery store may get new customers due to the increased quality of their location stemming from the complementarities across stores. Let us think about this as an increase in the extensive margin: As long as the entering store is differentiated enough with regards to product range, this co-location effect is likely to be positive (positive demand effect). This positive effect of establishment should be stronger the closer the new establishment is located to the incumbent grocery store, and maximized if co-location allows for one-stop shopping. On the other hand, entry will increase competition for the product categories offered by both stores. This can be interpreted as a reduction in the intensive margin: some of the incumbent's existing customers may choose to purchase some products that they used to buy at the incumbent grocery store at the entrant discount variety store (fiercer competition).[2] This effect will be negative, and stronger the closer the establishment is to the grocery store.

The net effect of the two effects outlined above is not clear. Furthermore, while we expect both the positive and negative effects to decrease in size with distance, they may do so at different rates and thereby give rise to a non-monotonic relationship between distance between the stores and sales at the incumbent grocery store. For example, it may be that the agglomeration effect is important when the stores are fairly close, while the competition effect continues to be important also when the distance is relatively large.

In our empirical analysis, we find that one-stop shopping leads to positive agglomeration effects, increasing local demand when new stores enter. Perhaps more surprising, our results provide some support that this holds true both for competing products (offered by both chains) and non-competing products (offered only by the grocery chain). We also find clear evidence for a competitive effect that decreases with distance between the stores. What we find particularly intriguing is that the interplay between the positive agglomeration forces and the competition effect creates an S-shaped pattern: positive agglomeration forces dominate for one stop co-locations, but as stores are located further apart, the negative competition effect gets relatively larger. At some point, the competition effect becomes dominant before it eventually tapers off. The S-shaped relationship between grocery sales and distance to the newly established discount variety store suggests that the interplay of the positive agglomeration effect and the negative competitive effect varies with distance between the stores.

To gain some additional insight into the mechanisms at play, we develop a simple theoretical model that fits our empirical case closely. Using a framework inspired by Hotelling (1927), we consider how an incumbent store is affected by the entry of a competitor in its vicinity. The entrant offers a substitute to one of the incumbent's products

[2]The increased competition might also affect prices, but in our case the incumbent is already using national prices, and thus the effect of the new store will come through changes in sales.

at a lower price. This increases the overall value of shopping in the area where the two stores are located. While greater competition for products that are sold in both stores reduces the incumbent's sales to existing customers, the improved quality of the location attracts new customers. We find that the overall effect on sales may have an S-shape similar to what we observe in the empirical analysis. Assuming that one-stop shopping is feasible and provides an additional benefit, the increased sales to new customers outweigh the lost sales due to existing customers buying the substitute from the entrant. However, if the distance between the stores prevents one-stop shopping, the competition effect prevails. In line with the empirical results, we find that also the competition effect eventually fades out as the distance between the stores becomes sufficiently large.

We now discuss our empirical results in more detail. In our first main empirical analysis, we use a diff-in-diff approach to estimate the effect of establishments of discount variety stores on grocery stores' sales. When we distinguish between the new entries that allow for one-stop shopping and those that require customers to stop twice, we see a distinct pattern: one-stop shopping increases sales by nearly 9%, whereas entries that require the customers to stop twice have a negative impact on the incumbents' sales (-4%). The same pattern holds for store traffic.

The next question we address is how the magnitude of the two effects depend on the distance between the incumbent and the new store. We explore this question by splitting the two-stop shopping entries into different distance bins and re-estimating our models. We now uncover an intriguing pattern. When we move away from one-stop shopping and up to a distance of two km, we find a small negative effect (for competing products) on sales from new entries (-3%). For entries between two and five km away, the negative effect (for all products) is much larger (-7% to -9%), although it gets smaller and ultimately fades off for entries even further away.

We attribute this S-shape to the interplay between the two margins. For the entries relatively close by (250 meters to two km), the extensive margin effect of higher local demand still has some influence, though the intensive margin effect of fiercer competition dominates. As we move further away (in our case beyond two km), the competition effect peaks, generating the maximum negative overall effect. And as we move even further away in distance, the net effect goes towards zero, which is what we would expect given that both effects should taper off eventually. Interestingly, we find much the same pattern for both competing and non-competing product categories, but the effects are, not surprisingly, higher for the former group.

We show that the results are robust to including controls for local competition, demographics and cases where the change in distance is so small that we are unable to tell whether the distance has actually decreased. We also perform a Granger test to examine the presence of anticipatory effects and reverse causality, concluding that the test is consistent with our econometric diff-in-diff models.

Related literature Stahl (1982) was one of the first to model the trend towards co-location and one-stop shopping behavior theoretically. He models how the changes in the sellers' market demand influence location choices. In particular, he decomposes two effects: a negative substitution effect generated by competition for consumers' demand and a positive market area effect generated from joint location of sellers. If the increase in demand from joining the bigger market is higher than the effect of fiercer competition, co-location becomes the optimal choice. This will in turn become a positive externality for the incumbents already there. Stahl finds that co-location is an equilibrium outcome as long as customers are choosy enough about the variety of commodities.[3]

Our study speaks to the empirical literature on store choices. Messinger and Narasimhan (1997) formulate and estimate a model on grocery data that aims to explain the growth in one-stop shopping. Using U.S. data, they find that increased income and reduced store operation costs have both increased supermarket assortment and the gains from one-stop shopping. Over the period 1961-1986 they find that reduction in shopping time has led to a 2.2% reduction of households' expenditures on grocery products. Bell et al. (1998) model store choice behavior based on fixed and variable cost of shopping, attributing the former to the shopping list (products and quantities) and the latter to travel cost and store loyalty. They abstain from differences in store assortment. They also take the model to data for a bigger U.S. city, and find support for fixed cost – shopping list heterogeneity being a major factor behind store choices. Fox et al. (2004) undertake an exploratory analysis estimating a model on consumer reported data on purchases to understand how marketing policies affect shopping behavior across retail store formats. Vitorino (2012) looks at how positive and negative spillovers among firms affect location choices. She finds empirical support for firms co-locating despite potential business stealing effects. Her results suggest that the size of these effects determines the number of firms that can operate in a given local market. Picone et al. (2009) suggest that even if competitive forces make firms prefer distancing, they might end up co-locating because of few location options. Not surprisingly, this seems to be a more likely outcome among firms selling differentiated products. Related to the questions on store choices, Thomassen et al. (2017) study pricing in supermarkets. They estimate cross-category pricing effects, and find that the effects are higher the more consumers that prefer one-stop shopping. This has to do with these consumers being inclined to switch all their purchases to another store in response to a price change on one product category. Since supermarkets fully internalize the cross-category pricing effects (in contrast to specialized stores), one-stop shopping

[3]There are several theoretical studies modelling store choice and store location. Beggs (1994) looks at the rationale for malls rather than large department stores by modelling demand and pricing complementarities. Smith and Hay (2012) model competition between shopping centers, in particular, how agglomeration effects between products are accommodated through different organizational structures and to which extent competition in prices and product quality is internalized. They consider three scenarios: streets (no internalization), malls (developers internalize) and supermarkets (where both shops and developer internalize).

contributes to greater price competition.

Several empirical studies have analyzed spatial competition between retail outlets more generally. Lindsey et al. (1991) analyze the video-cassette-retail market in Alberta to understand product variety and pricing. In a more recent study of the video-retail market, Seim (2006) finds empirical support for firms using spatial differentiation in order to reduce local competition. Smith (2004) estimates consumer choice in the U.K. supermarket industry using data on profit margins to deduct price parameters in consumer utility. Davis (2004) estimates a demand model where products are location specific and consumers have preferences over geographic proximity and store/product characteristics, to understand substitution patterns between U.S. motion picture exhibition theaters. He concludes that travel costs result in limited theater (store) substitutability and localized markets. Houde (2012) estimates a structural model of spatial competition using consumers' commuting paths as instruments for the consumers' locations in a Hotelling-like model, using data from the Quebec City retail gasoline market. Based on the model, he simulates the effects of a merger, and shows that compared to a reduced form diff-in-diff analysis of the actual merger, the spatial model performs well. Turola (2016) estimates the intensity of competition in the French grocery retail sector. She builds a structural spatial competition model, where demand depends on both geography and heterogeneity in the customers' shopping lists. She recovers price-cost margins, and finds that the competitive pressure is very localized and depends on the presence of nearby competitors.

