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The Effect of Mergers on Variety in Grocery Retailing

Abstract

We study the effect of a merger between two Dutch supermarket chains to assess its effect on the depth as well as composition of assortment. We adopt a difference-in-differences strategy that exploits local variation in the merger's effects, controlling for selection on observables through a matching procedure when defining our control group. We show that the merger led the merging parties to reposition their assortment to avoid cannibalization in the areas where they directly competed before the merger. While the low-variety target's stores reduced the depth of their assortment when in direct competition with the acquirer, the latter increased their assortment. This suggests that variety is a strategic variable in retail chains' response to changes in local competition.

JEL-Codes: L100, L410, L660, L810, D220, K210, C230.

Keywords: variety, assortment, mergers, ex-post evaluation, retail sector, supermarkets, grocery.

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1. Introduction

In retail markets, firms can use various strategic choice variables, in addition to prices, to respond to local competitive conditions. The 2010 revision of the US Horizontal Merger Guidelines emphasizes the importance of non-price dimensions of competition. However, the evaluation of such effects and their interaction with price effects is not straightforward and it remains a controversial issue in merger control (OECD, 2013, p. 9). In particular, mergers' effects on variety are ambiguous, as they may "lead firms to spread similar products apart, to withdraw duplicative products, or to crowd products together to preempt entry" (Berry and Waldfogel, 2001, p. 1009).

The paper examines the impact of merger on non-price strategies in grocery retail. This represents an ideal setting to study the role of assortment choices and product positioning for competition. They are important tools to respond to changes in local competitive conditions, more so since retail chains have nationally uniform prices, as documented by DellaVigna and Gentzkow (2019) and Hitsch, Hortacsu and Lin (2019). Moreover, non-price attributes are an important determinant of consumers' preference and customer satisfaction. Yet, the competitive effect of variety in grocery retailing is still not fully explored.

We exploit the occurrence of a merger that diversely affected the competitive conditions in different local markets to study these issues. We analyze the merger between two large Dutch supermarket chains –Jumbo and C1000– that was conditionally approved by the Dutch competition authority – Autoriteit Consument & Markt (ACM) – in 2012. This merger is well suited to study firms' reaction to changes in local market conditions, as it is likely to unequally affect different local areas. Our empirical strategy exploits this geographic variation to causally identify the effect of the merger.

We adopt a Difference-in-Differences (DiD) strategy that relies on the comparison between areas where the merging parties were in direct competition (overlap areas) and areas where they are not (non-overlap areas). Our identification strategy relies on the proposition that the competitive effects of the merger are likely to be stronger in the former areas than in the latter ones, as, other things equal, only in overlap areas did the intensity of competition change because of the merger. By matching overlap and non-overlap areas with a propensity score procedure that is based on observable characteristics, we account for differences in demand and supply conditions across treated and non-treated areas. This identification strategy based on local variation is particularly appropriate for analyzing non-price dimensions of competitions such as assortment decisions, which are often made at the local level (Quan and Williams, 2018).

Focusing on a relatively small and homogeneous market, such as the Dutch grocery retailing, has the advantage of allowing the use of very granular data on the location of stores and on the characteristics of local areas. We use a rich database that entails quarterly information on average prices as well as the number of products – variety – for 122 product categories sold in a sample of 124 stores of the merging parties and their main competitors located in different areas scattered across the Netherlands for the 2010-2013 period. These categories almost completely cover the space of grocery products offered in the country during the sample period. As commonly done in the literature on retail markets, we define variety as the depth of assortment, i.e. the number of stock keeping units (SKUs) sold in each product category (Ren et al., 2011). We enrich this category-level dataset with more fine-grained monthly information on a sample of 33 specific products that were chosen to represent a typical basket for Dutch households.

We first provide evidence that variety decisions – thus also average category prices – appear to be made at the local level, while pricing decisions for individual products are not. We then show that the merger led to an average increase in product variety as well as in average category prices at the local market level, which would suggest a move toward a larger and more expensive assortment. Yet, these average effects are the result of two opposing forces. In overlap areas, the acquirer – Jumbo, the high-variety chain – substantially raised its assortment as well as its average category prices with respect to counterfactual areas.

On the opposite, C1000 decreased its assortment while leaving the average category prices unchanged in overlap areas, which implies a move toward a smaller, but not cheaper, assortment. These results seem to be driven by those stores that were not re-branded, while C1000 stores that took the Jumbo insignia, follow its pattern by substantially increasing their variety. Finally, the significant, yet much smaller, increase in the competitors' variety coupled with no significant change in their average category prices, signals that they also strategically react to the merging parties' repositioning, though by less.

We further qualify these findings through an event study analysis, which allows us to better compare the time evolution of variety and average category prices between treated and control areas. Differences in variety between overlap and non-overlap areas are small and follow a steady trend both for Jumbo and C1000 premerger. Instead, after the merger, variety in overlap areas substantially diverges from variety in non-overlap areas for both merging chains. In Jumbo's stores, variety is significantly higher in overlap than in non-overlap areas after the merger. Instead, C1000 stores in overlap areas substantially reduced the breadth of their assortment with respect to the counterfactual non-overlap stores. Moreover, it appears that these changes take a few quarters to materialize and then remain stable until the end of the sample period.

Thus, looking behind average effects allows us understanding the strategic effect of the merger. It led to a softening of competition through the repositioning of the assortment's depth and composition in areas where the two different insignias were still competing for customers. This is consistent with theoretical findings that merging parties move away from each other in the product space to avoid cannibalization following a merger (see section 2 for a discussion of the related literature).

The paper is structured as follows. In Section 2, we summarize the relevant literature. In Section 3, we provide some background information on the Dutch grocery market and on the merger under consideration. Section 4 describes the data. We present our econometric model in Section 5 and the empirical results in Section 6. Section 7 presents additional results and Section 8 concludes.

2. Related Literature

Our paper contributes to the literature studying the link between market concentration and product variety. In particular, both Gandhi et al. (2008) and Mazzeo, Seim and Varela (2014) theoretically study the issue of product repositioning after mergers and highlight the importance of considering effects on variety together with price effects. Lommerud and Sørgard (1997) show that merged firms might have a strategic incentive to narrow product ranges and that this is generally welfare detrimental. More recently, Rhodes and Zhou (2019) find that an asymmetric market structure might arise where some retailers decide to remain small (in terms of product range) to soften competition. Thus, as in our case, the flexibility in product offerings is a tool that managers have to target different types of consumers thereby avoiding fierce competition. The empirical evidence on the link between competition and variety in retail markets is scarce. Bauner and Wang (2019) explore the effect of competition and, in particular, of wholesale warehouse entry on pricing and product positioning. They find that the incumbents adopt a strategy of differentiation from the entrant firm. In a field experiment on the retail sector in the Dominican Republic, Busso and Galiani (2019) show that increased competition leads to a decrease in prices and to an increase in perceived service quality. Götz and Gugler (2006) find evidence of a reduction in variety after mergers in retail gasoline markets. Watson (2009) finds mixed evidence on the effect of geographic differentiation on competition and variety in retail eyeglasses. Fan and Yang (2020) and Fan and Yang (2021) perform merger simulations in the retail beer market and in the smartphone market respectively. In the latter, mergers reduce product offerings and welfare, while in the former the reduction in variety mainly takes place in smaller markets.

While the growing literature on retrospective merger evaluation substantially helps to improve the understanding of the effect of realized mergers, most of these studies focus solely on price effects (e.g. Ashenfelter, Hosken and Weinberg, 2014; Asker and Nocke, 2021). Thus, our paper also contributes to this discussion by complementing more traditional approaches and providing new evidence of the effect of mergers on non-price attributes such as variety and assortment decisions. We are only aware of one paper specifically analyzing the effect of mergers on variety. Pires and Trindade (2018) study a series of 14 different supermarket merger events, which affected 61 US cities. They show that these mergers did not have any effect on prices but increased variety on average by 3%. Their analysis differs from ours in several dimensions. As for the econometric approach, they do not account from selection on observables when constructing the control group. Secondly, their average treatment effect is estimated over several mergers that are potentially different one from the other. Moreover, their data only include five categories of beverage products, while we have information on the whole range of product categories that are sold in Dutch supermarkets. Differently from Pires and Trindade (2018), we also have information on average category prices, which allows us to draw implications on the composition of assortment. More fundamentally, we can cleanly identify the different reactions of the two merging parties in terms of product repositioning. Understanding that this is the driver of the average effect of the merger on variety is the main novel contribution we offer in this paper.

Most existing studies focus on very different industries from grocery retail and do not analyze the effect of a specific merger but rather consider several mergers or changes in concentration due to other factors such as entry or exit. A number of papers analyze the effects of the merger wave that took place in the US radio industry at the end of the 1990s. Berry and Waldfogel (2001) find that these mergers increase variety and Jeziorski (2014) quantifies the effect of this increased variety on both sides of the market (listeners and advertisers). Sweeting (2010) finds that firms buying competing radio stations tend to differentiate them, thereby avoiding audience cannibalization.

The evidence on other markets is mixed. George (2007) finds that content variety increases with ownership concentration in the US daily newspaper market. Based on the estimation of a structural demand model, Fan (2013) simulates the effect of a hypothetical merger between two local newspapers in the United States. She finds that, following the merger, newspaper publishers have an incentive to reposition their product and decrease their variety, leading to welfare losses for readers.[1] In an extension of their main price analysis, Ashenfelter, Hosken and Weinberg (2013) analyze the effects of a merger between home appliance manufacturers on the length of their product line. They find a substantial reduction in variety by the merging parties.

Finally, we also relate to the literature that analyzes variety and, more generally, non-price attributes in retail markets. Matsa (2011) shows that product availability is an important dimension of quality and is related to local competition. Bronnenberg (2015) builds a general equilibrium model that explains the optimal provision of variety in the market. Brynjolfsson, Hu and Smith (2003) estimate the effect of increased variety offered by online bookstores on consumer welfare and show that increased variety generates gains to consumer that are 7 to 10 times larger than the gains coming from price effect. Quan and Williams (2018) quantify the value of increased variety due to online retail taking into account the role of local tastes and retailer responses, and show that the positive welfare effect of increased variety are much lower than previously estimated. Hwang, Bronnenberg and Thomadsen (2010) explain the drivers of local variation in assortment choices by US supermarket chains. Ren et al. (2011) analyze instead the role of product variety as a tool of differentiation in consumer electronic retailing. Richards and Hamilton (2006) study price and variety competition among grocery retailers in the U.S. Draganska, Mazzeo and Seim (2009) build a model of price and product assortment decisions in differentiated products markets and estimate it on data of ice-cream retail sales. These contributions highlight the importance of variety as a strategic variable in retail markets, although they do not focus on the impact of mergers as we do.

[1] Similarly, Chu (2010) builds a structural model to analyze the cable TVs' response to satellite entry in terms of prices and quality (measured as number of channels), showing that eliminating quality competition implies softer price competition and reduced consumer welfare.

3. The Dutch Grocery Sector and the Merger

Between 2009 and 2012, several mergers took place in the Dutch grocery sector. The Dutch competition authority (ACM) cleared all of them, mostly subject to remedies. In this paper we focus on the last of these mergers, Jumbo's acquisition of C1000.

The main market players at the time of the mergers included the merging parties – Jumbo and C1000 – and several other supermarket chains. Jumbo is a full-service supermarket formula operating across the country. It had a regionally strong position in the southern regions of the Netherlands, which had already expanded thanks to the previous acquisition of Super de Boer (SdB) and Schuitema. The most important characteristic of the Jumbo core marketing proposition is the "every day low price" guarantee. Jumbo stores used to run few promotions. C1000 was also a full-service supermarket formula, which operated across the country. Its core strategy was on deep, short-lived, promotions. Its assortment was reportedly smaller than the other major national players.

Among competitors with a national footprint, Albert Heijn (AH) is the largest full-service supermarket chain and is perceived as the market leader. It operates across the country adopting various store formats. Its commercial offering is similar to Jumbo's offering, especially in terms of product variety. Moreover, it is the only other major chain of supermarkets operating across the whole of Dutch territory. Two large hard discounters have an important presence in the Dutch market: Aldi and Lidl. During the first half of the 2010s, hard discounters progressively increased their assortment and started selling a (limited) list of branded goods. However, significant differences with traditional supermarket formulas still exist. Finally, the market is characterized by a series of other, smaller, regional players, including Coop, Detail Group, Spar (part of an international group with a stronger position in other countries), Hoogvliet, and Jan Linders.

[insert Figure 1 here]

Figure 1 represents the time evolution of the market shares of all supermarket chains and discounters (at the national level) both in terms of net sales floor area (left panel) and in terms of the number of stores (right panel). AH is clearly the largest chain. The combination of SdB, C1000, and Jumbo has a net sales area similar to AH. A considerable number of stores belong to chains other than the ones listed. Overall, the total number of supermarkets has essentially remained constant from the beginning of 2009 through the end of 2014.

3.1. The Merger between Jumbo and C1000

In our analysis, we study Jumbo's acquisition of over 400 locations (the entire C1000 supermarket chain) that took place in February 2012. C1000 stores initially continued to operate under the C1000 insignia and were expected to be re-branded under Jumbo brand during the years following the merger. At the end of our sample period, almost two years after the merger took place, the re-branding from C1000 to Jumbo was not yet completed. The Jumbo/C1000 merger approval was conditional on the divestiture of eighteen stores, which were sold to Coop and Ahold (owner of the Albert Heijn chain) in July 2012.

We adopted the exact geographic market definition used by the ACM. The relevant geographic market is defined as a 15-minutes isochrone around stores or, when the 15-minutes isochrone goes beyond the administrative borders of a municipality, as the municipality itself. This is based on the fact that, according to the evidence collected by the ACM, Dutch consumers are not inclined to shop outside their neighborhood.[2] We drop all large cities from our sample since the geographic market definition is more complex in this case as there are clearly several geographical markets within a city.

With respect to the product dimension, the relevant markets defined by the ACM include both supermarket chains and hard discounters. In our study, we embrace the product market definition adopted by the ACM. However, we restrict our analysis to a particular format (i.e., regular supermarket), in order to maximize the similarity between the different stores analyzed and make our final sample more homogeneous. Moreover, given the increasing role covered by hard discounters (e.g., Lidl and Aldi) in the Dutch market in recent years, we explicitly control for their presence and strength in each relevant geographic market. Yet, we unfortunately cannot directly study how they strategically reacted to the merger as data on price and assortment is not available for these chains.

4. Data and Sample

For our empirical analysis, we collected store-level data for an appropriately selected sample of stores from Information Resources Incorporated (IRI), a firm specialized in collecting and

[2] The large majority of our areas (63%) have a radius that is smaller than 15 minutes by car. The mean size of such areas is 60 square kilometers. The other 37% of the areas are small towns, which are only slightly larger, with a mean area of 73 square kilometers.

analyzing data on retailing. The period under analysis is October 2010 to December 2013, with the date of the merger defined by the date of the ACM decision in February 2012. The composition of the estimation sample is affected by budget limitation and the willingness of the data provider to share only specific information. The supermarkets included in our sample are selected from areas where the merging parties overlap and from comparable areas where they do not overlap.[3]

To define comparable areas, we pairwise match areas where the merging parties overlap with non-overlap areas by applying a propensity score matching approach. We have precise location data for our sample of stores.[4] Thanks to this fine-grained information on local markets, we assess the level of similarity taking into account a full range of observable factors that could vary across overlap and non-overlap areas, such as demand and supply characteristics (for a similar approach, see Aguzzoni et al., 2016). Specifically, we use the average density population, average store size, HHI, number of stores, average income, stores' rental cost, and the market shares of hard discounters. Our selection ensures the widespread geographic coverage of the Netherlands and a balanced representation of all merging parties and of the selected subset of competitors. Further details on the propensity score matching procedure used in the analysis are reported in Appendix A.

Within areas of overlap and areas of non-overlap, we select a suitable number of stores both from the merging parties and from competing chains. Our final selection includes 124 different stores representing the merging parties' chains and two competitors (Albert Heijn and Coop) as represented in table 1.[5]

[3]Two further supermarkets mergers took place in December 2009 and March 2010. In order to isolate the effect of the merger under analysis, we restrict the choice of the areas and, consequently, of the stores in such a way that the average behavior of the treated and control group could not be biased by the occurrence of these other events (see the discussion in Argentesi et al., 2015). Moreover, although we have data from the beginning of 2010, we restrict the sample for the main estimation to start with the last quarter of 2010 in order to rule out the possible confounding effect of these mergers.

[4]These data come from the 'Supermarkt gids' database, which lists geographic data (including addresses, postal code, city, province) together with additional information (e.g., availability of parking or automatic counters) for all supermarkets in the Netherlands.

[5]A description of the criteria for choosing the stores in our sample is in Appendix A.0.1. Note that we did not have information on average category prices for 10 C1000 stores, one Jumbo store, and one Albert Heijn store. Therefore, the sample for the analysis on variety is slightly larger than the sample for the analysis on average prices.

[insert Table 1 here]

For these stores, we obtained data both at the category level and at the product level. In particular, we have information on turnover, volumes, and number of products (SKUs) for each of the 125 product categories collected in the IRI database. We exclude three categories for which we have less than 40 observations, since they were only sold in three stores. Our final sample therefore includes 122 categories. Moreover, we have information on turnover and volumes on a selection of specific products within several categories.