The paper is organized as follows. Section 2 discusses our empirical strategy, Section 3 presents the data and takes a first look at the market. In Section 4 we present and discuss our econometric results, and robustness is discussed in Section 4.3. In Section 5 we present a simple theory framework where we discuss the estimated effects, where we also simulate an outcome mirroring the empirical findings. Section 6 concludes.

2 Empirical strategy

We want to explore how proximity to a discount variety store (in our case, Europris) affects grocery store sales. Our empirical strategy exploits the fact that during our sample period, 69 Europris stores were established or relocated. Some grocery stores in our sample were affected by a Europris establishment in the sense that the distance to the closest Europris store changed after the establishment or relocation, while others were unaffected, enabling us to use a diff-in-diff approach to estimate the effect on grocery store sales of having a discount variety store in the vicinity.[4]

We refer to grocery stores that were affected by Europris establishments as treatment stores and to grocery stores that were unaffected as control stores. We know the distance to the closest Europris store for all the grocery stores in our data set in every week of our sample period. This implies that regardless of whether we look at relocations or new entries, we always consider a change from a given pre-distance. Hence, the estimated effect of a relocation and a new entry will be parallel, and we do not need to distinguish between these when evaluating the results. From now on, we will refer to both of them as establishments. Furthermore, while some of the treated grocery stores ended up with a Europris store next door after an establishment, other treatment stores remained some distance away. This allows us to break down the effect of a Europris establishment by distance bins and to explore how the effect of having a discount variety store close by depends on the distance between the stores. The underlying assumption that allows us to interpret our results causally is that the underlying trend in the grocery store sales is not dependent on treatment status. We provide visual support for this common trend assumption and show a Granger causality test in the Robustness section (section 4.3).

Since both the grocery chain and Europris have national pricing strategies, it is very unlikely that prices in local grocery stores are affected by the distance to the closest Europris store.[5] We are therefore confident that any effects of a Europris establishment will manifest themselves through changes in the sales volume and store visits in the grocery store (rather than in changes in prices).

A central distinction in our analysis is between one-stop and two-stop shopping. In some places, the grocery store and Europris are located close enough to one another for customers to reach both stores from the same parking area. We define one-stop shopping locations as those where the distance between the stores is 250 meters or less. In some

[4]We focus on grocery stores that experience a reduction in distance to the closest Europris store. During our sample period, the locations of all grocery stores are fixed, implying that any changes in distance stem from Europris entries or relocations.

[5]Meile (2020) studies the price setting of Norwegian grocery retail chains empirically, and finds that the grocery chain we consider follows a national, uniform pricing strategy. Uniform national pricing is also confirmed in Friberg, Steen and Ulsaker (2021). Regarding Europris, we look at the information on the chain's website. We find that the online prices (which at least apply to home delivery and in-store pickup) do not differ across stores and that weekly ads apply throughout the chain, suggesting that prices are decided centrally.

of our analyses we lump together all cases where the distance is above 250 meters as two-stop locations, while in other analyses we break down the two-stop locations into distance bins.

3 Data and a first look at the market

3.1 Data

We combine data from several sources. The main data set used in our analyses is sales data received from the grocery chain. We have weekly sales data at the store-category level as well as weekly store visits. We have data from all product categories, which implies that we can both look at total weekly sales at the store level and separate out sales for products that are also sold at Europris. The sample period is from 11 January 2016 to 22 December 2019.

The next step is to compile geographical location data. We obtained data on the address, opening date and closing date (where applicable) of all Europris stores in Norway directly from the chain (Europris, 2020). The data was received on 11 February 2019.[6] The sales data from the grocery chain also contains information about the grocery stores' addresses. The exact locations of the Europris and grocery stores were obtained through Google Maps Platform's Geocoding API.[7]

For a given grocery store in a given week, we want to find the distance and driving duration to the closest Europris store. To calculate distance and duration, we use the routing service of the Norwegian Public Roads Administration (NPRA).[8] For each grocery store and each week, we then use the distance and duration of the closest Europris store that was open in the week in question.

We include a number of additional control variables in our regressions. Statistics Norway publishes yearly municipality level data on persons and land area, as well as median after tax income and the percentage of the population with higher education (Statistics Norway 2020a,b,c). From the grocery chain, we obtained a data set with yearly information about all grocery stores in Norway (from all chains), including information about revenue at the store level. This data set was used to calculate the Herfindahl-Hirschman Index (HHI) at the municipality level, using market shares both at the store level and at the chain level.

3.2 A first look at the market

[6] With updates on 2 July 2019 and 15 May 2020.

[7] See https://developers.google.com/maps/documentation/geocoding/overview for documentation of this service. The locations were obtained on 15 October 2020.

[8] See https://labs.vegdata.no/ruteplandoc/ for documentation of this routing service. The routing service was accessed on 15 October 2020, which means that all duration and distances were calculated with the road network that applied on that date.

3.2.1 Discount variety retail in Norway

Among discount variety retailers in Norway, Europris is the largest with a market share of about 30%.[9] Since its foundation in 1992, both revenues and the number of stores have grown steadily, reaching more than six billion NOK in revenue and 264 stores in 2019. While the compound annual grown rate for total retail was about 3% for 2012-2017, variety retail grew almost twice as fast, suggesting that with overlapping product ranges grocery chains were loosing market shares to variety retail (Europris ASA capital markets day presentation 2018). Few other retail segments than discount variety retailers can look back at a similar increase in revenues in recent years. Table 1 and table 2 show the growth in Europris revenues and the number of store establishments and relocations in the years we consider (Europris ASA annual report 2017; Europris ASA annual report 2019).

Table 1: Europris growth rate 2016-2019

	2016	2017	2018	2019
Growth in Revenues	9.8%	6.6%	7.3%	7.2%

Table 2: Europris establishments and relocations 2016-2019

	2016	2017	2018	2019
New stores	11	11	9	6
Relocated stores	11	7	8	6

According to the latest Shopper Trend report (Nielsen 2020), more than 50% of the respondents answered that they had bought groceries from a discount variety retailer within the last six months, and the store most frequently visited was Europris.

A comparison of the assortment in Europris and the grocery chain shows that the extent of product overlap is large: as much as 35% of the grocery chain's product categories are also sold in Europris stores, and these product categories amount to 25% of the grocery chain's turnover.[10]

The Norwegian producers are more concentrated as compared to producers in other grocery markets e.g., Sweden. This, together with particular high tariff-barriers has led to very strong national brands, and though increasing, private labels have a relatively low share in the Norwegian grocery market. This implies that the same products are

[9] The first and second runners-up, Biltema and Clas Ohlson have approximately 20% and 15% respectively.

[10] To find the product overlap, we first looked up all the product categories that Europris offers online (such as detergent, filter coffee, and pick-and-mix candy). We then compared this to the data set we obtained from the grocery chain, which includes information about product categories.

often found in different stores - even across grocery chains. This is indeed also the case for many of the products that are sold by both Europris and the grocery chain.

The grocery stores

Our data sample consists of 190 distinct grocery stores. The stores are distributed all over Norway, but only stores located in municipalities where Europris establishments or relocations took place during our sample period place are included. Because retail competition is likely to function differently in city centres than in suburban and rural areas, we drop observations in the municipalities of Oslo, Bergen city center and Trondheim city center. In the main analysis, we also disregard stores in the vicinity of Europris entries but where it is unclear whether the distance to the closest Europris store was reduced or not after entry.[11] The number of active grocery stores in a given week ranges from 149 to 180. Figure 1 below shows the distribution of the stores by distance to the closest Europris store in the first and last sample week.

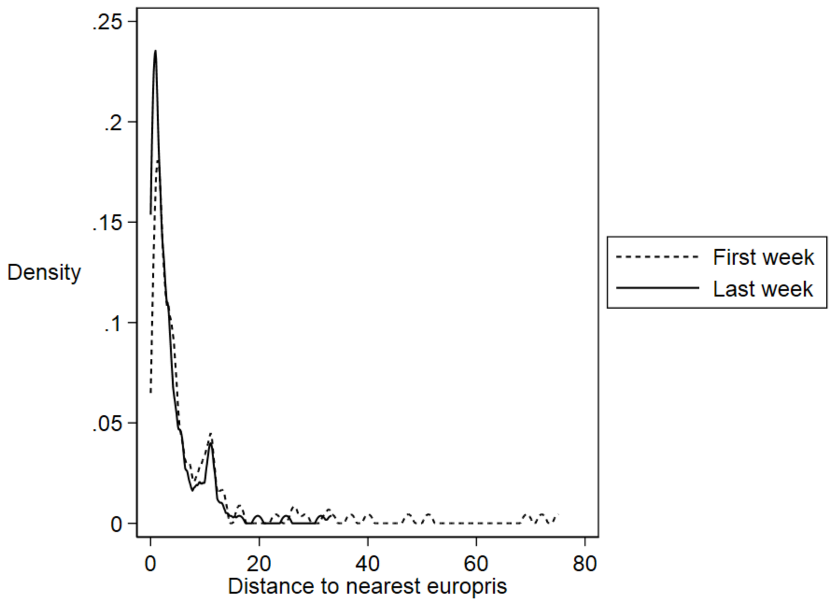


Figure 1: Density of grocery stores over distance to closest Europris store

Most of the grocery stores are located within a few kilometers of a Europris store, and the distribution shifts slightly to the left over the period we consider. In the first week, 134 out of 149 grocery stores are closer than 15 km to Europris. In the last week, the same is true for 175 out of 180 stores. The summary statistics in Table 3 provide closer details.

[11] In some cases, whether or not entry reduces the distance between the grocery store and the closest Europris store depends on the direction of travel or the exact route chosen. In appendix A.3 we include the model outcomes when these additional 16 stores are included

Table 3: Summary statistics

	Count	Mean	Sd	Min	Max	p25	p50	p75
Distance	34228	5.69	10.02	0.00	75.11	1.08	2.71	6.09

The average distance from a grocery store to the closest Europris is 5.69 km. The shortest distance is 0.0 km, while the longest distance is about 75 km.

The main variables of interest are activity indicators: sales and store traffic.[12] Table 4 shows the average store activity across all grocery stores in the data set.

Table 4: Average store activity

	Weekly sales	Store traffic
All stores	1 232 886	5503.63

Distance categories

As we argued above, the effect of establishment may depend on the distance between the stores. Hence, we define the following distance categories:

Table 5: Distance categories

	Distance bin	Binary category
Same parking	1	One stop
250m-2km	2	Two stops
2km-5km	3	Two stops
5km-15km	4	Two stops
More than 15km	5	Two stops

The grocery stores in category 1 are located within 250 meters from a Europris store, which we define as close enough for the customers to visit both the grocery store and Europris in one stop. Table 6 below shows store activity by distance categories.

Table 6: Average store activity by distance category

	Weekly sales	Store traffic	Number of stores
Same parking	1 341 951	5613.08	6
250m-2km	1 275 654	5980.73	67
2km-5km	1 265 425	5516.03	59
5km-15km	1 157 070	5176.06	45
More than 15km	1 076 884	4071.88	13

[12]Store traffic, as measured by the number of receipts, refers to the number of customers visiting per week.

The grocery stores that can be reached from the same parking area as a Europris store have the highest weekly sales and second highest store traffic, while the stores with the longest distance to a Europris store have the lowest turnover and store traffic. Overall, however, the differences are not large between the groups.

The store composition: Control and treatment groups

For descriptive purposes, we consider the 142 stores that are never affected as control stores and the 48 stores that at some point become affected as treatment stores.[13] Table 7 and Table 8 summarize the distance statistics by treatment status.

Table 7: Summary statistics for control group

	Count	Mean	Sd	Min	Max	p25	p50	p75
Distance	24738	4.43	4.76	0	40.07	1.30	2.96	6.04

Table 8: Summary statistics for treatment group

	Count	Mean	Sd	Min	Max	p25	p50	p75
Pre-distance	9490	15.66	19.67	0.41	75.11	3.03	5.67	23.05
Post-distance	9490	3.11	6.32	0.00	31.37	0.31	1.01	2.20
Change	9490	12.55	17.87	0.34	71.76	1.95	3.61	13.18

The average distance to Europris in the control group is 4.4 km, the shortest distance is 0.0 km and the longest distance is 40.1 km. 75% of the stores in the control group are located less than 6.0 km from a Europris store, 50% less than 3.0 km and 25% less than 1.3 km.

Compared to the control group stores that have an average distance to the closest Europris store of 4.4 km, the treatment stores were on average less exposed to Europris prior to the establishments (15.7 km), but are on average more exposed to Europris in the post-period (3.1 km).

Looking at the change within the treatment group, the relocations and new establishments led to an average change of approximately 12.6 km. In the pre-period, 50% of the grocery stores were located less than 5.7 km from a Europris store, and 25% were located less than 3.0 km away. In the post-period, 50% are located less than 1.0 km from Europris and 25% less than 310 meters. This shift is illustrated in Figure 2 below:

[13] Table 1 in Appendix A.1 shows the number of stores by treatment status and distance category.

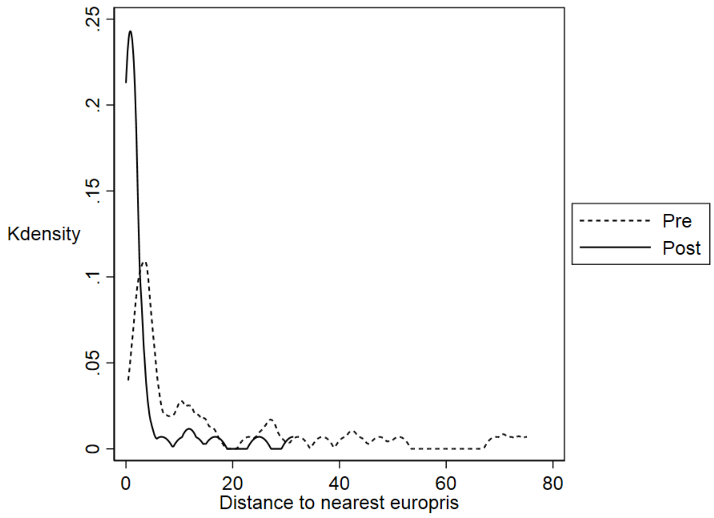


Figure 2: Density of grocery stores in the treatment group over distance

In the first week, 30 treatment stores are closer than 15 km from Europris and 12 stores are further away. In the last week, 46 out of 48 treatment stores are located within 15 km from Europris. Tables 9 and 10 below present the store activity measures by treatment status and whether the established Europris stores can be visited from the same parking area as the grocery stores in the post-period.

Store activity by treatment status

As many as 25% of our grocery stores ended up with a Europris store much closer than previously. As we saw from Figure 2 the shift was significant for most stores. To which extent does this shift result in a change in the activity level? Below in Tables 9 and 10, we scrutinize the change in two measures of activity level.

Table 9: Average weekly sales

	Pre establishment	Post establishment	Overall	Change
Control	-	-	1 196 403	-
One stop	1 381 962	1 622 909	1 546 380	17.44 %
Two stops	1 189 723	1 302 516	1 264 461	9.48 %

Table 10: Average weekly store traffic

	Pre establishment	Post establishment	Overall	Change
Control	-	-	5508.14	-
One stop	6015.57	6552.26	6350.64	8.92 %
Two stops	4975.26	5130.27	5170.74	3.12 %

We find that for both measures, activity increases after the change. There is also a distinct pattern where the effect is between two and three times higher for the one-stop establishments, as compared to cases where customers need to drive between the two stores. However, these figures represent only a before-after effect. Obviously this change might be correlated with market growth stemming from other sources. The table also provides control group averages, and in the next section we will use a diff-in-diff approach where we use the activity development in the 142 non-affected stores as a control for general market growth. Note that we also account for the latter group's distance to the closest Europris stores and store heterogeneity through store fixed effects.

In Tables 2 and 3 in Appendix A.2, we show sales and store traffic by treatment status and post-period distance categories. We observe that generally, the effect from a new establishment falls with distance. For weekly store traffic we even see negative numbers for the 2-5 km bin, or basically no effect (0.93%) for the corresponding bin for weekly sales.