4.1. Category-level Data

To analyze the effect of the merger on product variety and category prices, we collected quarterly data on the number of SKUs for each of the 122 product categories sold in each store in our sample from the last quarter of 2010 until the end of 2013. This variable represents the depth of assortment and measures the product offerings available to consumers in each store. In addition, we compute an average price per category using quarterly data on turnover and sales volumes for each product category. Our database includes total turnover (in EUR) and volume (sales) measured at the store level.[6]

Panel B and C of table 2 reports descriptive statistics on the average category prices and variety, separately for the overlap and non-overlap areas as well as pre-merger and post-merger periods. While we do not observe large differences between overlap and non-overlap areas, neither before nor after the merger for the individual SKU prices as well as for the average category prices, variety seems to differ in both respects. With almost 100 SKUs per category, assortment size appears to be very large as it is the variation across categories, stores, and time. Some categories are not offered at all in some stores in a given quarter, while other categories have up to 1,689 different SKUs (for instance, sauces).[7] Assortment is ca. 3% lower in overlap areas before the merger but is slightly higher in non-overlap areas after the merger.

[insert Table 2 here]

[6] The average category price is constructed by dividing total turnover over volumes for each product category, and is net of promotional measures.

[7] In our sample, we have around 1% of observations where variety is zero, i.e. categories with zero products (1,927 observations on a sample of 183,994). See Section 7.2 for further discussion.

4.2. Product-level Data

To assess whether individual SKU prices are set at the local or at the national level, we collected information on a balanced sample of products that were sold throughout the entire sample period. This allows us to use SKU-specific fixed effects that significantly enhance the quality of our specification. Due to several constraints, we could not collect product-level price data on all products sold in each store. Hence, we based our selection of categories and products on best practices from the academic literature and ideas originating from the 2014 inquiry in the food retail sector carried out by the German Cartel Office (Bundeskartellamt (2015)). The final list of categories includes coffee, cola, cleaners, diapers, fresh milk, traditional Dutch sausage (frikandel), mayonnaise, olive oil, sanitary napkins, shampoo, and toilet paper.[8]

To assess price dynamics, it is important that the selected products are comparable both over time and across stores. Dutch supermarket assortments usually include at least one A-brand item, such as 'Coca-Cola', one private label, and one first-price (i.e., cheapest) item for each product. We exclude first-price items from our sample, as the data provider indicates that these may differ significantly in quality. Similar problems hold for fresh articles, which we also exclude. For each product defined at the SKU level, we have three time series: two SKUs for 'A-brands' and one SKU for private labels. We try to ensure comparability across stores using the same quality and format (e.g., 'fresh whole milk, 1 liter bottle') as well as comparability over time (e.g., not mixing different SKU over time unless necessary to ensure a sufficient coverage of the period under scrutiny).[9]

Our weekly SKU prices are defined as total turnover over volumes, and are net of promotional measures. Measurements are weekly but are provided with a four-week periodicity starting with week 4 of 2009. Panel A of table 2 reports descriptive statistics on prices for our sample of products distinguishing between overlap and non-overlap areas as well as between the pre-merger and post-merger periods. Because we have very different products in our sample, the price variation is large, ranging from few cents to 20 EUR. While we do not observe large differences

[8]Our selection of these categories is based on the following criteria: i) the inclusion of both 'food' and 'non-food' items; ii) the inclusion of traditional items for which comparisons across geographic markets are easier; iii) the inclusion of items belonging to the basket of goods typically consumed in the Netherlands; and iv) the inclusion of items whose characteristics set them apart from other items, either because we expect lower price sensitivity or due to higher level of differentiation and innovation (e.g., diapers).

[9]The list of selected SKUs for the price analysis is reported in Appendix B.

between overlap and non-overlap areas both pre- and post-merger, prices appear to have increased on average after the merger (11% and 9% in overlap and non-overlap areas respectively).

4.3. Control Variables

To identify the appropriate control areas as well as to disentangle the effect of the merger on prices and variety from the effect of market conditions, we collected data on demand and supply shifters in order to control for them in our analysis. We used two main sources: the Central Bureau of Statistics – Statistics Netherlands (http://www.cbs.nl/en-GB/menu/home/default.htm) and the Department of Spatial Economics & Spatial Information laboratory of VU University Amsterdam. Local demand and market conditions are summarized in Table 3, which also reports preliminary statistics for each variable.

[insert Table 3 here]

5. Empirical Model

We aim to analyze the impact of the merger on local markets outcomes. Exploiting the reaction to a shock that is expected to have differential effects depending on the local market structure is a clean way to identify this effect within a Difference-in-Differences (DiD) framework. The strength of this method is that it isolates the (local) effect of the merger from other factors that (i) may affect the trend in outcomes and (ii) may be related to the differences between the treated and the control groups.

The matching procedure that we adopted to define the control group controls for selection into the treatment due to observable characteristics, while the double differencing entailed in the DiD approach removes the time-invariant group-specific unobserved heterogeneity as well as the common time effects that might be otherwise confounded with the effect of the merger.

The basic hypothesis of our empirical strategy is that competition in grocery markets works at the local level. This is in line with the geographic market definition commonly adopted by competition authorities and by the ACM in this specific case. The competitive effects of a merger are expected to be potentially stronger in areas characterized by an overlap between the merging parties – i.e., areas where stores of both chains were present at the time of the merger – than in areas where the parties did not compete with each other door to door. The former areas, in fact, would be the ones experiencing stronger changes in competitive conditions as a decrease in the number of competitors occurs. Therefore, we can identify the potential effect of mergers by comparing outcomes – variety and category prices – in areas of overlap (treated group) vis-à-vis areas of no overlap (control group).[10]

However, the choice of the appropriate counterfactual to evaluate the effects of a merger strictly depends on the geographic extent of competition. A comparison between outcomes in areas where the merging parties overlap (i.e. areas affected by the merger) vis-à-vis areas of no overlap (i.e. not affected by the merger) identifies the effect of the merger only if competition is, at least to some extent, local. Thus, before further discussing our empirical framework, we first provide evidence on what variables appear to be chosen at this local level.

5.1. Local or National Competition?

Retail chains may have national or local pricing strategies and retail offerings.[11] For instance, DellaVigna and Gentzkow (2019) and Hitsch, Hortacsu and Lin (2019) document uniform pricing policies in US retailing, while Ater and Rigbi (2019) and Eizenberg, Lach and Yiftach (2021) show significant local price dispersion in grocery prices in Israel and Rickert, Schain and Stiebale (2021) documents local pricing in Germany.

Since the issue of the nature of local competition was not fully explored during the review of the Jumbo/C1000 merger, we carried out a more in-depth assessment, examining both qualitative evidence – such as questionnaires to market participants and evidence collected during phone interviews (see Argentesi et al., 2015) – and quantitative evidence on the variation of retail offers across stores.

With respect to pricing strategies, both the questionnaires and the interviews support the view that prices are generally set at the national level, although promotions are occasionally set at store level. However, the interviews also indicated a consensus that Jumbo allows for greater degree of autonomy in price setting at store level than other chains. As for variety, most

[10]This identification strategy is similar to the one used in, for instance, Aguzzoni et al. (2016) to evaluate the price effect of a merger between U.K. book retailers, Hosken, Olson and Smith (2018) to study the effect of U.S. grocery mergers on prices, as well as Allain et al. (2017) and Rickert, Schain and Stiebale (2021) to study the price effect of mergers in France and Germany respectively.

[11]Dobson and Waterson (2005) analyze in a theoretical setting the relative profitability of uniform and local pricing if compared to a national pricing strategy. A joint report by the UK Competition Commission and the Office of Fair Trading (Competition Commission and Office of Fair Trading (2011)) stresses the relevance of this issue in retail mergers.

of the interviewed market participants report that, although the overall range of assortment is generally set at central level, individual stores are allowed a substantial degree of autonomy in their individual assortment decisions. Stores belonging to each chain may adapt their own assortment to the local conditions of supply (e.g. competitive pressure coming from the other local players), demand (e.g. distribution of consumer preferences), and individual constraints (e.g. size of the stores, shelf space, etc.).

To quantitatively assess the extent to which SKU prices, variety, as well as average category prices respond to local market conditions, we run simple panel regressions using the pre-merger sample.[12] This should help to better understand which of these outcome variables mostly respond to local shocks. We choose a log-linear specification since all outcome variables have skewed distributions. The following regression also constitute the basis for our difference-in-difference specification presented in section 5.2:

$$\ln Out_{ijt} = \beta Z_{jt} + \mu_{jit} + \varepsilon_{ijt}, \tag{1}$$

where Out_{ijt} is the variety (average category price) for product category i at store j during quarter t. In the regression on individual prices, Out_{ijt} is the price of product i at store j during month t. The vector Z_{jt} contains variables capturing local demand and supply conditions – average density population, average store size, HHI, number of stores, average income, stores' rental cost, and the market shares of hard discounters. We control for the average difference in the variety (category price) across different supermarkets by including different combinations of fixed-effects μ_{jit} as discussed below. We try different correlation structures for the error term ε_{ijt} adopting different clusterings. Finally, we use three additional quarters of available data if compared to our estimation sample to increase the sample size and the time variation as much as possible.

Concerning the fixed-effects, we use various combinations along three dimensions: store, category, and time. The idea is to capture unobserved heterogeneity for each of the 124 stores, the 122 categories, as well the 16 quarters in our sample. We experiment with two specifications.

[12] In Appendix C, we also perform a graphical analysis of local variability in prices and variety. We analyze the distribution of SKU prices, variety and category prices for each SKU (category) across different supermarket chains at different points in time by means of boxplots. Moreover, we compute, for each SKU (category) and each month the coefficient of variation, a measure of the price (variety) dispersion, and analyze its distribution. Price variation appears to be very limited, whereas we show the existence of substantial local variation in assortment decisions for several exemplifying categories.

The first one uses each of these fixed-effects for store, category, and quarters separately. The second is more flexible and uses fixed-effects for the store as well as fixed-effects for the interaction between category and quarters. The latter is our preferred specification, as it essentially allows to have category-specific non-linear time trend.

The clustering issue is more complex. Abadie et al. (2017) take the view that clustering is either a sampling design or an experimental design issue. Clustering is justified if either the sampling or the assignment varies systematically with groups in the sample, whereby they think that the latter is more relevant in most cases. In our case, both might play a role. Yet, we also think that assignment to the treatment plays a more important role, as the sampling is done in order to mimic randomness. We try three different constellations. Below each coefficient estimates reported in table 4, we report the standard errors clustered at the category-store combination (in bold) in the first row, we report the clustering at the category level (in italics) in the second row, and the clustering at the store level in the third row.

[insert Table 4 here]

Consistent with the descriptive analysis, while SKU prices do not seem to respond to local market conditions, variety and, to a lesser extent, average category prices do. This is additional evidence that prices are mainly set at the national level. Thus, our DiD setting does not allow for identifying the effect on individual prices, since they do not seem to change at the local level. Therefore, in what follows, we focus the analysis on variety and average category prices.

These findings also highlight two additional points. First, the choice of the fixed-effects does not seem to be crucial as the point estimates for each of the explanatory variables do not substantially change between the two specifications. Second, the level of the clustering matters for inference. Our preferred clustering is to use the interaction between store and category as this allows for more precisely accounting for potential autocorrelation within different categories in a store. If we believe that local managers optimally choose the assortment within a category to respond to current market-specific conditions and that the demand in the different category is only partially correlated, this seems to be the most natural choice. However, clustering at the store level leads to substantially larger standard errors. Yet, clustering at this too aggregate a level leads to standard errors that are unnecessarily conservative (Abadie et al., 2017). In our case, this is mostly due to the fact that there is heterogeneity in treatment effects, as the effect of the merger appears to differently affects variety in the various categories (see Section 7.2).

5.2. The Difference-in-Differences Specifications

We run our difference-in-differences analysis for the full sample, including the merging firms and competitors, as well as separately for each of the two merging parties and their competitors. The estimation on the full sample aims at measuring the overall effect of the merger at the market level, which is possibly the most relevant for consumers. The estimations on the sub-samples aim to identify the strategic reactions of the different players in the market, which helps us study the mechanism driving the average effects and better explain the post-merger competitive dynamics.

We compare the change in an outcome variable in a selection of stores that were located in overlap areas with the change in the same outcome variable in other stores picked from the best-matched non-overlap areas before and after the merger. As discussed above, we use fixed-effects at the store as well as category-quarter combination and different clustering assumptions for the error terms. We estimate the following equation:

$$\ln Out_{ijt} = \delta post_t \times overlap_s + \beta Z_{jt} + \mu_j + \mu_{it} + \varepsilon_{ijt}, \tag{2}$$

where Out_{ijt} is again the variety (average category price) for product category i at store j during quarter t, μ_j is a store-specific fixed-effect and μ_{it} and μ_{it} are fixed-effects for each combinations of product categories and quarters thus representing category-specific time trends. The error term ε_{ijt} is assumed to be heteroskedastic and correlated at different levels, as discussed in Section 5.1.

The main variable of interest is the interaction between the dummy $overlap_s$, which takes on the value of one if the store is located in an overlap area, and $post_t$, a dummy that takes on the value of one in the post-merger period (i.e. after the first quarter of 2012). The coefficient of their interaction measures the average treatment effect of the merger.[13] It identifies the additional variation in variety and category prices experienced by the stores in overlap areas compared to the control stores after the merger took place.

Further, we run an event study version of equation 2 where, instead of interacting the *overlap* dummy with the *post* dummy, we interact it with each of the quarters in our sample. This allows us to study the dynamics of the treatment effect over time as well to further check the common trend assumption. To avoid perfect multicollinearity, we drop the quarter before the merger as suggested by Sun and Abraham (2020). Thus, we run the following regression:

[13] The coefficients of the individual dummies are not identified given our fixed effects.

$$\ln Out_{ijt} = \sum_{\tau=T_0}^{\tau=-2} \alpha_\tau \times overlap_s + \sum_{\tau=0}^{\tau=T_1} \alpha_\tau \times overlap_s + \beta Z_{jt} + \mu_j + \mu_{it} + \varepsilon_{ijt}, \tag{3}$$

where T_0 and T_1 are the lowest and highest number of lags and leads, respectively, to consider surrounding the treatment period, respectively.

5.3. Identification

To causally identify the effect of the merger on the outcomes of interest, we need to ensure that the difference in the average behavior in the control group adequately represents the change with respect to the average behavior that would have occurred absent the merger (i.e., the counterfactual scenario). Our matching approach for the selection of the relevant areas and stores should help ensuring that the control group is comparable to the treatment group in terms of observable characteristics before the treatment. In Appendix A we show that observables are balanced between overlap and non-overlap areas.

To support our identification strategy, we further analyze whether the pre-merger common trend assumption is verified in our data. If this assumption is met, with the treatment and control groups behaving similarly pre-merger, we can be confident that the control group is a good comparator for the treatment group after the merger. For each of the outcome variables (variety and average category prices), we first provide a descriptive visual inspection of the trends, then we perform a formal test of the common trend assumption. In what follows, we show the average evolution of the outcome variables in treated and control stores without differentiating between the merging parties and the competitors, in order to obtain the aggregate picture at the market level, which is possibly the one most relevant for consumers. We get similar findings if we test the common trend assumption by insignia, as in our main empirical specifications.

Figure 2 compares the evolution of the total number of SKUs per store – our measure of variety – in the overlap areas to the average level of product variety in non-overlap areas, across all product categories for the full sample and the different chains. While, for almost all chains – up to Jumbo – there appear to be a difference in the breadth of the assortment in the pre-merger period between overlap and non-overlap areas, there is a quite clear common trend. This common trend is even more evident when looking at the same pictures disaggregated at the category level, which are reported in Appendix D.

[insert Figure 2 here]

Strikingly, the trends between overlap and non-overlap areas seem to substantially diverge post-merger for Jumbo and C1000. For Jumbo, while the average number of products per category significantly drops in non-overlap areas, it seems even to increase in overlap ones. For C1000, instead, we observe the opposite pattern. Variety seem to have a slight increase in non-overlap areas and a substantial decrease in overlap ones. The trends for competitors stay quite constant before and after the merger. We will come back to these patterns when we discuss the results of the econometric analysis.

Figure 3 plots the series of average prices per category in overlap and non-overlap areas across all product categories and for the different chains. Again, for all chains, the two series seem to follow the same trend in the pre-merger period. However, they start to substantially diverge some time after the merger for Jumbo, when prices in non-overlap areas significantly drop whereas increasing in overlap areas. For both C1000 and the competitors, there does not appear to be a post-merger divergence in the trends.

[insert Figure 3 here]

On the whole, the graphical evaluation seems to confirm that the key assumption for the validity of the DiD methodology – the common trend assumption – appears to be met in our sample. Yet, to provide more evidence on this key element of our identification strategy, we also perform a formal test of the common trend hypothesis. Like Ashenfelter, Hosken and Weinberg (2014), we first estimate the deviation of the treated areas variety (category price) from the average variety (category price) of the control areas in each quarter. Next, we compute the slope of a linear trend of these deviations in the pre-merger period and test whether the estimated slope is statistically different from zero. The test confirms that only one category out of 122 does not show a common trend for variety. For average prices, 10 categories out of 122 do not show a common trend.[14]

6. Main Results

In this section, we discuss the results of our analysis on the average effect of the merger both on the entire sample and by insignia differentiating between the two merging parties and their

[14] If we exclude categories without common trend from our sample, the estimated treatment effect is not affected. Similar results are obtained if we run these regressions by insignia. All these analyses are available upon request.

main competitors (Albert Heijn and Coop). The latter analysis is particularly relevant as it allows a heterogenous response to the merger of the different market players that helps us better identifying the mechanism at play.