4 A diff-in-diff analysis of co-location effects

The descriptive analysis above suggested that the arrival of a new discount variety store close by affects the activity level of the grocery stores. In fact, to the extent that we could see some clear patterns, co-location – and, in particular, co-location allowing for one-stop shopping – increased the incumbent grocery stores' traffic and sales. Regarding the effect of vicinity in terms of distance when customers need to drive between the stores, the descriptive evidence of an increase in grocery store activity is weaker. Now, we investigate these effects econometrically, where we control both for the development in these measures over time in other grocery stores not affected by establishments, and for the competitive environment faced by the different stores and the demographics of the area.

4.1 Diff-in-diff analysis disregarding product heterogeneity

Our diff-in-diff model includes several control variables for local competition and local demographics. We estimate the following generic model:

$$ln(y_{it}) = \alpha_i + \lambda_t + \eta X_{it} + \beta D_{it} + \epsilon_{it}$$

Where y is a measure of activity, either weekly sales or store traffic. Subscript i, refers to store, and t refers to week. The matrix X_{it} consists of several local controls: Municipality Herfindal-Hirchman indices on grocery store level, grocery chain level and grocery chain-umbrella level to control for local and national competition. Demographics are included through inhabitants per square kilometer, inhabitants per store and the share of higher education in the municipality. All controls are changing annually and by municipality. We include fixed effects for store (α_i) and week-year (λ_t), and we allow for clustered standard errors on the store level.

Our diff-in-diff parameter is β, which measures the effect of the change in distance to the closest Europris store for the stores in the treatment group. D_{it} is thus our treatment variable that for store i in the treatment group takes the value 0 prior to the Europris establishment, and 1 after.

In Table 11 we estimate the overall effect of a reduction in distance to Europris on the grocery store for the two activity measures:

Table 11: Effect of establishment

	Log weekly sales	Log weekly store traffic
Establishment	-0.00428	-0.0125
	(0.0207)	(0.0179)
Store FE	✓	✓
Week-year FE	✓	✓
Control variables	✓	✓
N	32328	32328
r2	0.835	0.839

Clustered (store level) standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Using this overall approach, we find no significant effects of the new arrivals of Europris stores. However, this is an overall average effect that combines the effects from both nearby establishments and more distant ones. As we argued above and later show in a simple theoretical model, there are reasons to believe that the sign of the effect may depend on the distance between the grocery store and the newly established Europris store. We could then fail to find an overall effect even if there are actually significant effects for the different co-location distance bins. Hence, we next differentiate the treatment effect into bins for different co-location distances, and extend the model to allow for more treatment dummy variables:

$$ln(y_{ti}) = \alpha_i + \lambda_t + \eta X_{it} + \sum_b \beta_b D_{itb} + \epsilon_{it}$$

Now, each β_b refers to a separate distance bin. We start by differentiating between one-stop and two-stop shopping: Comparing our distance bin 1 to distance bins 2 to 5 (as defined in Table 5). In Table 12 we show the results:

Table 12: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
One stop	0.0986**	0.0618
	(0.0487)	(0.0405)
Two stops	-0.0390**	-0.0377**
	(0.0189)	(0.0176)
Store FE	✓	✓
Week-year FE	✓	✓
Control variables	✓	✓
N	32328	32328
r2	0.836	0.840

Clustered (store level) standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

In line with the descriptive figures above in Tables 9 and 10, we now obtain a very clear result. For both activity measures we find that one-stop co-location increases the grocery stores' turnover and store traffic in the range of 6% to 10%. The results reported in Table 12 suggest that the net effect of establishment is negative for the grocery stores where one-stop shopping is not possible. This applies to both sales and traffic, considering the reduced activity in the order of -4%. Thus, when accounting for underlying time trends using a control group and when including control variables, the apparent positive effect observed in Tables 9 and 10 only holds for grocery stores where one-stop shopping becomes possible after the establishment of a Europris store. For the other grocery stores, the estimated effect is negative.

That co-location can be beneficial to the incumbent grocery store is in line with most of the models looking at one-stop shopping. The positive effect found for establishments that allow for one-stop shopping suggests that the net effect of the positive agglomeration effect (what we refer to as the extensive margin) and the negative competition effect (what we refer to as the intensive margin) is positive for these stores. We expect that both effects are present also when two stops are required to visit both a grocery store and a Europris store, but that their relative magnitude may depend on the distance between the stores. Our next step is therefore to differentiate the treatment effects even further, allowing for different distance bins for the "two-stop-shopping" group of stores. Now we estimate separate effects for all our five distance bins. The results are shown in Table 13.

Table 13: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
Same parking	0.0986**	0.0619
	(0.0487)	(0.0405)
0.25km - 2km	-0.0296	-0.0276
	(0.0254)	(0.0232)
2km-5km	-0.0808***	-0.0849***
	(0.0193)	(0.0244)
5km-15km	-0.0330*	-0.0273
	(0.0199)	(0.0237)
More than 15km	-0.0170	-0.0120
	(0.0154)	(0.0243)
Store FE	✓	✓
Week-year FE	✓	✓
Control variables	✓	✓
N	32328	32328
r2	0.836	0.840

Clustered (store level) standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Now an interesting pattern emerges. The effect of an establishment is positive when the stores can be reached from the same parking area. When the stores are between 250 meters and two km apart, there is no statistically significant effect. When the distance between the stores is between two and five km, an establishment reduces sales by 8%. When the distance is even larger, the effect diminishes and becomes statistically insignificant for stores where the distance is more than 15 km. Figure 3 illustrates how the effects on grocery weekly sales and traffic vary with distance to the new Europris store. We observe that both activity measures have an S-shaped pattern.

Figure 3: Illustration of estimated S-shape

4.2 Diff-in-diff analysis accounting for product heterogeneity

Clearly, we would anticipate to observe heterogeneous effects of Europris establishments depending on whether we look at competing or non-competing product categories. We now estimate our model where we allow the treatment effect to depend on the product type. Hence, we include product interactions in our model:

$$ln(y_{ti}) = \alpha_i + \lambda_t + \eta X_{it} + \sum_b \beta_b D_{itb} + \sum_b \beta_b^s D_{itb} Comp_i + \epsilon_{it}$$

As before, each β_b refers to separate distance bins, but now we estimate separate effects for all bins for competing product categories (sold by both chains) and non-competing product categories (only sold by the grocery chain).[14] To do so we include separate interactions for each bin, where the indicator $Comp_i$ takes the value 1 for products in categories that are sold by both chains. This allows us to identify separate effects across product groups as measured by the β_b^s. In Table 14 we show the results.

[14] The grocery store data has information about category sales at different levels of aggregation. We consider an intermediate level of aggregation, which refers to categories such as ketchup, chocolate bars and detergents.

Table 14: Effect of establishment by product heterogeneity and distance category (rows 11-15 are gross estimates for the competing product categories calculated from the estimated parameters in the model)

	Log weekly sales
Non-competing, same parking	0.105**
	(0.0480)
Non-competing, 250m-2km	-0.0228
	(0.0257)
Non-competing, 2km-5km	-0.0738***
	(0.0185)
Non-competing, 5km-15km	-0.0330
	(0.0214)
Non-competing, More than 15km	-0.0133
	(0.0155)
Difference competing, same parking	-0.0241**
	(0.00937)
Difference competing, 250m-2km	-0.0263***
	(0.00661)
Difference competing, 2km-5km	-0.0275***
	(0.0101)
Difference competing, 5km-15km	0.000863
	(0.00623)
Difference competing, More than 15km	-0.0115***
	(0.00189)
Competing, same parking	0.0811
	(0.0516)
Competing, 250m-2km	-0.0492*
	(0.0253)
Competing, 2km-5km	-0.101***
	(0.0233)
Competing, 5km-15km	-0.0322**
	(0.0164)
Competing, more than 15km	-0.0249
	(0.0155)
Store FE	✓
Week-year FE	✓
Control variables	✓
N	64656
r2	0.952

Clustered (by stores) standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

In rows 11 to 15 in Table 14, we also calculate the gross effects for the competing product categories and their respective standard errors.[15]

Separating competing and non-competing product categories, we find a similar pattern as we did for all products overall: One-stop shopping increases the activity level, suggesting that the extensive margin dominates. For other distance bins, the estimates are negative, suggesting that the competition effect prevails if the stores cannot be reached from the same parking area. The interaction-term-treatment parameters (β_b^s) are negative and significant for most of the bins, indicating that the competing products are more prone to competition from the Europris stores. For instance, in the groups that have a new Eurpris store two to five km away, the competition effect increases from -7.4% to -10.1%, a difference of 2.7 percentage points that is also highly significant. Additionally, we now find a negative and significant parameter for the competing product categories for the distance bin '250m-2km' which is both bigger (-4.9%) and now significant, as opposed to what we found above for all products. This is what we would intuitively anticipate: competition over products that are offered by both the incumbent grocery store and the entering discount variety store is expected to be higher.