6.1. The Merger Effects on Variety

We first analyze the effects of the merger on variety presented in Table 5. At the market level (column 1), the estimated average effect suggests that the merger caused a significant average increase in variety by 6.9%.[15] Yet, if we separately look at the effect on the two merging parties and on their competitors (columns 2, 3, and 4), this average effect is the result of opposing trends. In particular, C1000, the low-assortment chain, reduced variety by 8% after the merger, whereas Jumbo sharply increased its assortment by ca. 34%. This is compatible with a substantial repositioning in terms of the depth of assortment whereby the two chains tend to differentiate themselves after the merger when they compete in the same local market. The estimated effect of the merger on competitors' variety (column 4) indicates that they slightly increase their assortment in overlap areas by 2.4%

[insert Table 5 here]

The effect for the target stores appears to be solely driven by those 33 out of the 50 C1000 stores that were not re-branded to Jumbo. In table 6, where we report a specification with an interaction of the treatment variable with a "no-re-branding" dummy, which is equal to one for those stores that were not re-branded.[16] The reduction of variety in these stores (column (1)), derived from the sum of the two interaction coefficients, is substantial and equal to almost 14%.

In contrast, those stores that changed insignia during the sample period followed the pattern observed for Jumbo and increased their variety by almost 10%. This would suggest that re-branded C1000 stores adapted their assortment to Jumbo's. It should be noted, however, that we do not have information on the reasons behind the decision to re-brand, which might raise endogeneity concerns. These findings should therefore be interpreted with some caution.

[insert Table 6 here]

[15] Note that, in the log-linear model, the percentage marginal effect of a dummy is calculated as $100 \times [exp\hat{\delta} - 1]$.

[16] We cannot perform this analysis for Jumbo as there are few areas where we have data for both merging chains and we do not know whether, in the areas were we only have Jumbo stores, C1000 stores were re-branded.

To better understand the merger's effect and its dynamic, we run the event study specification of equation 3. Figure 4 reports the results. The quarter before the merger is the reference group and is not reported. First, for all samples, this analysis confirms the pre-merger common trend assumption between treated and control areas. Only for competitors, there appears to be a slightly increasing, but not significant, trend pre-merger. The effect of the merger on the full sample is again mostly driven by Jumbo's behavior. While Jumbo's stores in overlap areas offered a slightly higher breadth of products pre-merger than in non-overlap areas, after the merger they significantly differentiate one from another: Variety is significantly higher in overlap than in non-overlap areas. For C1000, instead, stores in overlap areas also offered a slightly higher variety than stores in non-overlap areas pre-merger. However, after the merger, stores in overlap areas substantially reduced the breadth of their assortment to a lower level than the level of the counterfactual non-overlap stores. The behavior of competitors mimics the Jumbo's behavior, but is much less pronounced. Stores in overlap areas offered lower variety pre-merger and the gap between overlap and non-overlap stores becomes significantly positive after the merger.

Figure 4 also shows that the effect of the merger on variety materializes after two or three quarters and is pretty stable afterwards. For both the merging parties and their competitors, we observe a sharp change, followed by a more steady pattern. Adjusting assortment seems therefore to require some time and to be done in a discrete rather than in a continuous fashion.

[insert Figure 4 here]

The merging parties' behavior after the merger may be better understood by interpreting our results together with the descriptive evidence reported in figure 2. For Jumbo, the estimated significant difference in variety between overlap and non-overlap areas after the merger is mainly driven by a sharp drop in the breadth of the assortment in non-overlap areas. On the contrary, C1000's variety increased in non-overlap areas after the merger. This convergence in variety between the two chains in non-overlap areas may reflect an alignment in their assortment policy that may have taken place at the national level as a result of the merger. However, the discretionality of local managers allows them to adopt a different strategy in areas of overlap, where the two chains are still present and competing for customers mostly with two different brands after the merger. In these areas, C1000 sharply reduced its variety, whereas Jumbo slightly increased it. As we saw, the result for C1000 is driven by the stores that were not re-branded. Therefore, these patterns can be interpreted as a strategic repositioning effect, whereby the merging chains adjust their product offering in terms of assortment in order to avoid cannibalization and soften competition in areas where the two different brands are still competing for customers.

This explanation is consistent with a theoretical literature on the effect of mergers on product positioning (Gandhi et al., 2008; Mazzeo, 2003). In Appendix E, we present a simple theoretical model of competition in variety that rationalizes this evidence. The model shows that the merging parties' change in variety internalizes the effect on the other firm's demand. Thus, they may have an incentive to differentiate in the variety space after the merger in areas where they are both active.

6.2. The Merger Effect on Category-level Prices

To get an indication on the variation in the composition of assortment after the merger, we analyze the post-merger dynamics in average category prices, both for each of the two merging parties and for their competitors. Since the length of assortment did change, looking at average category prices may give us an indication of how retail chains modify the *composition* of their assortment within each category under the assumption that the price of individual products do not differently change between overlap and non-overlap areas. This should not be the case, given that we argued above that prices are set at the national level. Moreover, there is no evidence of a change in the merged entity's pricing strategy from national to local after the merger.

As shown in Figure 3, the series of average prices per category in overlap and non-overlap areas start to diverge some time after the merger, when prices in overlap areas become higher than prices in non-overlap areas. This graphical evidence is confirmed by our regression results, which are reported in Table 7. First, for the full sample, post-merger prices are higher in stores located in the overlap areas compared to stores located in the non-overlap areas. This means that the merger led to a slight increase in average category prices by almost 3%. This effect appears to be solely driven by the Jumbo's stores, which increased prices by almost 9%. The average treatment effect for C1000 and the competitors is, instead, very small and not statistically significant.

[insert Table 7 here]

The evidence provided so far suggests that the effect on average category prices might be due to a composition effect. Consider Jumbo: since variety substantially increased in overlap areas compared to control areas, the increase in the average category price between treatment and control areas can be explained by the choice to add high-priced SKUs after the merger in overlap areas. C1000 instead decreased its assortment without affecting category prices.[17] In other words, in overlap areas, the high-variety and high-price chain Jumbo became even more high-variety and high-price, whereas the low-variety and low-price chain C1000 became even more low-variety keeping low prices.

[insert Figure 5 here]

Looking at the dynamics of the treatment effect through the event study, these results come again solely from Jumbo's stores in overlap areas that substantially increase the average category prices if compared to stores in counterfactual areas without direct competition between the merging parties, as shown in Figure 5. As for variety, also these effects take three quarters to materialize, which is an indication that the measured average price effect is a composition effect: Jumbo introduced new and more expensive products in overlap than in non-overlap area post-merger. The average category prices for C1000 and the competitors are, instead, not statistically different between overlap and non-overlap areas both before and after the merger.

7. Additional Results

7.1. Market Concentration & Divestitures

In order to explore further the drivers of the repositioning effect highlighted so far, we estimate two additional models that assess its heterogeneity. First, we investigate whether the effect of the merger varies across areas depending on the level of post-merger concentration. the full results are reported in Appendix E, Tables 11 and 12. We find that the repositioning effect on variety is significantly lower in areas where concentration is high (Herfindal-Hirschmann-Index – HHI – higher than 4,000). For C1000, the cumulative effect of the merger in these areas is essentially zero, whereas the increase in variety for Jumbo is reduced by one third with respect to the average effect. In contrast, the differential effect of the merger on average category prices in highly concentrated areas if compared to less concentrated markets is not significant for the merging parties. These results suggest that, in highly concentrated areas, the need to reposition in terms of assortment breath – but not composition – after a lessening of competition is less marked than in less concentrated areas.

[17] As shown in column (2) of table 6, we do not observe a significant differential effect on average prices between C1000 stores that were re-branded or not.

Second, we further analyze whether the effect of the merger was different in areas affected by structural remedies. The ACM required the merged entity to divest 18 stores, which were sold to Coop and to the Albert Heijn chain.[18] Again, the full results are reported in Appendix F, Tables 13, and 14. In all samples, we estimate a coefficient for the triple interaction that is of the opposite sign and of equal size if compared to the effect measured in the areas not affected by the divestitures. This means that, in the areas where the divestitures were applied, they nullified the effect of the merger as the cumulative effect is a well-estimated zero. The same patterns can be observed for average category prices. These results indicate that, in areas where remedies were imposed, variety and category prices did not change and the strategic repositioning effect both in terms of depth and composition of the assortment was eliminated.

7.2. Heterogeneous Effects by Category

The results presented so far represent average effects across all 122 categories in our sample. While we think that this is the right approach, as we want to measure the average effect for a consumer who buys a basket of goods potentially including products from all categories, it is interesting to understand whether the average effect is driven by any specific categories. Therefore, we run our basic DiD regression at the category level. Figure 23 in Appendix F graphically represents the coefficient estimates of the average treatment and their significance.

In the full sample, the effect of the merger at the category level is positive for 113 out of the 122 but not significant at 5% level, except for two categories. As for C1000, 115 out of the 122 estimates are negative and 40 of them significantly so at the 5% confidence level. For Jumbo, instead, we estimate a positive effect for 120 of the 122 categories. Yet, these effects are significantly different from zero only for 3 categories. Lastly for competitors, 86 estimates are positive and the 9 of them significantly so. The fact that several coefficients are not significant is most likely due to the limited power of our regression.

This evidence suggests that, for each chain, the sign of the average treatment effect reported in table 5 is not driven by some specific category, but is pretty uniform across all categories. Yet, we also observe quite some heterogeneity in the size of the estimated treatment effects, which is

[18] The divestiture dummy takes value of 1 for all the stores located in the areas where they occurred. We then interact this variable with the 'Overlap × Post' dummy. Thus, the coefficient of this double interaction measures the difference between the treatment effect measured in overlap areas where one of the C1000 stores were divested if compared to areas without a divestiture.

one reason why we choose to use the store-category combination as a cluster for the standard errors. Concerning the category types for which we find significant effects, we have both food and non-food products. Thus, there does not seem to be a clear pattern driving the average effect along this dimension.

To further check whether other dimensions might explain the heterogeneity of the variety effect, we look at whether it depends on the assortment breadth. To do this, we look at the distribution of the average number of products per category in 2011 and we allocate categories to the quartiles of this distribution. We then augment our base specification adding interactions of the 'post × overlap' dummy with dummies for these quartiles of the variety distribution. The reference group is the first quartile. The other coefficients measure the additional effect coming from categories with a higher number of products. The full results are reported in table 15 in Appendix F. It is only for Jumbo that we observe categories with a larger number of products are more affected, as the coefficients of the triple interactions are always positive, increasing in size with the quartile, and the differences between the various coefficients of the distribution are mostly significant. As for C1000 and the competitors, the reduction in variety is not significantly different in categories with a larger number of varieties.

Finally, we also look at the potential extensive margin of addition or deletion of entire product categories. In our sample, we only have 1,927 observations out of 183,994 where a category has zero products. Most of these observations are sporadic, so they most likely just represent temporary inventory shortfalls. Given the small number of observations, we cannot perform any econometric analysis on this extensive margin. We can however provide some descriptive information on the patterns of addition and deletion of product categories. We observe very few occurrences where some C1000 stores drop product categories after the merger, i.e. categories for which we have variety equal to zero in a store for more than two quarters after the merger. In particular, the categories "Baby products" and "Perfumes" are absent in five stores after the merger. The category "Slimming products" is absent in three stores after the merger. The category "Hair and beauty accessories" is absent in two stores. Finally, the categories "Frozen desserts," "Newspapers," and "Nylon Panties" are absent in one store. As for Jumbo, we have instead evidence of one category – Baby Products – in which variety was zero for at least two quarters before the merger, and that was added after the merger. This occurred to the store in Kollum (overlap area) and in Diemen (non-overlap area). Thus, overall, we cannot identify any systematic pattern of deletion or addition of product categories related to the merger.

7.3. Further Robustness Checks

In this section, we discuss whether our previous results are robust to several checks. First, since we do not know exactly when the two merging parties became one single entity and because the competitive conditions could have started changing with the notification of the acquisition, we also run specifications where we exclude windows of 3 and 6 months around the merger date from our dataset (see Tables 16 and 17 in Appendix E). Results do not change, regardless of whether we look at the full sample, merging parties, or competitors. In particular, for the analysis on variety (Table 16 in the Appendix F), when we drop three and six months of data from around the merger date, the effects are even stronger than in our baseline regressions. Results for average category prices (see Table 17 in Appendix F) also show that the effect is larger when we drop 3 or 6 months around the merger decision. This is in line with the evidence of the event study analysis reported in Figures 4 and 5, showing that there is a delay in the realization of the effect of the merger.

Second, for the analysis on variety, we exclude from the dataset the products that show a seasonality in their assortment trend (namely sun protection products, insecticides, and greeting cards). Even in this case, our qualitative and quantitative results do not change. Finally, we re-balanced the sample dropping the few categories without common trend, as explained in Section 5.3 and results are not affected.

8. Conclusions

In industries where local competition plays an important role – such as the retail sector – firms might forgo profits for not being able to geographically price discriminate and, thus, respond to local market conditions. The empirical evidence presented in this paper shows that non-price terms and conditions are important strategic tools for managers in such situations. Thus, the analysis of these additional dimensions, in particular assortment decisions, is crucial for shedding light on the extent of competition in the market. This is the major contribution of this paper.

To assess if and how local competitive conditions affect assortment decisions, we analyze a major merger between the Dutch grocery retailers Jumbo and C1000 that differently affected competition in various local markets. First, we provide descriptive evidence that prices are not set at the local level, while variety shows substantial variation across similar stores in different areas. This is consistent with the nearly uniform pricing patterns across heterogenous local markets observed in the literature.

When shaken by a change in the local market structure – as in the case of the analyzed merger – local managers respond by changing assortment. Specifically, we show that the merger caused a significant increase in the average depth of assortment at the market level. This effect is driven by two opposing forces. On the one hand, Jumbo – the high-variety chain – increased the depth of its assortment and repositioned its offer toward high-price products. On the other hand, assortment in C1000 stores – the low-variety chain – shrank, leaving average category prices unchanged. This is driven by those stores that were not re-branded, since the incentive to differentiate in the variety space takes place in overlap areas where the two chains keep operating under two different insignias. Thus, by increasing differentiation and specializing on different types of customers, local supermarkets can avoid cannibalization and soften competition, while increasing their profits even without changing product pricing. At the market level, the change in variety in high-variety stores more than compensates the decrease in variety in low-variety stores. Moreover, this effect is potentiated by the strategic behavior of competitors that also slightly increase their assortment following Jumbo's repositioning.

These results have important implications for policy and welfare as well. Indeed, Brynjolfsson, Hu and Smith (2003) show that changes in variety affect consumer welfare even more than price effects. Yet, the effect of variety may be heterogenous if variety is a vertical differentiation attribute for some consumers and a horizontal one for others for which a deeper retail assortment might increase consumers' shopping costs (Klemperer and Padilla, 1997). While some consumers could benefit from having a larger set of more expensive products in some stores, other might be hurt by seeing some products disappear from their preferred stores or by the increased distance in terms of variety between the stores they can shop at. In such circumstances, merger policy might have redistributive effects across consumers that are difficult to evaluate. This consideration applies to any competitive dimension that may have a heterogeneous impact on consumers. Indeed, while an increase in price (or a reduction in quality) has an obvious negative impact for all consumers, a modification of other characteristics that consumers value differently might benefit some of them and harm others. In these cases, the consumer welfare standard that is frequently adopted to assess the competitive consequences of a merger seems less appropriate than a total welfare standard.

Thus, our findings confirm the importance of considering non-price effects in addition to price effects in *ex-post* evaluations of mergers in markets where non-price dimensions of competition are relevant for consumers. However, the results also highlight that the welfare effects of strategic repositioning are difficult to measure. This is an area that deserves further research.

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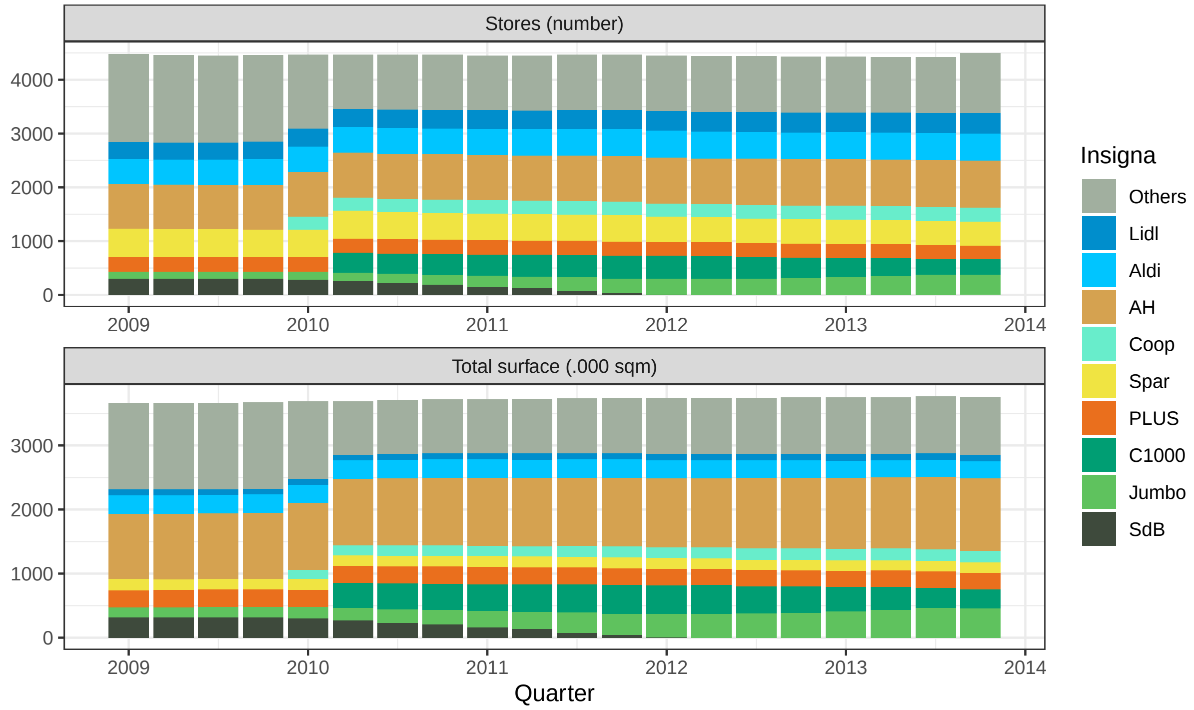
9. Figures and Tables

Figure 1: Stores' market position (national level) over time: number of stores (top) and net sales floor area (bottom)



Source: Our elaboration on Supermarket Gids data.