Interestingly, the gross effect for one-stop shopping for the competing product categories is not significant (though with a p-value equal to 0.116). On the other hand, the difference parameter β_b^s for the 'same parking' bin is only significant at a 5% level. Hence, in terms of significance it is not obvious that the effect of co-location with common parking is much different across the product groups. Actually, on a 1% level the models conclude that the effect is the same for the two product groups.

In Figure 4 we illustrate how the effects on grocery weekly sales vary with distance to the new Europris store for competing and non-competing product categories separately. We observe an S-shaped pattern similar to the overall outcome (Figure 3).

[15]The estimates for the competing products categories are simply the sum of the interaction-term-treatment parameters β_b^s and the treatment parameters β_b.

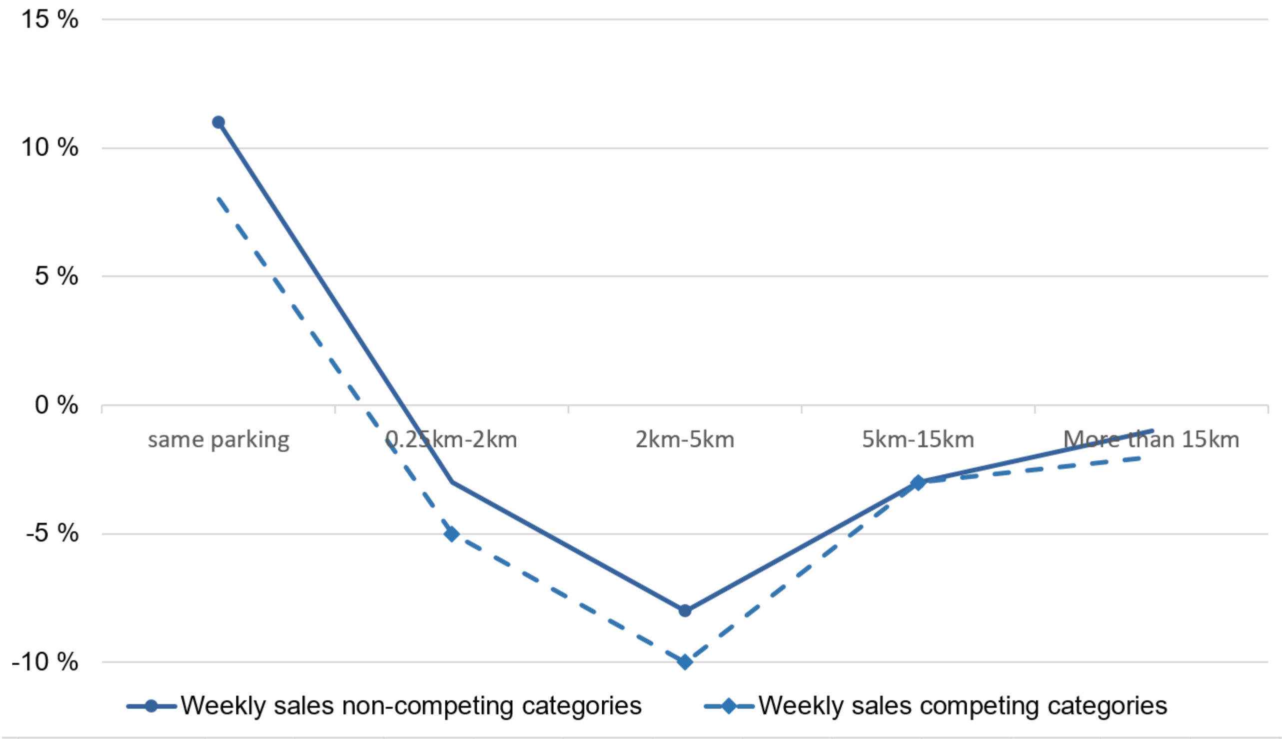


Figure 4: Illustration of estimated S-shape for competing and non-competing product categories, (circles and diamonds illustrate significant estimates)

In Table 14, we look at all competing and non-competing product categories. To explore the individual effects for some particularly relevant categories, we estimate the model for product categories where the grocery chain and Europris clearly compete, and for product categories where there is no competition. First, we estimate the effect for candy, coffee and detergent, categories that are known to be important in the Europris product portfolio, and where a number of strong national brands suggest that the products sold in Europris and the grocery chain really do compete. The results are reported in Table 15 below.

Table 15: Log weekly sales

	Candy	Coffee	Detergent
Same parking	0.0384	0.0840*	0.0575
	(0.0963)	(0.0500)	(0.0641)
0.25km - 2km	-0.158***	-0.00233	-0.124***
	(0.0438)	(0.0318)	(0.0332)
2km-5km	-0.198***	-0.115***	-0.181***
	(0.0608)	(0.0248)	(0.0358)
5km-15km	-0.177***	-0.0994**	-0.159***
	(0.0497)	(0.0441)	(0.0500)
More than 15km	0.127***	-0.0535**	-0.0982**
	(0.0339)	(0.0258)	(0.0443)
Store FE	✓	✓	✓
Week-year FE	✓	✓	✓
Control variables	✓	✓	✓
Control income	✓	✓	✓
N	32236	32298	32325
r2	0.817	0.636	0.833

Clustered (store level) standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

We still find a positive agglomeration effect for same-parking establishments, though only weakly significant for coffee. More noteworthy, we find much stronger competition effects. Already for establishments as close as 0.25-2 km, we see strong competition effects and for the second category (2-5 km), the competition effects are strong (between minus 12-20%) and significant for all three product groups. Turning now to product groups that are not sold in Europris stores, we estimate the effect for bread, fresh chicken and milk, and present the results in Table 16.

Table 16: Log weekly sales

	Bread	Fresh chicken	Milk
Same parking	0.103**	0.139**	0.118**
	(0.0499)	(0.0647)	(0.0544)
0.25km - 2km	-0.0229	-0.0267	-0.0159
	(0.0246)	(0.0361)	(0.0284)
2km-5km	-0.0837***	-0.0451*	-0.0891***
	(0.0281)	(0.0268)	(0.0217)
5km-15km	-0.0111	-0.0426	-0.0131
	(0.0274)	(0.0344)	(0.0102)
More than 15km	-0.0434	0.0120	0.00308
	(0.0488)	(0.0311)	(0.0161)
Store FE	✓	✓	✓
Week-year FE	✓	✓	✓
Control variables	✓	✓	✓
Control income	✓	✓	✓
N	32325	32322	32325
r2	0.882	0.859	0.878

Clustered (store level) standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

The results from the overall regression in Table 14 are enhanced, the local agglomeration effect now varies between 10 and 14%, as compared to 9% for the overall effect for non-competing product categories in Table 14, but we still see evidence of a competition effect from establishments further away.

4.3 Robustness

We perform two different exercises to make sure that our results are not biased by underlying dynamics in the treatment and control groups.

First, we take a closer look at how sales evolve over time in the treatment and control stores prior to the treatment taking place. We plot average monthly sales in Figure 5.