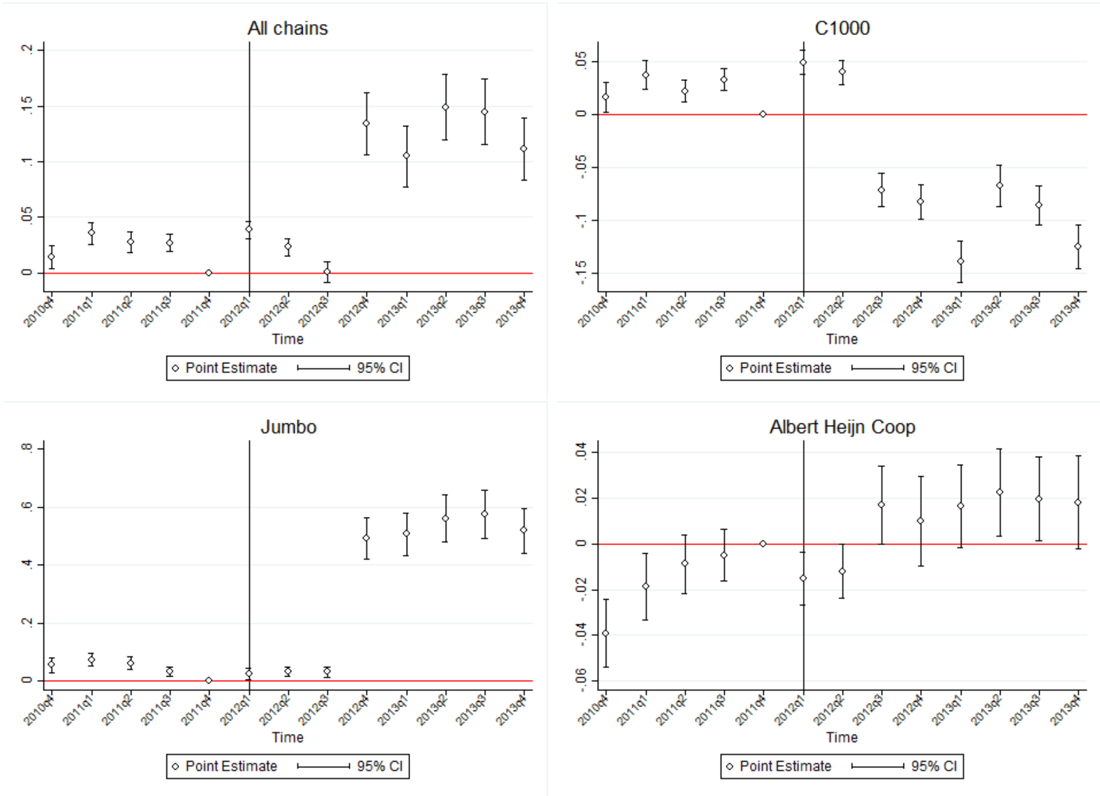
Figure 2: Trends for variety in treated and control areas – across all categories

Source: Our elaboration on IRI data

Figure 3: Trends for average category prices in treated and control areas – across all categories

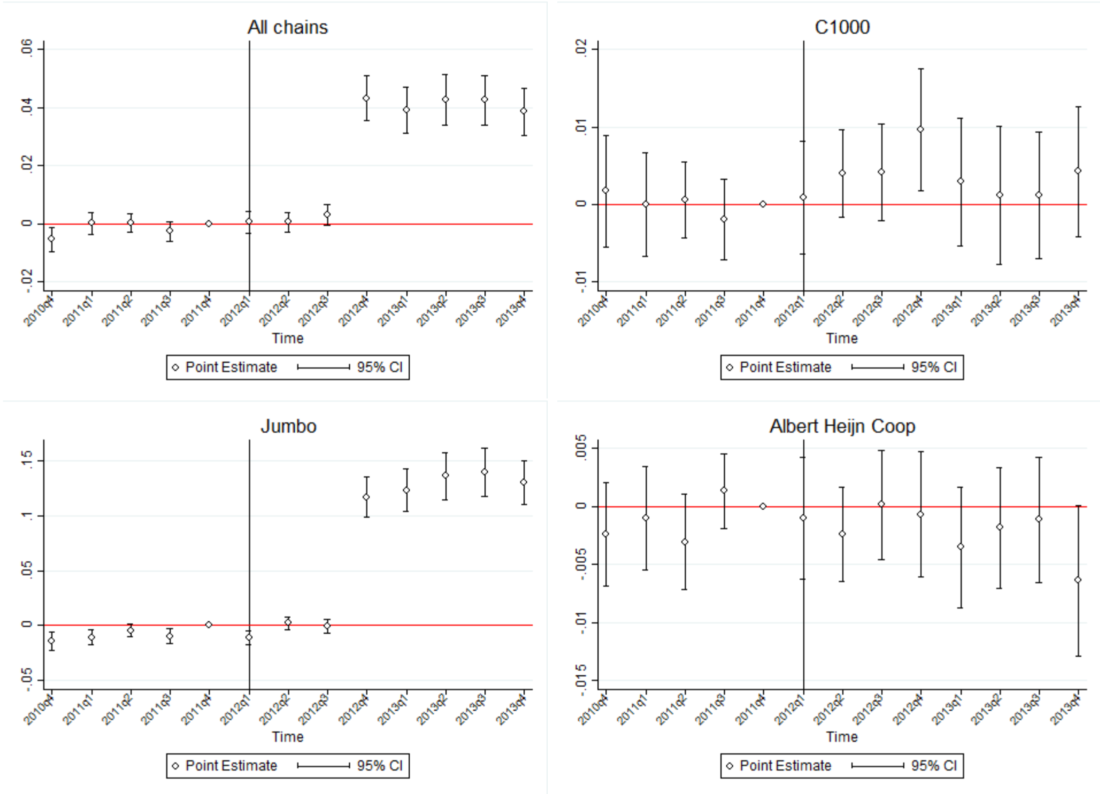
Source: Our elaboration on IRI data

Figure 4: Event study: difference in variety between treatment and control areas



We report the point estimates and the [5%-95%]confidence intervals for the coefficients α_τ from equation 3. The dependent variable is $ln(variety)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors clustered at the store-category level.

Figure 5: Event study: difference in average category prices between treatment and control areas



We report the point estimates and the [5%-95%]confidence intervals for the coefficients α_τ from equation 3. The dependent variable is $ln(categoryprice)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors clustered at the store-category level.

Table 1: The sample of Stores

		Variety		Average Price	
		Overlap	Non-Overlap	Overlap	Non-Overlap
C1000	Rebranded to Jumbo	7	10	9	8
	Not rebranded	20	13	13	10
Jumbo	Jumbo	23	14	22	14
Competitors	Albert Heijn	14	15	14	14
	Coop	5	3	5	3
Total		124		112	

Source: Our elaboration on 'Supermarkt gids' database

Table 2: Preliminary Statistics - Dependent variables

	Pre merger				Post merger			
	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Panel A								
Price – Treated	2.36	2.68	0.03	20	2.53	2.88	0.05	20
Price – Untreated	2.40	2.79	0.05	20	2.54	2.96	0.02	20
Panel B								
Average Category Price – Treated	1.80	1.24	0	12.49	1.85	1.27	0	36.5
Average Category Price – Untreated	1.84	1.25	0	12.84	1.84	1.29	0	12.42
Panel C								
Variety – Treated	98.08	117.27	0	1,689	96.95	109.62	0	1,398
Variety – Untreated	95.31	110.35	0	1,452	97.34	111.19	0	1,489

Source: Our elaboration on IRI data

Table 3: Description of the Control Variables

Control variables	Description	Time reference	Source	Mean	St. Dev
Local market features: demand side					
Population	Number of inhabitants per City (thousands)	yearly	CBS - NL[1]	1731	1912
Population density	Average number of inhabitants per square kilometer per City	yearly	CBS - NL	2333	2473
Households with children	Percentage of households with children (unmarried couples with children, spouses, couples with children and single-parent households) per city	yearly	CBS - NL	40	10.96
Income	Weighted average of income per capita per city (thousands, weights equal to number of income recipients per city)	yearly	CBS - NL	21.88	4.3
Local market features: supply side					
Rental price	average value of residential real estate	yearly	VU University Amsterdam[2]	281.66	79.03
HHI	Hirschman-Herfindall Index per city (stores market shares are proxied by the net sales floor)	quarterly	Supermarket Gids	3432.2	1824.4
Number of stores	Number of stores per city	quarterly	Supermarket Gids	6.67	4.69
Net sales floor	average net sales floor of all the stores in the City	quarterly	Supermarket Gids	1022.6	515.67
Aldi	Average net sales floor of all the Aldi stores in the city	quarterly	Supermarket Gids	717.57	217.78
Lidl	Average net sales floor of all the Lidl stores in the city	quarterly	Supermarket Gids	849.27	206.32
Discounter market shares	sum of the market shares of Lidl and Aldi stores (computed on the basis of the store's net sales floor) in the city	quarterly	Supermarket Gids	0.125	0.11

[1] Central Bureau Statistics – Statistics Netherlands (http://www.cbs.nl/en-GB/menu/home/default.htm)
[2] Department of Spatial Economics & Spatial Information laboratory, VU University Amsterdam

Table 4: Preliminary Regression on the Pre-merger sample: Local or National competition?

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	SKU price	SKU price	Variety	Variety	Average Category Price	Average Category Price
Population	0.0759	0.086	-0.769	-0.721	0.028	0.067
	(0.250)	**(0.118)**	**(0.260)*****	**(0.254)*****	**(0.175)**	**(0.170)**
	(0.127)	*(0.137)*	*(0.277)****	*(0.272)****	*(0.196)*	*(0.190)*
	(0.113)	(0.115)	(0.582)	(0.583)	(0.286)	(0.281)
Average Income	-0.112	-0.112	-0.906	-0.933	-1.047	-1.062
	(0.177)	**(0.090)**	**(0.231)*****	**(0.226)*****	**(0.146)*****	**(0.142)*****
	*(0.042)***	*(0.042)***	*(0.119)****	*(0.120)****	*(0.082)****	*(0.084)****
	(0.081)	(0.097)	(1.785)	(1.794)	(1.023)	(1.025)
Discounters Market Share	0.065	0.086	-0.560	-0.558	-0.210	-0.207
	(0.129)	**(0.062)**	**(0.106)*****	**(0.101)*****	**(0.089)****	**(0.084)****
	(0.049)	*(0.047)*	*(0.091)****	*(0.091)*	*(0.092)***	*(0.091)***
	(0.048)	(0.045)*	(0.394)	(0.397)	(0.167)	(0.166)
HHI	-0.001	-0.001	0.001	0.001	0.003	0.003
	(0.001)	**(0.000)***	**(0.000)***	**(0.000)***	**(0.000)*****	**(0.000)*****
	*(0.000)***	*(0.000)***	*(0.001)*	*(0.000)*	*(0.000)****	*(0.000)****
	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.002)
Net Sales Floor	-0.001	-0.001	0.030	0.029	0.016	0.016
	(0.002)	**(0.001)**	**(0.003)*****	**(0.003)*****	**(0.003)*****	**(0.002)*****
	(0.001)	*(0.001)*	*(0.002)****	*(0.002)****	*(0.002)****	*(0.002)****
	(0.001)	(0.001)	(0.028)	(0.028)	(0.017)	(0.017)
House Value	0.076	0.094	0.105	0.113	0.016	0.023
	(0.111)	**(0.050)***	**(0.101)**	**(0.104)**	**(0.071)**	**(0.074)**
	*(0.037)**	*(0.031)***	*(0.103)*	*(0.103)*	*(0.079)*	*(0.081)*
	(0.059)	(0.067)	(0.393)	(0.395)	(0.189)	(0.190)
Constant	0.050	-0.216	9.185	7.544	3.883	3.041
	(0.957)	**(0.503)**	**(0.938)*****	**(1.336)*****	**(0.617)*****	**(0.659)*****
	(0.476)	*(0.518)*	*(0.989)****	*(1.005)****	*(0.533)****	*(0.518)****
	(0.440)	(0.541)	(4.273)**	(4.451)*	(2.242)*	(2.222)
Observations	73,998	73,998	113,955	113,955	108,699	108,699
R-squared	0.957	0.961	0.795	0.801	0.603	0.613
FE	Store-Time-Category	Store-CategoryTime	Store-Time-Category	Store-CategoryTime	Store-Time-Category	Store-CategoryTime
Cluster	**StoreCategory**	**StoreCategory**	**StoreCategory**	**StoreCategory**	**StoreCategory**	**StoreCategory**
Cluster	*Category*	*Category*	*Category*	*Category*	*Category*	*Category*
Cluster	Store	Store	Store	Store	Store	Store

Standard errors clustered at different levels in parentheses: in the first row below each coefficient estimate (in bold) the clustering is at the store-category level, in the second row (in italics) the clustering is at the category level, while in the third row it is at the store level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 5: Average Treatment Effect per Insigna: Variety

	(1) Full sample	(2) C1000	(3) Jumbo	(4) Competitors
Overlap X Post	0.067	-0.083	0.296	0.023
	(0.009)* **	**(0.007)*** **	**(0.025)*** **	**(0.007)*** **
	*(0.005)****	*(0.006)****	*(0.011)****	*(0.006)****
	(0.087)	(0.051)	(0.254)	(0.021)
Population	4.532	2.606	11.730	-0.128
	(0.354)* **	**(0.275)*** **	**(0.907)*** **	**(0.198)**
	*(0.142)****	*(0.262)****	*(0.352)****	*(0.237)*
	(3.562)	(1.911)	(9.462)	(0.537)
Average Income	-1.386	0.381	-3.843	-0.965
	(0.193)* **	**(0.192)** **	**(0.389)*** **	**(0.192)*** **
	*(0.139)****	*(0.149)***	*(0.200)****	*(0.224)****
	(1.580)	(1.220)	(3.693)	(0.426)
Discounters Market Shares	1.699	0.426	2.65	-0.004
	(0.128)* **	**(0.121)*** **	**(0.233)*** **	**(0.079)**
	*(0.073)****	*(0.086)****	*(0.112)****	*(0.072)*
	(1.224)	(1.000)	(2.391)	(0.230)
HHI	-0.003	-0.007	-0.002	-0.001
	(0.000)* **	**(0.001)*** **	**(0.000)*** **	**(0.001)** **
	*(0.000)****	*(0.001)****	*(0.000)****	*(0.001)***
	(0.002)*	(0.005)	(0.003)	(0.002)
Net Sales Floor	-0.020	0.011	-0.087	-0.001
	(0.003)* **	**(0.001)*** **	**(0.007)*** **	**(0.001)**
	*(0.001)****	*(0.001)****	*(0.003)****	*(0.001)*
	(0.030)	(0.009)	(0.074)	(0.002)
House Value	0.438	-0.638	1.052	-0.021
	(0.065)* **	**(0.072)*** **	**(0.119)*** **	**(0.053)**
	*(0.034)****	*(0.056)****	*(0.047)****	*(0.049)*
	(0.643)	(0.581)	(1.226)	(0.137)
Observations	183,994	73,669	58,854	51,471
R-squared	0.892	0.940	0.855	0.940
FE	Store-Time × Category	Store-Time × Category	Store-Time × Category	Store-Time × Category
Cluster	**StoreCategory**	**StoreCategory**	**StoreCategory**	**StoreCategory**
Cluster	*Category*	*Category*	*Category*	*Category*
Cluster	Store	Store	Store	Store

The dependent variable is $ln(variety)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors clustered at different levels in parentheses: in the first row below each coefficient estimate (in bold) the clustering is at the store-category level, in the second row (in italics) the clustering is at the category level, while in the third row it is at the store level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 6: Heterogenous Effects of Rebranding

	(1) Log Variety	(2) Log Average Price
Overlap × Post	0.094***	0.001
	(0.008)	(0.004)
Overlap × Post × No Rebrand	-0.243***	0.005
	(0.009)	(0.004)
Population	1.623***	0.128
	(0.281)	(0.143)
Average Income	0.525***	0.254**
	(0.193)	(0.109)
Discounters Market Shares	0.189	0.062
	(0.122)	(0.060)
HHI	-0.006***	-7.56e-05
	(0.001)	(0.000)
Net Sales Floor	0.012***	-0.001*
	(0.001)	(0.001)
House Value	-0.731***	0.0212
	(0.071)	(0.034)
No Rebrand	4.818***	0.039
	(0.804)	(0.049)
Observations	73,669	63,461
R-squared	0.941	0.865
FE	Store-Time × Category	Store-Time × Category
Cluster	StoreCategory	StoreCategory

The dependent variable is $ln(variety)$. We only present regressions for C1000. We control for fixed effects at the store level as well at the category-quarter level. Standard errors clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 7: Average Treatment Effect per Insigna: Average category price

	(1)	(2)	(3)	(4)
	Full sample	C1000	Jumbo	Competitors
Overlap X Post	0.028	0.003	0.087	-0.001
	(0.003)* **	**(0.003)**	**(0.007)*** **	**(0.002)**
	*(0.002)****	*(0.005)*	*(0.003)****	*(0.002)*
	(0.024)	(0.003)	(0.067)	(0.002)
Population	1.081	0.116	2.872	0.150
	(0.106)* **	**(0.142)**	**(0.245)*** **	**(0.049)*** **
	*(0.060)****	*(0.136)*	*(0.107)****	*(0.070)***
	(1.005)	(0.168)	(2.503)	(0.065)**
Average Income	-0.351	0.265	-1.102	-0.025
	(0.062)* **	**(0.109)** **	**(0.106)*** **	**(0.047)**
	*(0.047)****	*(0.081)****	*(0.059)****	*(0.051)*
	(0.485)	(0.091)***	(0.993)	(0.050)
Discounters Market Shares	0.280	0.055	0.542	-0.003
	(0.039)* **	**(0.059)**	**(0.067)*** **	**(0.023)**
	*(0.026)****	*(0.034)*	*(0.033)****	*(0.022)*
	(0.335)	(0.058)	(0.650)	(0.037)
HHI	-7.84e-06	-6.96e-05	3.00e-04	2.47e-05
	(0.000)	**(0.000)**	**(0.000)** **	**(0.000)**
	(0.000)	*(0.000)*	*(0.000)****	*(0.000)*
	(0.000)	(0.000)	(0.001)	(0.000)
Net Sales Floor	-0.010	-0.001	-0.025	2.60e-04
	(0.001)* **	**(0.001)* **	**(0.002)*** **	**(0.000)**
	*(0.000)****	*(0.001)**	*(0.001)****	*(0.000)*
	(0.008)	(0.001)*	(0.018)	(0.000)
House Value	0.191	0.015	0.359	0.001
	(0.019)* **	**(0.034)**	**(0.032)*** **	**(0.021)**
	*(0.011)****	*(0.031)*	*(0.015)****	*(0.017)*
	(0.159)	(0.025)	(0.313)	(0.019)
Observations	176,442	63,461	58,774	54,207
R-squared	0.852	0.865	0.849	0.944
FE	Store-Time × Category	Store-Time × Category	Store-Time × Category	Store-Time × Category
Cluster	**StoreCategory**	**StoreCategory**	**StoreCategory**	**StoreCategory**
Cluster	*Category*	*Category*	*Category*	*Category*
Cluster	Store	Store	Store	Store

The dependent variable is *ln(categoryprice)*. We control for fixed effect at the store level as well at the category-quarter level. Standard errors clustered at different levels in parentheses: in the first row below each coefficient estimate (in bold) the clustering is at the store-category level, in the second row (in italics) the clustering is at the category level, while in the third row it is at the store level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Appendices

Online appendix – Not for publication

A. Propensity Score Matching for Areas Selection and the Stores' choice

This appendix describes the methodology used to select the stores. The ACM provided us with historical location data on all supermarkets in the Netherlands, the 'Supermarkt gids' database, which lists geographic data (including addresses, postal code, city, province) together with additional information (e.g., availability of parking or automatic counters). In 2013, the guide counts 6,641 stores. Our budget allowed selecting a total of 171 stores. As described in the paper, we compare the merging stores in the overlapping areas (treated stores) and the merging stores in the non-overlapping areas (control stores). To select appropriate stores for our analysis, we started by identifying the overlapping and non-overlapping areas. There were 253 overlapping areas out of a total of 1,145 areas in the whole sample.

In order to identify the areas for the selection of 171 stores, we follow an approach based on the propensity score matching (PSM) methodology. PSM was developed as a technique to correct for sample selection bias that may affect the estimation of the treatment effect in non-randomized experiments. In randomized experiments, the results in the treated and control groups may often be directly compared because the two samples are likely to be similar (the assignment to the treated and control 'status' is indeed random). In non-randomized experiments, the direct comparison between the treated and control units may be misleading because units exposed to the treatment systematically differ from the units not exposed to the treatment. Propensity score matching allows to group treated and control units according to their probability of receiving the treatment based on observable characteristics. The propensity score is defined as the conditional probability of receiving the treatment given a set of pre-treatment variables:

$$p(X) = Pr(D = 1|X)$$

The PSM technique allows for collapsing the multiple dimensions along which treated and control units might differ into one single dimension: the propensity score. In the case under examination, the probability of receiving the treatment may coincide with the probability of being an overlapping area. We computed a propensity score for each area and grouped overlapping and non-overlapping areas according to the similarity of their score. We estimate the probability of treatment running a logistic regression. The dependent variable is a discrete variable that takes value one if the area is overlapping and zero otherwise. The independent variables include demand and supply factors that may influence the decision of a supermarket insignia to locate its stores in a given area.

We then group treated and control cities according their estimated scores. Treated and control units with exactly the same propensity score are rarely found. Instead, each treated unit is usually matched with its closest control, as indicated by the propensity score value. We had to allow for multiple uses of the same control city in order to maximize the number of treated cities included in our final sample (i.e., to prevent some treated cities from falling 'off support').[19]

Post matching, we then checked if treated and control areas are indeed similar in observable characteristics except for the treatment. We do that by testing the equality of means for the relevant explanatory variables and we conclude that the means across the treated and control areas are not statistically different (see Table 8).

[19] In some of the control matched cities, there were no merging stores. The empirical strategy underpinning the analysis across areas requires that at least one of the merging chains is present in the non-overlapping (control) cities. For this reason, we could not limit the match to the 'nearest neighbor', but had to extend the match to the third nearest neighbor.

Table 8: Equality of the means between treated and control areas

	Means			t-test	
	Treated	Control	%bias	t-test	p > t
Pscore	0.3906	0.3712	10.8	1.18	0.237
Average population density	13,580	11,830	8.4	0.78	0.434
Average store size	922.67	927.57	-1.6	-0.18	0.855
Average income	2,407.7	2,416.4	-2.8	-0.31	0.757
Number of stores (squared)	37.226	31.381	8.0	0.74	0.459
HHI	4,731.1	5,088.7	-11.7	-1.27	0.204
Average land price	142.34	147.41	-5.2	-0.52	0.604
HHI Discounters	1,757.2	1,776.9	-1.0	-0.11	0.916

Table 9 presents the list of areas obtained from the matching process and indicates those areas that, among the treated ones, were deemed problematic (i.e. where the merged entity had a combined market share above 50%). Moreover, we highlight in which of the former areas a divestiture was required.

Table 9: List of matched areas

City	Province	Treated	Overlap MS>50%	Overlap MS<50%
'S-HEERENBERG	Gelderland	Treated	0	1
DEN BURG	Noord-Holland	Untreated	0	0
DEN HAM OV	Overijssel	Treated	1	0
TERSCHELLING FORMERUM	Friesland	Untreated	0	0
BARNEVELD	Gelderland	Treated	0	1
ASSENDELFT	Noord-Holland	Untreated	0	0
BEMMEL	Gelderland	Treated	0	1
BEST	Noord-Brabant	Untreated	0	0
BODEGRAVEN	Zuid-Holland	Treated	0	1
OOSTERBEEK	Gelderland	Untreated	0	0
CAPELLE AAN DEN IJSSEL	Zuid-Holland	Treated	0	1
LISSE	Zuid-Holland	Untreated	0	0
DE MEERN	Utrecht	Treated	0	1
DALFSEN	Overijssel	Untreated	0	0
LICHTENVOORDE	Gelderland	Treated	1	0

EDE GLD	Gelderland	Untreated	0	0
DIEMEN	Noord-Holland	Treated	0	1
OUDDORP ZH	Zuid-Holland	Untreated	0	0
EERSEL	Noord-Brabant	Treated	0	1
DELFT	Zuid-Holland	Untreated	0	0
ENTER	Overijssel	Treated	0	1
BERGEIJK	Noord-Brabant	Untreated	0	0
GOOR	Overijssel	Treated	0	1
GEMERT	Noord-Brabant	Untreated	0	0
GROESBEEK	Gelderland	Treated	0	1
HATTEM	Overijssel	Untreated	0	0
HARDERWIJK	Gelderland	Treated	0	1
MILL	Noord-Brabant	Untreated	0	0
HEEMSKERK	Noord-Holland	Treated	0	1
ALPHEN AAN DEN RIJN	Zuid-Holland	Untreated	0	0
HOLTEN	Overijssel	Treated	0	1
MAKKUM FR	Friesland	Untreated	0	0
HOOGERHEIDE	Noord-Brabant	Treated	0	1
ANNA PAULOWNA	Noord-Holland	Untreated	0	0
HOUTEN	Utrecht	Treated	0	1
MIDDELBURG	Zeeland	Untreated	0	0
IJSSELSTEIN UT	Utrecht	Treated	1	0
SEVENUM	Limburg	Untreated	0	0
KAATSHEUVEL	Noord-Brabant	Treated	0	1
MAASSLUIS	Zuid-Holland	Untreated	0	0
KERKRADE	Limburg	Treated	0	1
BOXMEER	Noord-Brabant	Untreated	0	0
LANDGRAAF	Limburg	Treated	0	1
HOORN NH	Noord-Holland	Untreated	0	0
LEIDEN	Zuid-Holland	Treated	0	1
EMMER-COMPASCUUM	Drenthe	Untreated	0	0
LOCHEM	Gelderland	Treated	0	1
VROOMSHOOP	Overijssel	Untreated	0	0
OMMEN	Overijssel	Treated	0	1
TIEL	Gelderland	Untreated	0	0
OOST-SOUBURG	Zeeland	Treated	0	1
NORG	Drenthe	Untreated	0	0
STADSKANAAL	Groningen	Treated	1	0
SEVENUM	Limburg	Untreated	0	0

CULEMBORG	Gelderland	Untreated	0	0
ROOSENDAAL	Noord-Brabant	Treated	0	1
ENKHUIZEN	Noord-Holland	Untreated	0	0
SAPPEMEER	Groningen	Treated	0	1
NIEUWE NIEDORP	Noord-Holland	Untreated	0	0
SITTARD	Limburg	Treated	0	1
HILLEGOM	Zuid-Holland	Untreated	0	0
SOEST	Utrecht	Treated	0	1
SMILDE	Drenthe	Untreated	0	0
SOMEREN	Noord-Brabant	Treated	0	1
ZETTEN	Gelderland	Untreated	0	0
SON	Noord-Brabant	Treated	0	1
LIENDEN	Gelderland	Untreated	0	0
STEENBERGEN NB	Noord-Brabant	Treated	0	1
EDE GLD	Gelderland	Untreated	0	0
THOLEN	Zeeland	Treated	0	1
RENESSE	Zeeland	Untreated	0	0
TWELLO	Gelderland	Treated	0	1
OOSTERWOLDE FR	Friesland	Untreated	0	0
URK	Overijssel	Treated	0	1
KROMMENIE	Noord-Holland	Untreated	0	0
VELDHOVEN	Noord-Brabant	Treated	0	1
OSS	Noord-Brabant	Untreated	0	0
VINKEVEEN	Utrecht	Treated	0	1
ZEVENHUIZEN ZH	Zuid-Holland	Untreated	0	0
WASSENAAR	Zuid-Holland	Treated	0	1
KOLLUM	Friesland	Untreated	0	0
WESTERBORK	Drenthe	Treated	1	0
OPHEUSDEN	Gelderland	Untreated	0	0
WIERDEN	Overijssel	Treated	0	1
SCHAGEN	Noord-Holland	Untreated	0	0
WIJCHEN	Gelderland	Treated	0	1
GENNEP	Limburg	Untreated	0	0
WINSCHOTEN	Groningen	Treated	0	1
EERBEEK	Gelderland	Untreated	0	0
WOUDENBERG	Utrecht	Treated	0	1
ZEEWOLDE	Flevoland	Untreated	0	0
ZELHEM	Gelderland	Treated	0	1
AALSMEER	Noord-Holland	Untreated	0	0

IJSSELSTEIN UT	Utrecht	Treated	1	0
CULEMBORG	Gelderland	Untreated	0	0
ZEVENBERGEN	Noord-Brabant	Treated	0	1
WOERDEN	Utrecht	Untreated	0	0
DEURNE	Noord-Brabant	Treated	Divestiture	0
LIENDEN	Gelderland	Untreated	0	0
GRAVE	Noord-Brabant	Treated	Divestiture	0
BERGEIJK	Noord-Brabant	Untreated	0	0
KAMPEN	Overijssel	Treated	Divestiture	0
EERBEEK	Gelderland	Untreated	0	0
OIRSCHOT	Noord-Brabant	Treated	Divestiture	0
DALFSEN	Overijssel	Untreated	0	0
RAALTE	Overijssel	Treated	Divestiture	0
VROOMSHOOP	Overijssel	Untreated	0	0
RAAMSDONKSVEER	Noord-Brabant	Treated	Divestiture	0
HILLEGOM	Zuid-Holland	Untreated	0	0
ZUIDLAREN	Drenthe	Treated	Divestiture	0
BOXMEER	Noord-Brabant	Untreated	0	0
IJSSELMUIDEN	Overijssel	Treated	1	0
BRUMMEN	Gelderland	Untreated	0	0

To conclude, the propensity score matching technique allows us to identify the areas from which we finally selected our sample of stores. In the next section, we describe this second selection exercise.

A.0.1. The choice of stores

Within areas of overlap and areas of non-overlap, we select a suitable number of stores from both the merging parties and the competing chains.[20] However, we restrict the choice to two competitors' chains: Albert Heijn and COOP. This choice is based on a number of considerations.

First, available information on chains' strategy and the economic literature suggest that it might be appropriate to include in the analyses an explanatory variable attempting to capture "chain-specific effects." Consequently, we restrict the number of chains in order to ensure that a sufficient number of stores is available for each chain.

[20]Among the stores of the merging parties, we wanted to have stores from the acquirer Jumbo and the target C1000. Moreover, we also tried to have stores that were re-brandend during the sample period –i.e., adopted the Jumbo insignia – as well as stores that were not re-branded.

Second, we want to include in our selection both a national competitor and a local competitor, to exploit any differences in their responses to a change in competition.

Third, we adjust our selection in order to take into account data availability issues. In particular, some supermarket chains – especially discounters like Aldi and Lidl – denied access to store level data. In addition, the data provider warned us about (i) missing data for some supermarket chains; and (ii) limited availability of data on private label goods in 2009 and 2010.

Our selection also attempts to ensure a widespread coverage of the Dutch territory as well as a balanced representation of merging parties and of the subset of competitors selected, across areas of overlap and areas of non-overlap. Moreover, we do not select stores from the largest cities. The main reason we excluded the largest cities from our selection is related to the difficulties of matching them with appropriate control regions. Data completeness proved to be an additional problem as supply level data are incomplete for most of the largest cities.

Concerning the kind of stores, the ACM defines a single 'product' market encompassing all supermarket formulas, including regular supermarkets, hypermarkets, and discounters. The difference between the various formulas is determined mainly by the shop size.[21] The assortment size can be a further element of differentiation among stores. Hypermarkets typically have the broadest assortment (20,000 SKUs is a common figure for food products). Supermarkets typically sell between 5,000 and 10,000 different food SKUs. Finally, discounters have the narrowest assortment, typically between 1,000 and 2,000 SKUs. In our study, we follow a different approach. For each supermarket chain, we limit our selection to regular formula only, in order to focus on the stores that are the closest substitutes.

Our final selection includes over 171 different stores representing the merging parties' chains and two competitors (Albert Heijn and Coop). For the scope of this paper, we only used data on 124 stores (the remaining stores were involved in different mergers analyzed in Argentesi et al. (2015)). For this list of stores, we asked for data on turnover, volume, promotional turnover, promotional share, and variety for a selection of products, as described in the data section. Note that we have a slightly different sample for the price and variety specifications. Table 1 reports the sample of stores used in our regressions.

[21] In a recent study (European Commission, 2014), the European Commission adopted the following definition: i) supermarkets: stores whose size is between 400 and 2,499 square meters; ii) hypermarkets: stores whose size is equal to or greater than 2500 square meters; iii) discounters: all stores size.

B. List of SKUs

The following table presents a list of the selected SKUs per products' category used in the price analysis. In the cells we report the number of stores for which we have information on that particular product.