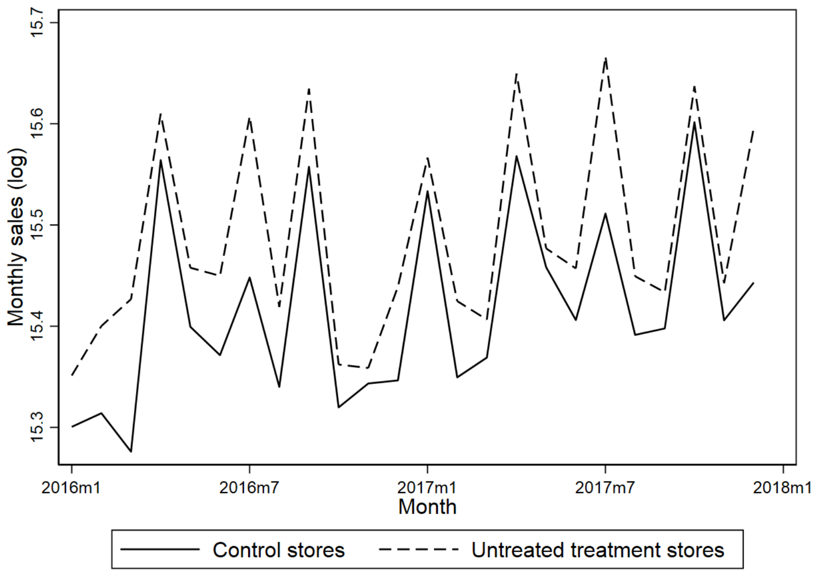


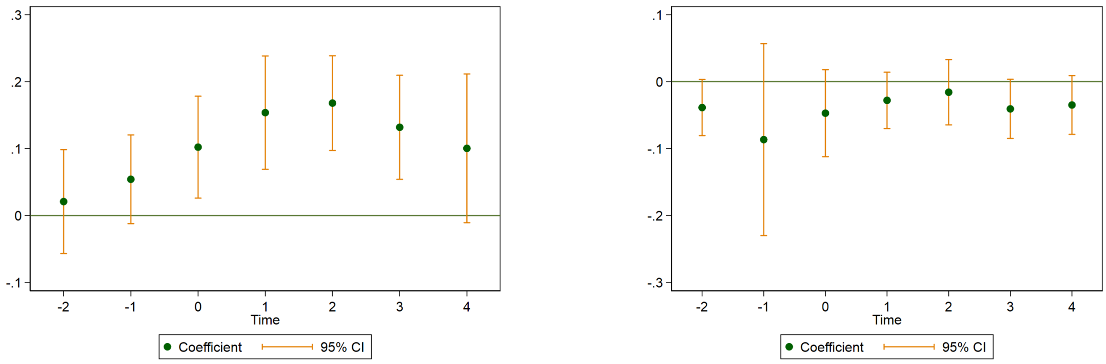
Figure 5: Pre-trends in sales

The dashed line represents the average monthly sales in stores that never receive treatment, while the solid line shows the average monthly sales in treatment stores that have not yet received treatment. The trends in sales in the two groups share dynamics, suggesting that the activity changes in the control and treatment groups have a common trend.

Second, since treatments occur at different times for different stores we choose to also perform a Granger causality test. Following the approach used by Author (2003), we now estimate:

$$ln(y_{ti}) = \alpha_i + \lambda_t + \eta X_{it} + \sum_{\tau=-2}^{-1} \varphi_\tau D_i 1(t - T_i^* = \tau) + \sum_{\tau=0}^{4} \phi_\tau D_i 1(t - T_i^* = \tau) + \epsilon_{it}$$

The binary indicator D_i equals *one* if a store received treatment during the period we consider. We interact D_i with event-time dummies, $1(t - T_i^* = \tau)$. The dummies take on the value *one* when the time of observation (t) is $\tau \in [-2, 4]$ months from the treatment month (T_i^*). Earlier pre-months ($t - T_i^* \leq -2$) serve as baseline. Observations more than four months after a treatment are included through the dummy $1(t - T_i^* \geq 4)$. The coefficients on leads and lags of establishment are represented by φ_τ and ϕ_τ respectively. If it is indeed the case that entries affect store activity, and not the other way around, we expect non-significant leads and significant lags. The results of the estimation are plotted below in Figure 6.



(a) One stop *(b) Two stops*

Figure 6: Event study

Neither the one-stop results (Panel a) nor the two-stop results (Panel b) show significant leads. This suggests that there are no anticipatory effects of establishments. In Panel a, we notice a much higher and significant estimate in the month of establishment, which is also sustained in the subsequent months. The lags provide evidence of increased store activity in the post-periods. In Panel b, the lags are insignificant. Considering that we found no significant treatment effect for half of the distance bins within two stops, this is not surprising. Overall, the panels are consistent with what we observe in our econometric analysis.

We undertake two additional sets of robustness tests. First we include stores that have Europris entries in the vicinity but where it is unclear whether the entries reduce the distance to the closest Europris store (refer Footnote 11). The results are presented in Appendix A.3, Tables 4, 5 and 6. Next, we re-estimate the models excluding our control variables. These results are presented in Appendix A.4, Tables 7, 8 and 9. Generally we get the same results for the whole set of models. There are some marginal changes in significance levels but, generally, all our results are robust to these alternative specifications and data sets.

5 Extensive- and intensive margins: How to understand co-location forces

5.1 A simple theory model

In the empirical analysis we find that whether the grocery store ends up being better or worse off upon Europis' entry depends on the distance between the two stores. We also find a clear S-shaped pattern. The effect ultimately depends on the distance between the two stores. If Europris ends up sufficiently close, the grocery store tends to benefit. In contrast, an establishment that does not bring Europris close enough appears to be harmful. We attribute these findings to the interplay between the extensive margin (increased localized demand) and the intensive margin (fiercer competition and reduced purchases by existing customers). In this section, we develop a simple theoretical example that shows how decomposing the effect into an extensive and an intensive margin provides an intuitive explanation of the results.

Suppose that the market is represented by a line that starts at 0 and ends at an indefinite point. the grocery store is located at $x_G = 0$. It sells n products at a common price p. The customers are uniformly distributed at discrete intervals along the line. They value store proximity, and face travel costs (t) that increase in distance to the grocery store. Hence, the utility a customer located at x obtains from shopping at the grocery store is given by

$$u_G = nv - tx - np$$

Where v is the customer's gross willingness to pay per product. Note that the customers only shop at the grocery store if the utility exceeds their reservation utility u_R [16].

Pre Europris establishment

Consider first a market without a Europris store located close enough to affect the grocery store's demand. The consumer that is indifferent between shopping and not shopping at the grocery store is located at

$$\hat{x} = \frac{nv - np - u_R}{t}.$$

The location of the grocery store and the indifferent consumer is illustrated in figure 7.

[16] The reservation utility reflects the attractiveness of the customers' outside options, such as rival grocery stores.

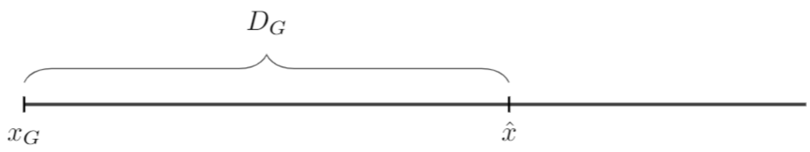


Figure 7: Pre establishment

The figure also shows that the grocery store's demand before a Europris establishment is given by

$$D_G = \hat{x} = \frac{nv - np - u_R}{t}.$$

Post Europris establishment

Suppose then that Europris establishes a store at $x_E \in [0, \hat{x}]$. Europris offers one of the products sold by the grocery store, but at a lower price αp, where $\alpha \in (0, 1)$. The utility of just shopping at the grocery store is unchanged, but the customers might obtain an additional value by purchasing the cheaper product from Europris. Visiting both stores provides a utility equal to

$$u_{E,G} = nv - (n-1)p - \alpha p - tx - t(x_E - x) - F$$

for customers located at $x \in (0, x_E)$, and

$$u_{E,G} = nv - (n-1)p - \alpha p - tx - F$$

for customers located at $x > x_E$ [17]. The parameter F denotes the additional cost that customers face if the stores cannot be visited in one stop, i.e., unless $x_E \leq 250$m. We find that the location of the consumer that is indifferent between just shopping at the grocery store and shopping at both the grocery store and Europris is given by

$$\tilde{x} = x_E - \frac{p(1-\alpha) - F}{t}.$$

The shorter the distance between the grocery store and Europris, the more customers prefer joint shopping. The customer that is indifferent between shopping at both stores and none of them is located at

$$\hat{x}' = \frac{nv - p(n-1) - \alpha p - u_R - F}{t}.$$

[17] These customers pass Europris on their way to the grocery store and no extra travel costs occur. We assume that the customers do not care where on the way Europris is located, only about whether they have to stop once or twice.