Table 10: Selected SKUs per Product Category – Price Analysis

		PRODUCTS			CHAINS		
Category			C1000	Jumbo	SdB	Coop	AH
Cleaners	A-brand	Ajax	61	66	37	10	50
		CITRONELLA			37		
		WITTE REUS	61	66		10	50
	Private label	Albert heijn					50
		C1000	61				
		JUMBO		66			
		MARKANT				10	
		O'LACY		66			
		PERFEKT					
		SUPER			37		
Coffee	A-brand	Douwe egberts			37	10	50
		KANIS & GUNNINK	61	66	37	10	50
		VAN NELLE SUPRA	61	66			
	Private label	C1000	61				
		HOOGVLIET					
		JUMBO		66			
		MARKANT				10	
		PERLA					50
		SUPER DE BOER			37		
Cola	A-brand	Coca cola	61	66	37	10	50
		PEPSI	61	66	37	10	50
	Private label	Albert heijn					50
		C1000	61				
		JUMBO		66			
		MARKANT				10	
		O'LACY		66			
		PERFEKT					
		SUPER			37		
Diapers	A-brand	Huggies super dry		66			50

		HUGGIES SUPER FLEX		66			
		PAMPERS BABY DRY		66	37	10	50
		PAMPERS NEW BABY	61				
	Private label	Albert heijn					50
		BUMBLIES				10	
		C1000	61				
		JUMBO		66			
		SUPER			37		
		SUPER DE BOER			37		
Fresh Milk	A-brand	Arla biologisch					50
		BIO PLUS				10	
		CAMPINA	61	66	37		50
		FRIESCHE VLAG	61	66	37	10	
		VECOZUIVEL					
	Private label	Albert heijn					50
		JUMBO		66			
		MELKAN		66		10	
		SUPER			37		
		ZUIVEL	61				
Frikandels	A-brand	Beckers	61	66	37	10	50
		MORA	61		37	10	50
		VAN RIJSINGEN		66			
	Private label	Albert heijn					50
		C1000	61				
		EUROSHOPPER					50
		JUMBO		66			
		MARKANT				10	
		O'LACY		66			
		PERFEKT					
		SUPER			37		
Mayonaise	A-brand	Calve			37		
		REMIA	61	66	37	10	50
		ZAANSE MAYONAISE	61	66		10	50
	Private label	Albert heijn					50
		C1000	61				
		JUMBO		66			
		MARKANT				10	
		O'LACY		66			
		PERFEKT					

		SUPER DE BOER			37		
Olive Oil	A-brand	Bertolli	61	66	37	10	50
		BIO PLUS		66	37	10	
		BIORGANIC					
		MONINI	61				50
	Private label	C1000	61				
		EUROSHOPPER					50
		JUMBO		66			
		MARKANT				10	
		O'LACY'S		66			
		PERFEKT					
		SUPER DE BOER			37		
Sanitary Napkins	A-brand	Always ultra	61			10	
		ALWAYS ULTRA NORMAAL	61			10	
		KOTEX MAXI SUPER		66	37		50
		LIBRESSE INVISIBLE	61	66	37	10	50
	Private label	Albert heijn					50
		C1000	61				
		JUMBO		66			
		NEWWAY		66		10	
		SUPER			37		
Shampoo	A-brand	Guhl	61	66	37		50
		NEUTRAL				10	
		SYOSS SHINE BOOST					
Toiletpaper	A-brand	Edet soft	61	66	37	10	50
		PAGE KUSSENZACHT		66	37	10	50
		PAGE ZACHT EN STERK	61				
	Private label	Albert heijn					50
		C1000	61				
		JUMBO		66			
		MARKANT				10	
		PERFEKT					
		SUPER DE BOER			37		

C. Local Variation

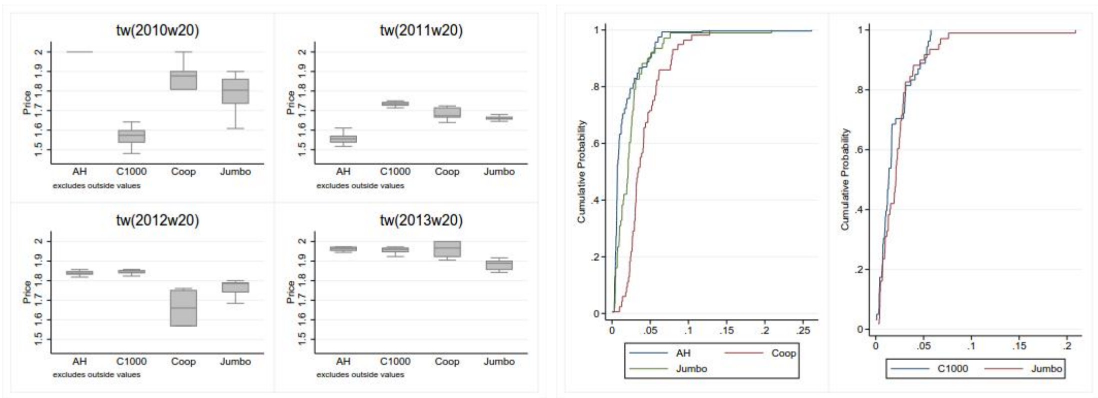
As explained in section 5.1, in this appendix we more carefully analyze the geographic extent of price and assortment variability. First, we graphically analyze the distribution of SKU prices, variety and category prices for different supermarket chains at different points in time by means of boxplots. Second, we compute a coefficient of variation for each SKU (category) and each month. For SKU prices, we first compute the standard deviation of price from SKU's average price of that month. We then divide the price standard deviation of each SKU by the average price of that SKU in order to obtain a measure of the price dispersion independent of the price level. In a similar way, we compute the coefficient of variation for variety and category prices. Below, we present a selection of the discussed graphs. Figures 6 to 10 show the geographic price variability of five SKUs. Figures 11 to 14 show the geographic variability in stores' assortment for four selected categories. Finally, figures 15 to 18 show the variability in category prices for the same product categories.

For each SKU (category), the first graph (boxplot) shows the SKU price (variety/category price) dispersion in May 2010, May 2011, May 2012, and May 2013. These graphs allows comparing the SKU price (variety/category price) dispersion of Jumbo with:

- SKU price (variety/category price) dispersion of the same SKU (category) sold by two competitors: the market leader (Albert Heijn) and a smaller player (Coop). Both reportedly have adopted a national pricing strategy.
- SKU price (variety/category price) dispersion of the same SKU (category) sold by C1000. The data in the graph refer to those C1000 stores that did not change their insignia to Jumbo during the period under study, even after the merger.

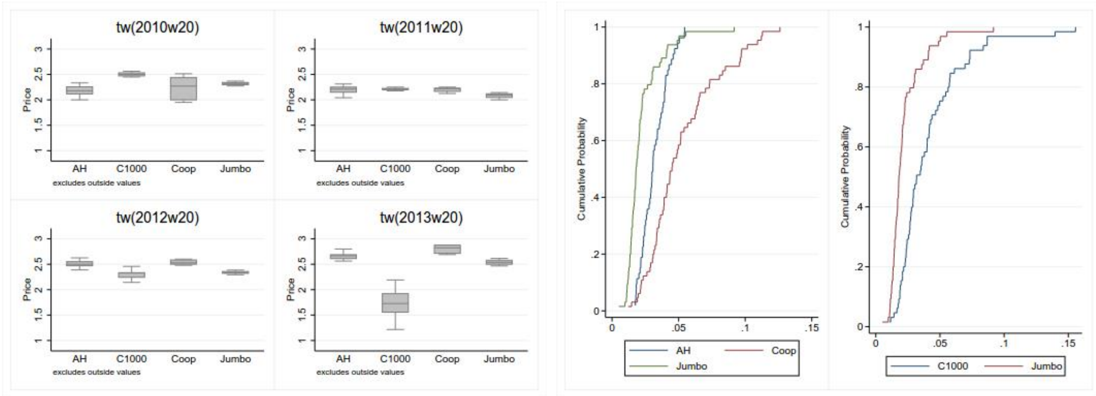
The second graph shows the cumulative distribution function of the coefficient of variation for SKU prices (figures 6 to 10), variety (figures 11 to 14) and category prices (figures 15 to 18) respectively. The coefficient of variation for SKU price (variety/category price) of each SKU (category), for each point in time and for each chain, is computed as the ratio between the SKU price (variety/category price) standard deviation and the average SKU price (variety/category price), and then plotted in a single graph, irrespective of the moment of their measurement. The cumulative distribution function of the coefficient of variation shows the cumulative probability that the coefficient of variation is below a given threshold. If the distribution concentrates around zero, the coefficient of variation over the period of analysis for a given chain and SKU (category) is likely to be low; hence the conclusion is that the chain sets national prices (variety/category prices), i.e. there is no variation across stores. A more evenly distribution, instead, shows that the coefficient of variation is higher than zero. In the latter case, we would expect local SKU prices (variety/category prices). The inclusion of the cumulative distribution function of different chains in the same graph allows across-chains comparisons. Chains whose curve is close to the vertical axis are expected to set national SKU prices (have national assortment/category prices) with higher probability than the other chains: indeed, for that chain, the probability that the variation coefficient is around zero is higher. In the first panel, Jumbo is compared to its competitors Albert Heijn and Coop; in the second panel, Jumbo is compared to the target chain in the acquisition of C1000.

Figure 6: SKU prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for Ajax (cleaner brand)



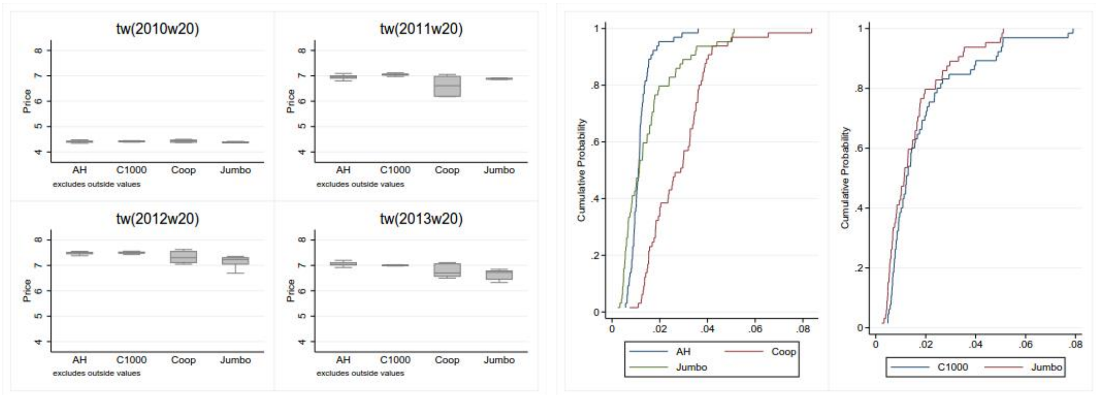
Source: our elaboration on IRI data.

Figure 7: SKU prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for REMIA (a mayonnaise brand)



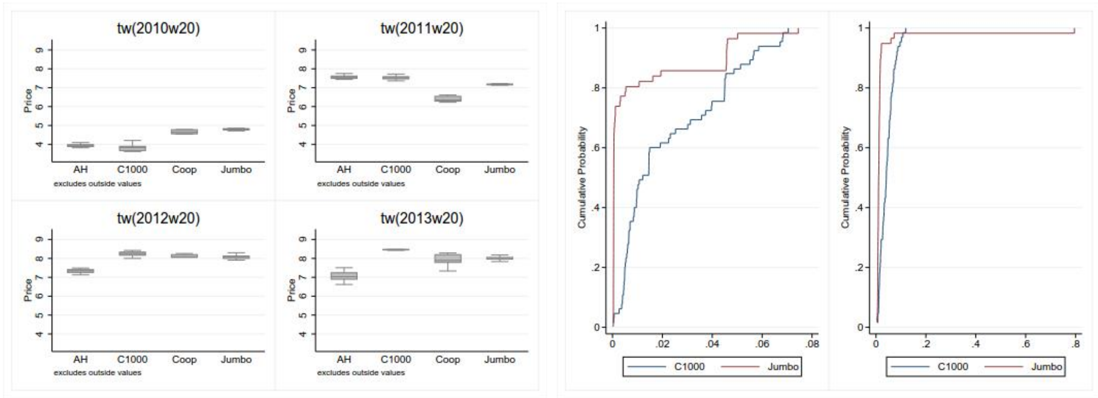
Source: Our elaboration on IRI data.

Figure 8: SKU prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for Kanis & Gunnink (coffee brand)



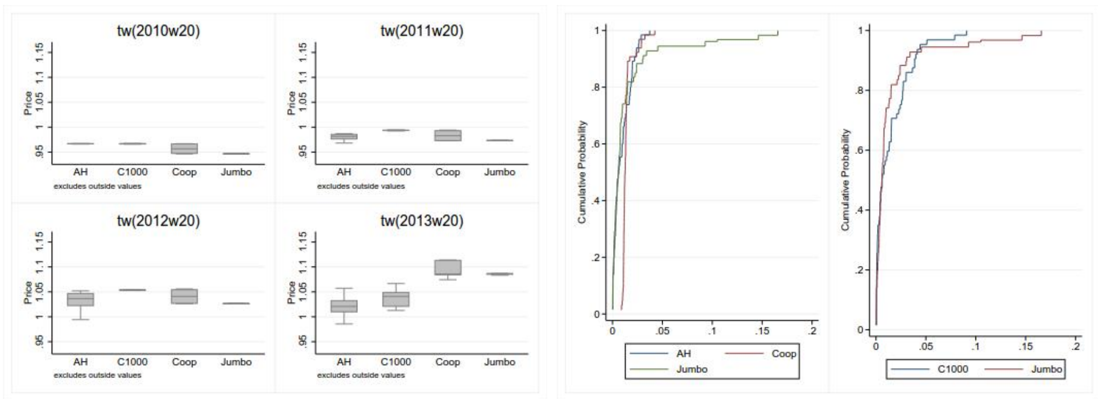
Source: Our elaboration on IRI data.

Figure 9: SKU prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for private label coffee brands



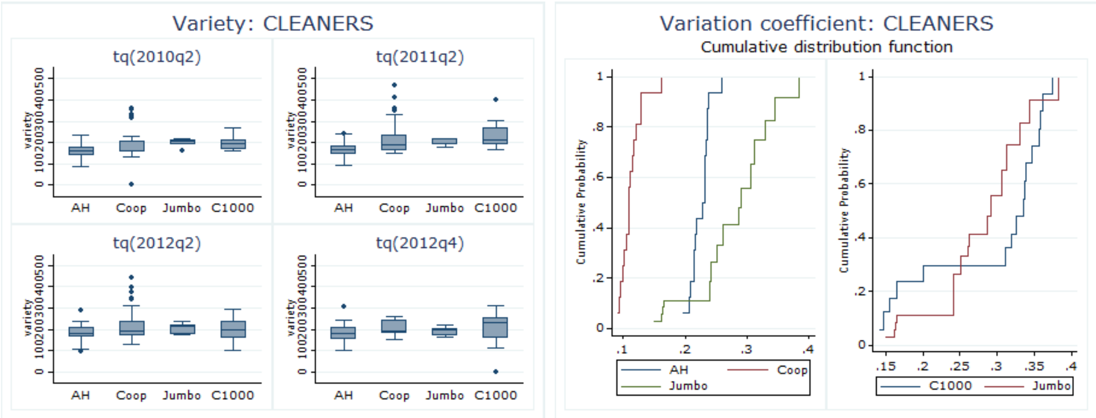
Source: Our elaboration on IRI data.

Figure 10: SKU prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for Coca cola (brand)



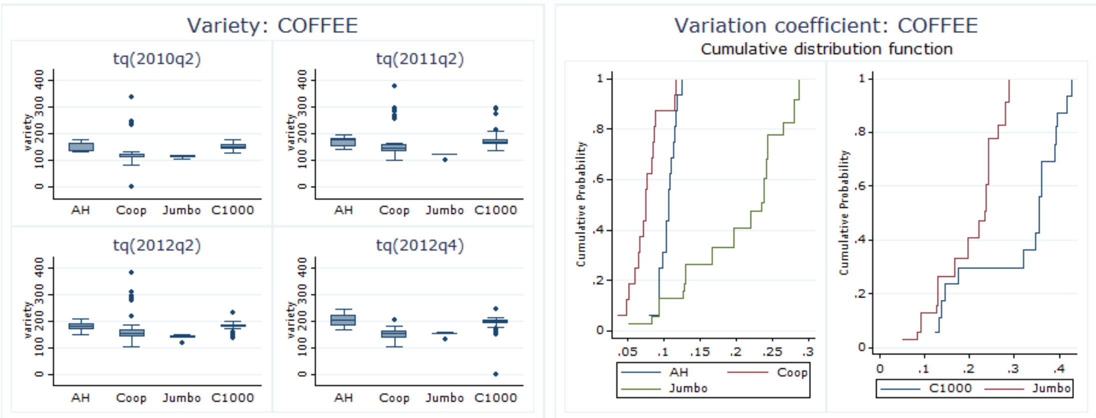
Source: Our elaboration on IRI data.