Consequently, customers that only shop at the grocery store are located to the left of $\tilde{x}$, while customers who shop at both stores are located between $\hat{x}'$ and $\tilde{x}$. Figure 8 outlines the grocery store's exclusive demand (D_G) and shared demand ($D_{E,G}$).

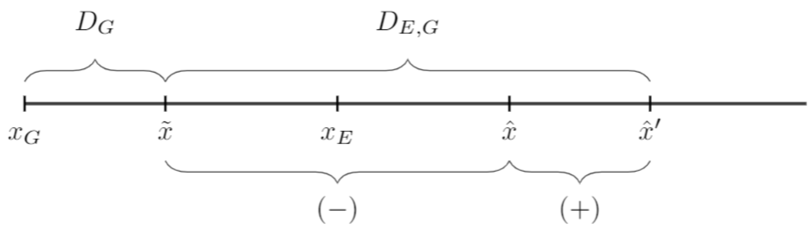


Figure 8: Post establishment

The extensive margin

For customers to the right of x_E, the presence of Europris increases the utility of travelling to the left on the line. As a result, some of the customers that previously did not shop at the grocery store change their mind now that they can visit Europris during the same trip. This effect is what we refer to as *the extensive margin* in response to a Europris establishment. Graphically, the extensive margin is captured by $\hat{x}'$ being located further to the right than $\hat{x}$. New grocery store customers are given by

$$\hat{x}' - \hat{x} = \frac{1}{t}(p(1-\alpha) - F)$$

Since the new customers purchase $(n-1)$ products from the grocery store and 1 product from Europris, the increase in the grocery store's revenue equals

$$(\hat{x}' - \hat{x})p(n-1)$$

The intensive margin

After the Europris establishment, some of the customers who previously purchased all n products from the grocery store decide to purchase the discounted product from Europris. This response to the increased competition is called *the intensive margin.* For the grocery store this effect is always negative as it implies lower demand. A comparison of figure 7 and figure 8 shows how the customers located between $\hat{x}$ and $\tilde{x}$ went from being exclusive grocery store customers to becoming shared customers in the wake of the establishment. Formally, we have that

$$\hat{x} - \tilde{x} = \frac{nv - u_R - p(n-1) - \alpha p - F}{t} - x_E$$

customers purchase less at the grocery store. This corresponds to a revenue loss equal to

$$(\hat{x} - \tilde{x})p$$

The total effect is simply the sum of the gained revenues due to the extensive margin and the lost revenues due to the intensive margin.

5.2 Numerical illustration of the co-location forces

Figure 9 graphs the effect of a Europris establishment on the grocery store revenues. It shows the effects from the extensive margin, the intensive margin and the total. The parameter values are set to $v = 1$, $t = 2$, $\alpha = 0.5$, $n = 10$, $p = 0.75$, $u_R = 0,1$ and $F = 0.33$.

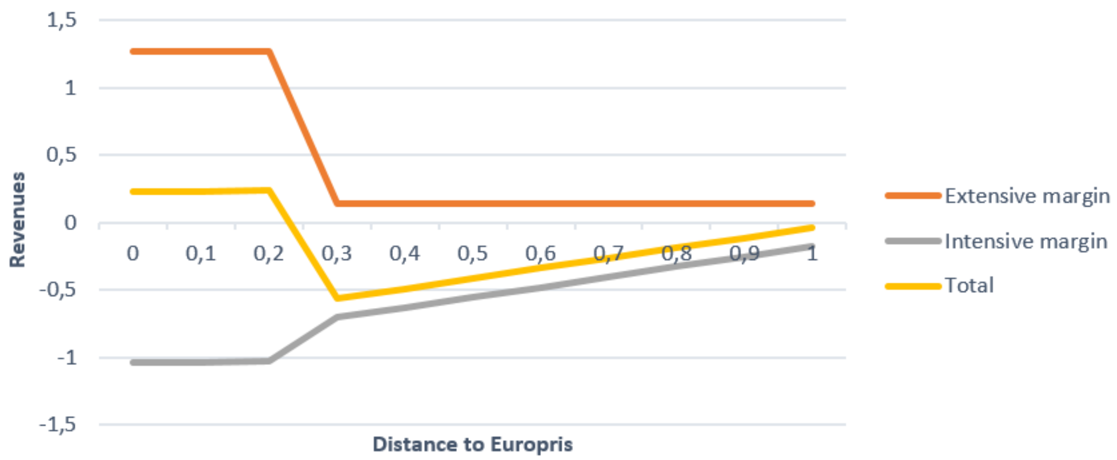


Figure 9: Intensive vs extensive margin

Notice that the effect of the extensive margin is dominating when the distance between Europris and the grocery store is short. There are two main reasons for this. First, the customers do not have to make an additional stop to visit Europris, which attracts more customers. Second, the gain from attracting a new customers is greater than the loss from an exclusive customer turning into a shared customer. Recall that new customers purchase $(n-1)$ products, while shared customers only purchase one product less than before the Europris establishment. However, as the distance between the grocery store and Europris increases, the effect of the intensive margin becomes dominant. When shopping at both stores requires two stops, a Europris establishment might not attract sufficiently many customers for the grocery store to benefit from it. Eventually, the competition effect also fades out and the total effect approaches zero.

While the predictions from our modelling framework will be sensitive to the parameters chosen, we do find in Figure 9 a very similar pattern to the S-shape observed in our empirical analysis, as illustrated in, e.g., Figure 3. The observed and estimated S-shape is thus consistent with a simple theoretical framework.

6 Conclusion

We analyze a number of entries and relocations by the Norwegian discount variety chain Europris during the period 2016 to 2019. We measure how location choices affect local grocery stores' sales and traffic, using a diff-in-diff strategy and data from a large Norwegian grocery chain. We combine detailed data on travelling distance between new entries/relocations and local grocery stores and data on local grocery store activity to measure the entry effects. The granularity of the data enables us to estimate separate effects for competing and non-competing product categories.

We find significant effects from entries and relocations. Moreover, our findings suggest an S-shaped relationship between distance and store activity; sufficiently close entries increase local demand since more customers are attracted to the market, but as the distance increases the competitive effect of a new discount variety store dominates, and local grocery sales and traffic are reduced. As we move further away, the entry effect is gradually reduced to zero. We show that this empirical finding can be squared with a simple location theory model, showing a similar pattern.

When Europris is not locating very close to the grocery chain we consider, it could possibly locate close to a rival grocery chain. This might obviously increase the rival grocery chain's attractiveness, and thus represent a negative competitive effect for our grocery chain. Since we do not control for the neighbouring stores at Europris' new location in our analysis, this effect would be embedded in the negative competition effect we observe in our data. If Europris locates near a rival, it would increase the value of the rival's location and shift more local demand towards the competing grocery store.

Most of the empirical literature accommodating local competition in retail markets treats local competition as a linear effect: the closer a competitor is located, the fiercer the competition (see e.g., Seim (2006) and Picone et al. (2009)). In line with existing literature, we do find that a competitive effect is present, but our results also suggest that this competition effect is dominated by a local and positive agglomeration effect leading to more demand if the distance between stores stores is short enough. However, the agglomeration effect seems to be very local: as soon as the consumer needs to travel even short distances between the stores, the agglomeration effect wears off and becomes dominated by the negative competition effect.

Our results are clearly supporting some of the insights from theory, like Stahl's (1982) conjectures that depending on product overlap and demand heterogeneity co-location can be positive. Moreover, our findings are in line with what others have found, such as Vitorini (2012) who finds empirical support for firms co-locating despite potential business stealing effects. Picone et al. (2009) find that co-location is more likely if the firms sell differentiated products. However, this does not necessarily imply that co-location requires maximal differentiation. Our results suggest that even a relatively large product overlap is compatible with co-location. We complement existing literature by providing evidence that the net effect of agglomeration forces and competitive pressure depends on the distance between the stores.