Figure 11: Variety: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category cleaners



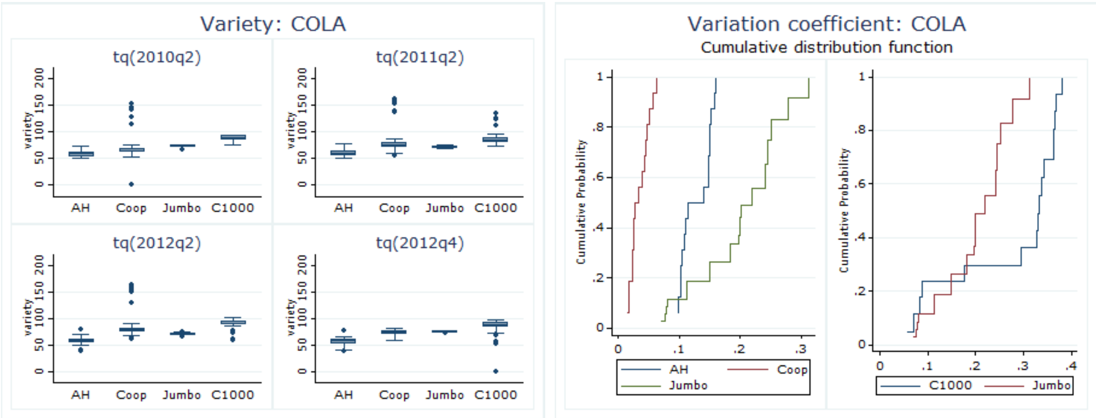
Source: our elaboration on IRI data.

Figure 12: Variety: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category coffee



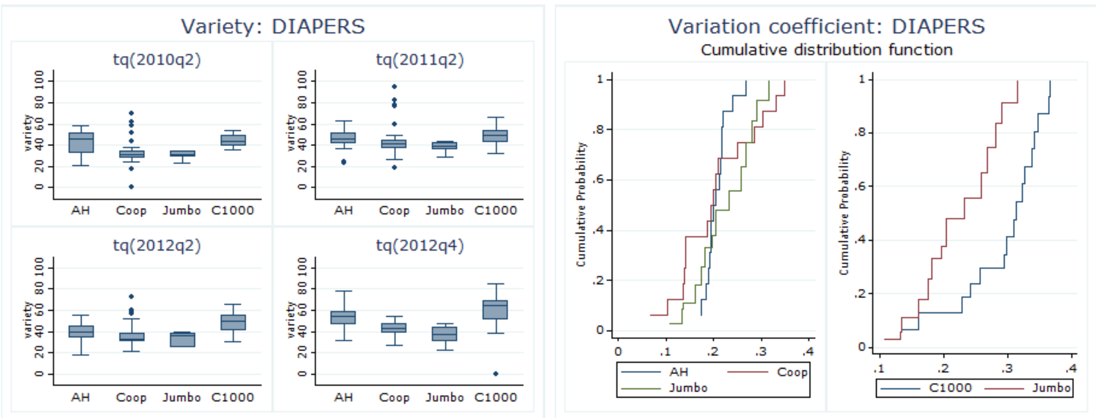
Source: Our elaboration on IRI data.

Figure 13: Variety: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category cola



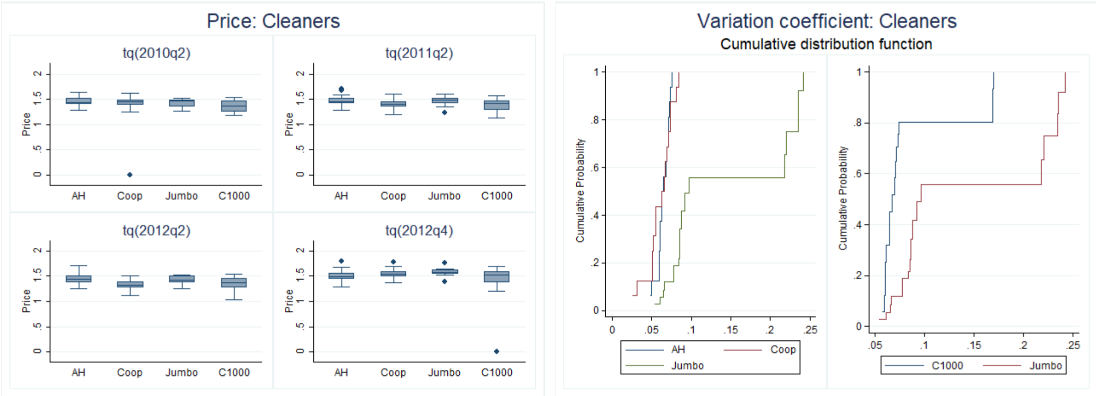
Source: Our elaboration on IRI data.

Figure 14: Variety: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category diapers



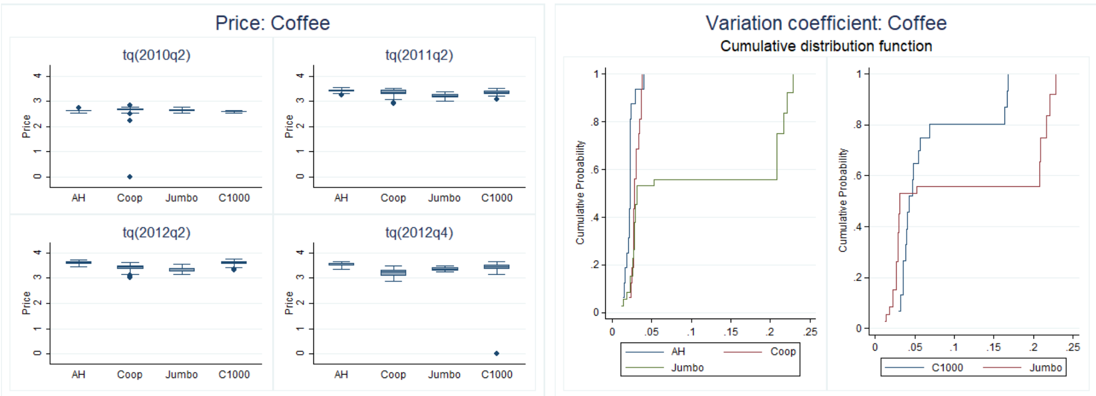
Source: Our elaboration on IRI data.

Figure 15: Average prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category cleaners)



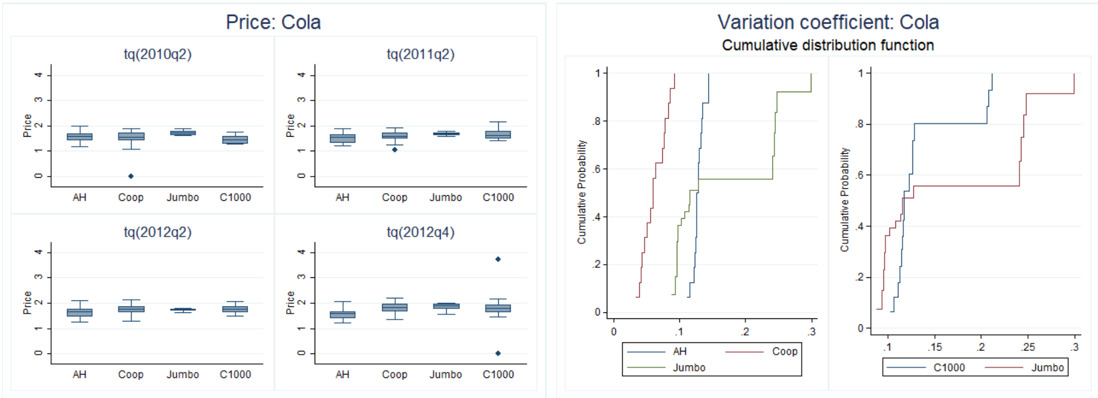
Source: our elaboration on IRI data.

Figure 16: Average prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category coffee



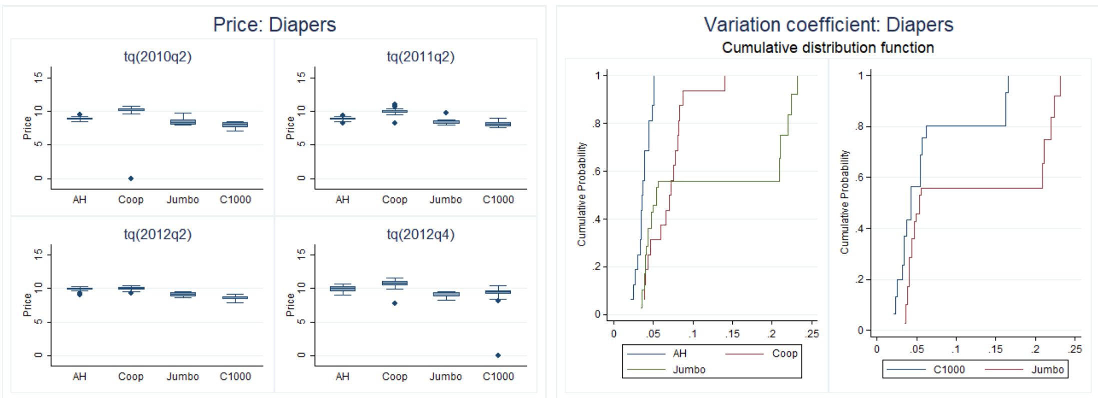
Source: Our elaboration on IRI data.

Figure 17: Average prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category cola



Source: Our elaboration on IRI data.

Figure 18: Average prices: Box-plot (first panel) and cumulative distribution function of the coefficient of variation (second panel) for the category diapers

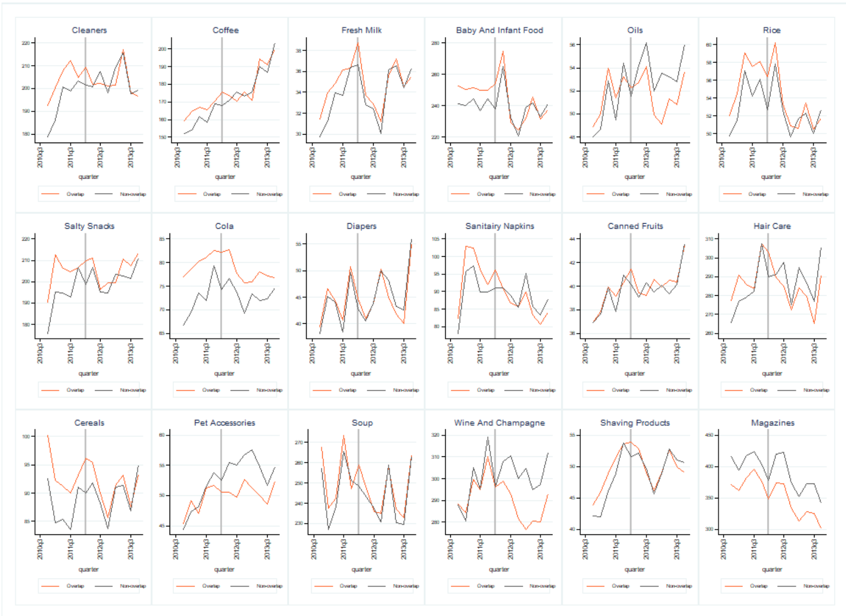


Source: Our elaboration on IRI data.

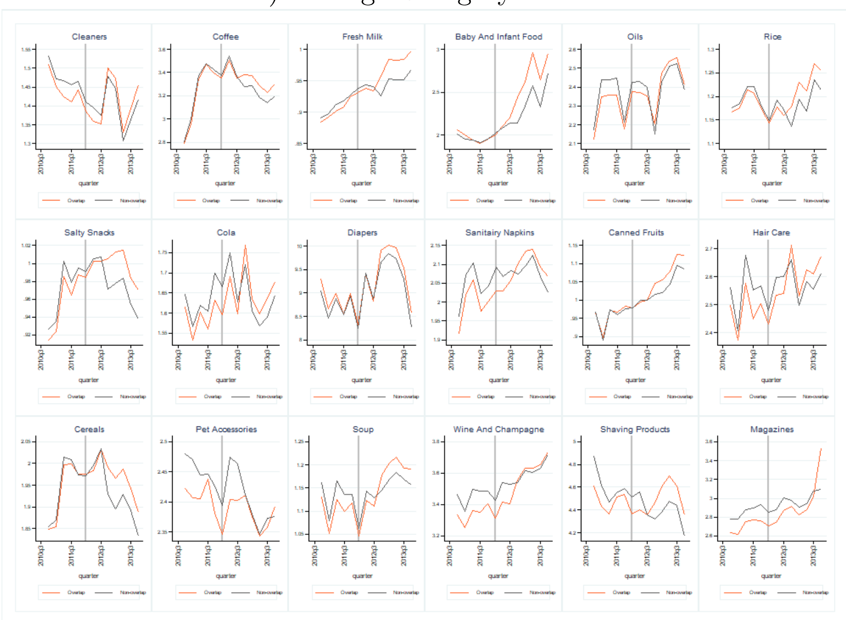
D. Additional Figures on the Common Trends

Figure 19: Trends for variety and average category prices in treated and control areas per categories – All chains

a) Variety



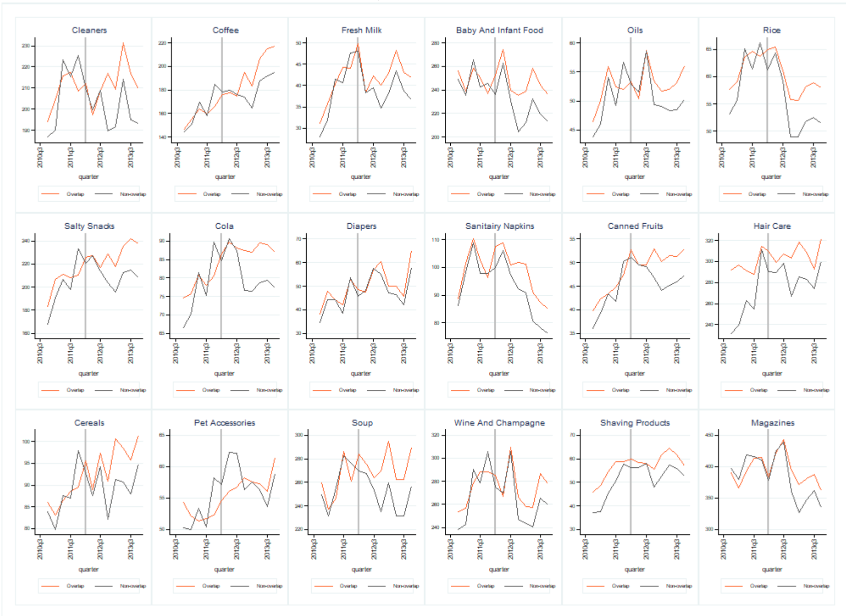
b) Average Category Prices



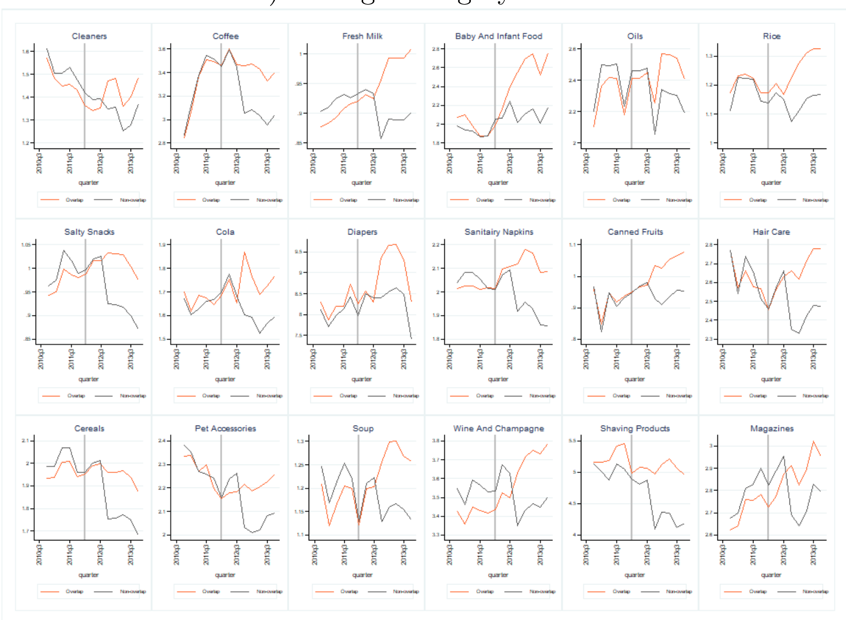
Source: Our elaboration on IRI data

Figure 20: Trends for variety and average category prices in treated and control areas per categories – Jumbo