Our results also have relevance for the ongoing public discussion on store location policies in several countries. Some countries (e.g., Denmark and Sweden) have imposed local competition regulations regarding new store locations to maximise local competition. Our results seem to support the development of larger areas where several shops can be established (e.g.in malls), sharing joint parking areas rather than regulating areas for single store establishments. The stores can anticipate higher local demand, though they will be exposed to a competitive effect from stores offering competing products. The first effect is obviously positive to the retail firms. The latter effect is not, but it is positive for the consumers.

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Appendix

A.1 Store number by distance category and treatment status

Table 1: Number of stores

	Number of stores
Control	142
Same parking	13
250m-2km	23
2km-5km	6
5km-15km	3
More than 15km	3

A.2 Store activity distance bins and treatment status

Table 2: Average weekly sales

	Pre establishment	Post establishment	Overall	Change
Control	-	-	1 196 403	-
Same parking	1 381.962	1 622 909	1 546.38	17.44 %
250m-2km	1 247.753	1 402 328	1 343.209	12.39 %
2km-5km	1 227.563	1 239 016	1 251.796	0.93 %
5km-15km	814 134	848 312	842 879	4.20 %
More than 15km	1 044 728	1 118 496	1 107 640	7.06 %

Table 3: Average weekly store traffic

	Pre establishment	Post establishment	Overall	Change
Control	-	-	5508.14	-
Same parking	6015.57	6552.26	6350.64	8.92 %
250m-2km	5214.69	5481.83	5490.48	5.12 %
2km-5km	5421.41	5189.43	5382.92	-4.28 %
5km-15km	3636.14	3665.31	3687.39	0.80 %
More than 15km	3586.40	3781.66	3778.39	5.44 %

A.3 Include unclear treatment stores

Table 4: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
One stop	0.0948**	0.0600
	(0.0441)	(0.0367)
Two stops	-0.0446***	-0.0405***
	(0.0165)	(0.0155)
Store FE	✓	✓
Week-year FE	✓	✓
Control variables	✓	✓
N	34835	34835
r2	0.844	0.847

Clustered (by store) standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
Same parking	0.0951**	0.0604
	(0.0441)	(0.0367)
0.25km - 2km	-0.0228	-0.0195
	(0.0222)	(0.0202)
2km-5km	-0.0861***	-0.0812***
	(0.0170)	(0.0205)
5km-15km	-0.0771**	-0.0718*
	(0.0368)	(0.0391)
More than 15km	-0.0180	-0.0114
	(0.0142)	(0.0225)
Store FE	✓	✓
Week-year FE	✓	✓
Control variables	✓	✓
N	34835	34835
r2	0.845	0.847

Clustered (by store) standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 6: Effect of establishment by product heterogeneity and distance category (rows 11-15 are gross estimates for the competing product categories calculated from the estimated parameters in the model)

	Log weekly sales
Non-competing, same parking	0.102**
	(0.0434)
Non-competing, 250m-2km	-0.0169
	(0.0224)
Non-competing, 2km-5km	-0.0813***
	(0.0167)
Non-competing, 5km-15km	-0.0772**
	(0.0372)
Non-competing, More than 15km	-0.0142
	(0.0143)
Difference competing, same parking	-0.0252***
	(0.00855)
Difference competing, 250m-2km	-0.0228***
	(0.00616)
Difference competing, 2km-5km	-0.0200**
	(0.00843)
Difference competing, 5km-15km	0.00110
	(0.00419)
Difference competing, More than 15km	-0.0114***
	(0.00183)
Competing, same parking	0.0814*
	(0.0469)
Competing, 250m-2km	-0.0327*
	(0.0184)
Competing, 2km-5km	-0.0648***
	(0.0212)
Competing, 5km-15km	0.0298
	(0.0264)
Competing, more than 15km	-0.0163
	(0.0124)
Store FE	✓
Week-year FE	✓
Control variables	✓
N	69670
r2	0.954

Clustered (by store) standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

A.4 Without control variables

Table 7: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
One stop	0.100**	0.0632
	(0.0474)	(0.0398)
Two stops	-0.0473**	-0.0433**
	(0.0194)	(0.0177)
Store FE	✓	✓
Week-year FE	✓	✓
N	34228	34228
r2	0.838	0.842

Clustered (by store) standard errors in parentheses
* p0¡0.10, ** p<0.05, *** p<0.01

Table 8: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
Same parking	0.100**	0.0633
	(0.0474)	(0.0398)
0.25km - 2km	-0.0390	-0.0345
	(0.0270)	(0.0241)
2km-5km	-0.0830***	-0.0850***
	(0.0192)	(0.0241)
5-15km	-0.0520***	-0.0426***
	(0.0170)	(0.0161)
More than 15km	-0.0179	-0.0105
	(0.0129)	(0.0229)
Store FE	✓	✓
Week-year FE	✓	✓
N	34228	34228
r2	0.838	0.842

Clustered (by store) standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 9: Effect of establishment by product heterogeneity and distance category (rows 11-15 are gross estimates for the competing product categories calculated from the estimated parameters in the model)

	Log weekly sales
Non-competing, same parking	0.107**
	(0.0467)
Non-competing, 250m-2km	-0.0327
	(0.0274)
Non-competing, 2km-5km	-0.0762***
	(0.0184)
Non-competing, 5km-15km	-0.0507***
	(0.0180)
Non-competing, More than 15km	-0.0146
	(0.0130)
Difference competing, same parking	-0.0247***
	(0.00945)
Difference competing, 250m-2km	-0.0249***
	(0.00654)
Difference competing, 2km-5km	-0.0270***
	(0.0100)
Difference competing, 5km-15km	-0.00361
	(0.00678)
Difference competing, More than 15km	-0.0110***
	(0.00201)
Competing, same parking	0.0820
	(0.0505)
Competing, 250m-2km	-0.0576**
	(0.0264)
Competing, 2km-5km	-0.103***
	(0.0232)
Competing, 5km-15km	-0.0543***
	(0.0156)
Competing, More than 15km	-0.0255**
	(0.0130)
Store FE	✓
Week-year FE	✓
N	68456
r2	0.953

Clustered (by store) standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

A.5 With income control variable

Table 10: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
One stop	0.104**	0.0636
	(0.0498)	(0.0418)
Two stops	-0.0376*	-0.0372**
	(0.0192)	(0.0178)
Store FE	✓	✓
Week-year FE	✓	✓
Control variables	✓	✓
Control income	✓	✓
N	32328	32328
r2	0.836	0.840

Clustered (store level) standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 11: Effect of establishment by distance

	Log weekly sales	Log weekly store traffic
Same parking	0.104**	0.0637
	(0.0499)	(0.0418)
0.25km-2km	-0.0287	-0.0272
	(0.0257)	(0.0233)
2km-5km	-0.0802***	-0.0847***
	(0.0187)	(0.0240)
5km-15km	-0.0234	-0.0238
	(0.0214)	(0.0246)
More than 15km	-0.0203	-0.0132
	(0.0157)	(0.0245)
Store FE	✓	✓
Week-year FE	✓	✓
Control variables	✓	✓
Control income	✓	✓
N	32328	32328
r2	0.836	0.840

Clustered (store level) standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 12: Effect of establishment by product heterogeneity and distance category (rows 11-15 are gross estimates for the competing product categories calculated from the estimated parameters in the model)

	Log weekly sales
Non-competing, same parking	0.110**
	(0.0492)
Non-competing, 250m-2km	-0.0219
	(0.0260)
Non-competing, 2km-5km	-0.0732***
	(0.0179)
Non-competing, 5km-15km	-0.0237
	(0.0227)
Non-competing, More than 15km	-0.0165
	(0.0158)
Difference competings, same parking	-0.0241**
	(0.00937)
Difference competing, 250m-2km	-0.0263***
	(0.00661)
Difference competing, 2km-5km	-0.0275***
	(0.0101)
Difference competing, 5km-15km	0.000863
	(0.00623)
Difference competing, More than 15km	-0.0115***
	(0.00189)
Competing, same parking	0.0862
	(0.0528)
Competing, 250m-2km	-0.0482*
	(0.0255)
Competing, 2km-5km	-0.101***
	(0.0227)
Competing, 5km-15km	-0.0228
	(0.0182)
Competing, more than 15km	-0.0280*
	(0.0158)
Store FE	✓
Week-year FE	✓
Control variables	✓
Control income	✓
N	64656
r2	0.953

Clustered (by stores) standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$