a) Variety



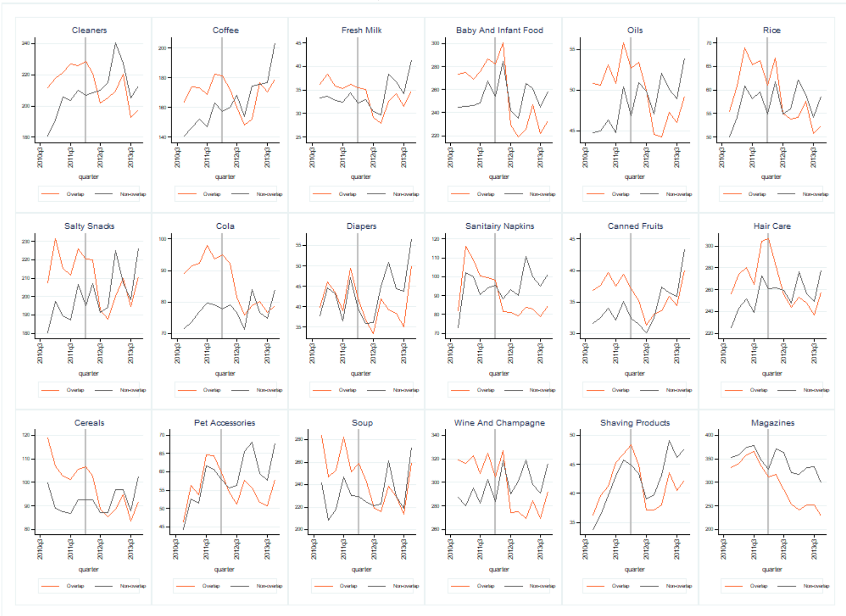
b) Average Category Prices



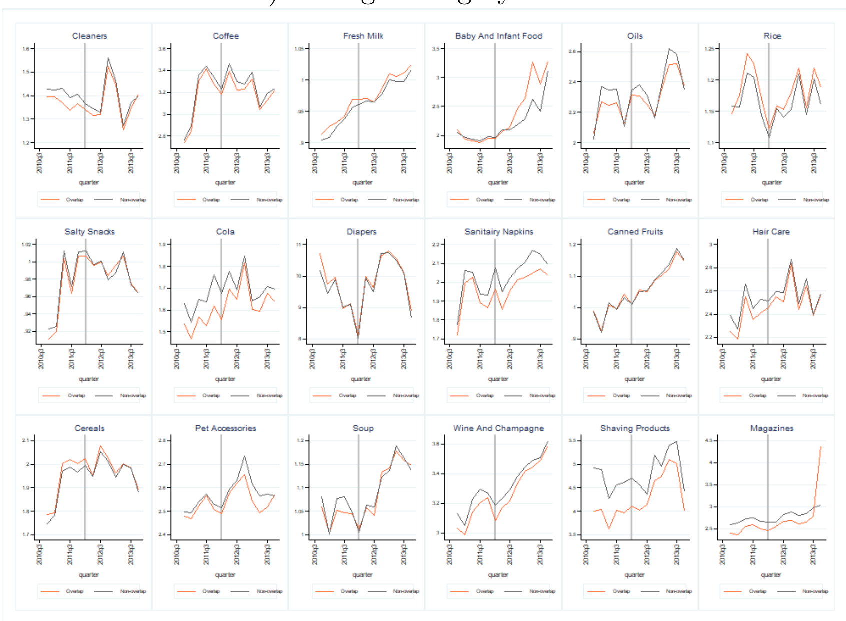
Source: Our elaboration on IRI data

Figure 21: Trends for variety and average category prices in treated and control areas per categories – C1000

a) Variety



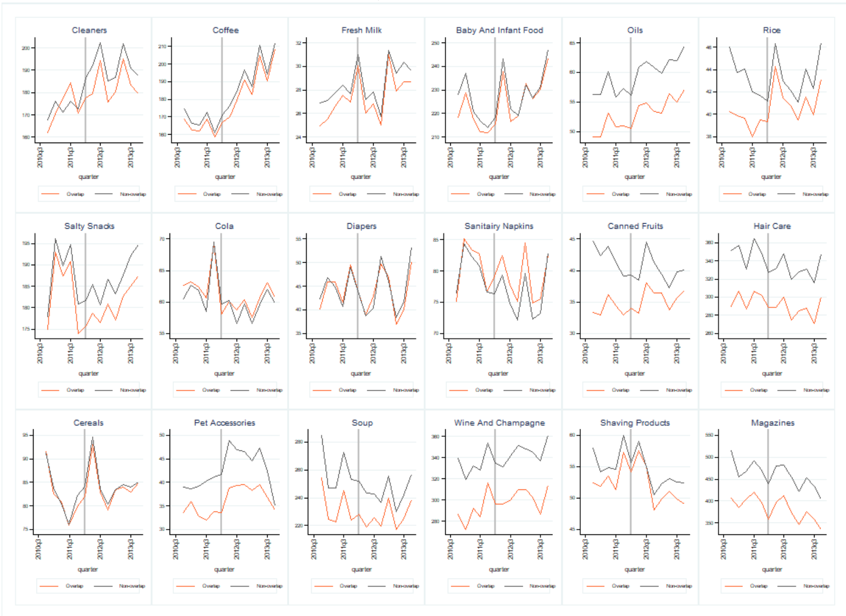
b) Average Category Prices



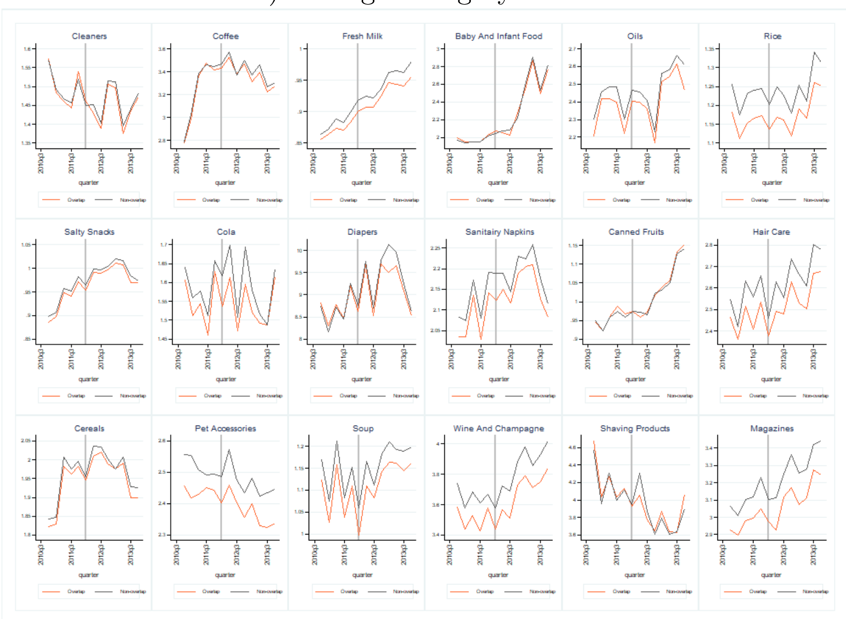
Source: Our elaboration on IRI data

Figure 22: Trends for variety and average category prices in treated and control areas per categories – Competitors

a) Variety



b) Average Category Prices



Source: Our elaboration on IRI data

E. Theoretical model

E.1. A Simple Model of Variety Competition

The model of variety competition presented in this section should help us to better understand the mechanisms behind the empirical results discussed so far. The purpose of this simple model is to study the impact of a merger on retail firms (stores) that compete on variety at local level.

We consider a local market where there are n stores that belong to n independent firms. We study a merger between two firms focusing on the stores' managers decision to adjust the depth of the assortment. We further assume that prices are unaffected. This assumption is consistent with our empirical findings and can be motivated by a national pricing strategy.

To model this situation we assume that each store j $(j = 1, ..., n)$ sells a composite good and sets the value of a variable $v_j \in [0, 1]$, where 0 represents the minimum level and 1 the maximum level of variety. The vector $v = (v_1, ..., v_n)$ identifies a strategy profile. A store offering a variety v_j bears a cost equal to $c(v_j)$, with $c(0) = 0$, $c'(v_j) > 0$, and $c''(v_j) \geq 0$. Marginal cost is assumed constant and normalized to zero. We order the stores according to their pre-merger level of variety so that:

$$v_j < v_{j+1}, \ j = 1, ..., n - 1.$$

Moreover, we assume that stores that pre-merger offer a higher level of variety charge a higher price.[22] This assumption has empirical validation: in our sample, chains with larger variety tend to have higher prices.

Consumers make their purchasing decisions taking into account both the price a store charges for the composite good and the store's variety. For some consumers, variety is a quality feature. They prefer shopping at the store with the highest variety if all stores charge the same price. These consumers will be referred to as "vertical consumers" (v-consumers, hereafter) because for them variety is a feature that vertically differentiates stores. Other consumers incur decision costs that increase in the level of variety offered by the store at which they shop. These consumers have a preferred level of variety. They are named "horizontal consumers" (h-consumers, hereafter), because they consider variety a feature that horizontally differentiates stores.

To model this demand heterogeneity, we assume that there is a unit mass of consumers with a unitary demand for the composite good offered by the n stores and that this mass of consumers

[22] Note that this condition will hold in the equilibrium of a game in which stores have to decide both the level of variety and the price.

can be split in two disjoint subsets; the first subset, of size α, with $0 \leq \alpha \leq 1$, includes v-consumers; the second subset, with size $1-\alpha$, includes h-consumers.

V-consumers, indexed by i, vary according to the intensity of their preference for variety. Thus the level of gross utility (in monetary terms) v-consumer i obtains when she buys from store j is described by the following C^2 function:

$$u\left(v_j, w_i\right),$$

with $u_{v_j} > 0$, $u_{v_j v_j} \leq 0$ and where w_i is an idiosyncratic v-consumer's characteristic such that $u_{v_j w_i} > 0$; w_i represents how much consumer i cares about variety (i.e. consumers with a higher w obtain a higher marginal utility from variety). This idiosyncratic characteristic is distributed according to the cumulative $G\left(w_i\right)$ over a compact set that can be normalized to $[0,1]$, without any loss of generality. We assume that $G''\left(w_i\right) \leq 0$.

H-consumers have a preferred level of variety. If a h-consumer, indexed by h, buys from store j, her level of gross utility (in monetary terms) is described by the following C^2 function:

$$b\left(v_h\right) - t\left(d\left(v_h, v_j\right)\right),$$

where v_h is the preferred level of variety for h-consumer h, $b\left(v_h\right) > 0$ is the gross benefit of buying at the (ideal) store that offers the preferred assortment, $d\left(v_h, v_j\right)$ is a measure of the distance between v_h and the level of variety in store j, v_j, and $t\left(\cdot\right)$ is a "transportation cost" function that is increasing in $d\left(\cdot\right)$, with $t\left(0\right) = 0$ and $t'' \geq 0$. H-consumers are distributed over the variety space, $[0,1]$, according to the cumulative $H\left(v_h\right)$, with $H''\left(v_h\right) \leq 0$.

Let us define w_j and h_j as the v-consumer and the h-consumer that are indifferent between buying from store j and store $j+1$, respectively. We assume that the price differential between two adjacent stores is such that $h_j < v_{j+1}$, i.e. that the h-consumer that is indifferent between j and $j+1$ has a preferred level of variety that is below that offered by store $j+1$. The overall demand for firm j is $q_j\left(v\right) = q_{vj}\left(v\right) + q_{hj}\left(v\right)$ where:[23]

$$q_{vj}\left(v\right) = \alpha\left[G\left(w_j\right) - G\left(w_{j-1}\right)\right]$$

is the demand function for store $j = 1, ..., n$ stemming from v-consumers, and

$$q_{hj}\left(v\right) = \left(1-\alpha\right)\left[H\left(h_j\right) - H\left(h_{j-1}\right)\right]$$

[23]We derive the stores' demand functions in Section E.2

is the demand function for store $j = 1, ..., n$ stemming from h-consumers.

We assume that before the merger the equilibrium profile $v^* = (v_1^*, ..., v_n^*)$ is such that the following FOCs are satisfied:

$$\frac{\partial \pi_j}{\partial v_j} = \frac{\partial q_j}{\partial v_j} p_j - \frac{\partial c}{\partial v_j} = 0 \text{ for any } j = 1, ..., n.$$

Suppose that stores j ($j = 1, ..., n-1$) and $j+1$ merge. In this merger between "close competitors," we refer to store j as the "low-variety store" and to $j+1$ as the "high-variety store."[24] The new entity resulting from the merger, denoted by m, will have to decide the level of variety in the two stores (j and $j+1$) it now controls. It will do so with the aim of maximizing the following profit function:

$$\pi_m(v) = \pi_j(v) + \pi_{j+1}(v).$$

In Section E.2, we prove the following proposition:

Proposition E.1 *After a merger between two close competitors, the new entity decreases variety in the low-variety store. The new entity decreases variety in the high-variety store only if there are "many" v-consumers.*

If the two merging parties are close competitors, they have an incentive to change variety if this entails an increase in the demand of the other merging party. Let us consider v-consumers first. Both the low-variety store and the high-variety store have an incentive to decrease variety because the demand originating from v-consumers of the other merging party increases if they do so. On the contrary, the two merging parties increase the demand for the other party stemming from h-consumers if they increase the distance between them. This means that the low-variety store has an incentive to decrease variety and the high-variety store has the opposite incentive. As a consequence, the prediction is not ambiguous for the low-variety store: it will decrease variety considering the effect of this choice both on v-consumers and on h-consumers. For the high-variety store, the incentive to decrease variety only exists if there are "many" v-consumers, as the former effect dominates the latter. Since the presence of many v-consumers makes the stores' offer a vertically differentiated product and this tends to lead to more concentrated markets, we can argue that the negative impact on variety is likely to be larger in markets that show a higher level of concentration.

[24] In Section E.2 we also discuss the case of a merger between distant competitors, i.e. firms whose stores are not adjacent in terms of variety.

The above predictions are consistent with our empirical findings. Indeed, we find that C1000, the low-variety chain, reduces variety as a consequence of the merger. Jumbo increases variety, although to a lower extent, which in our model is possible only if there are not many v-consumers.

E.2. Additional results and Proofs

Given the modeling assumptions described in the previous section, we can derive the stores' demand and profit functions. Let us start with the demand stemming from v-consumers. We can define $n+1$ indifference points, denoted by w_j, with $j = 0, ..., n$, that partition the set $[0,1]$ in $n+2$ subsets such that the v-consumer with characteristic w_j is indifferent between buying from store j and store $j+1$. We interpret w_0 as the consumer who is indifferent between shopping at store 1 and not buying at all; similarly w_n identifies the consumer who is indifferent between shopping at store n and not buying. These indifference points are implicitly defined by the following conditions:

$$u\left(v_{j+1}, w_j\right) - u\left(v_j, w_j\right) = \Delta_j, \tag{4}$$

where $\Delta_j = p_{j+1} - p_j$, $u\left(v_0, w_0\right) = 0$, $\Delta_0 = p_1$, $u\left(v_{n+1}, w_n\right) = 0$ and $\Delta_n = -p_n$. The implicit solutions of equations (4) are denoted by $w_j\left(v_{j+1}, v_j\right)$. Their relevant characterization is given in the following Lemma.

Lemma E.1 *For any $j = 1, ..., n-1$, $w_j\left(v_{j+1}, v_j\right)$ is decreasing in v_{j+1} and increasing in v_j.*

proof 1 *Lemma 1 is proved formally by the sign of the following derivatives:*

$$\frac{\partial w_j\left(v_{j+1}, v_j\right)}{\partial v_{j+1}} = -\frac{\frac{\partial u_j\left(v_{j+1}, w_j\right)}{\partial v_{j+1}}}{\frac{\partial u_j\left(v_{j+1}, w_j\right)}{\partial w_j} - \frac{\partial u_j\left(v_j, w_j\right)}{\partial w_j}} < 0$$

as $\frac{\partial u_j\left(v_{j+1}, w_j\right)}{\partial v_{j+1}} > 0$ and $\frac{\partial u_j\left(v_j, w_j\right)}{\partial w_j} - \frac{\partial u_j\left(v_{j+1}, w_j\right)}{\partial w_j} < 0$ by definition (see the meaning of w_i); similarly

$$\frac{\partial w_j\left(v_{j+1}, v_j\right)}{\partial v_j} = -\frac{-\frac{\partial u_j\left(v_j, w_j\right)}{\partial v_{j+1}}}{\frac{\partial u_j\left(v_{j+1}, w_j\right)}{\partial w_j} - \frac{\partial u_j\left(v_j, w_j\right)}{\partial w_j}} > 0$$

The results can also be explained intuitively as follows. Let w_j be the consumer indifferent between j and $j+1$, suppose that store $j+1$ increases variety (i.e. v_{j+1} increases), consumer w_j is no longer indifferent between j and $j+1$; she now prefers buying from $j+1$ as the monetary saving she obtains if she buys from j (i.e. Δ_j) does not suffice to offset the increased utility she gets by shopping at $j+1$. Hence, the new indifferent consumer is the one with a less intense preference for *variety; this explains why $w_j(v_{j+1}, v_j)$ is decreasing in v_{j+1}. Now suppose that store j increases variety (i.e. v_j increases). Again consumer w_j is no longer indifferent between j and $j+1$; she prefers buying at j because the higher utility she gets if he shops at $j+1$ is no longer sufficient to compensate for the extra-price he has to pay. The new indifferent consumer is the one with a more intense preference for variety; this explains why $w_j(v_{j+1}, v_j)$ is increasing in v_j.*

All consumers with $w_i > w_j(v_{j+1}, v_j)$ prefer buying from store $j+1$, while all those with $w_i < w_j(v_{j+1}, v_j)$ prefer buying from store j. Hence, demand for store $j = 1, ..., n$ stemming from v-consumers is:

$$q_{vj}(v) = \alpha\left[G(w_j) - G(w_{j-1})\right].$$

We assume that all v-consumers are served and therefore that $G(w_n) = 1$ and that $G(w_0) = 0$.

Let us now turn to h-consumers. Again, we have to partition the set of h-consumers in $n+2$ sub-sets. To do so, we have to identify $n+1$ indifference points h_j $(j = 0, ..., n)$ such that a consumer located at $h_j \in [0, 1]$ is indifferent between shopping at j and $j+1$. h_0 and h_n have the same interpretation as the one given for v-consumers. These indifferent consumers are identified by the following conditions:

$$b(h_j) - t(d(h_j, v_j)) - p_j = b(h_j) - t(d(h_j, v_{j+1})) - p_{j+1}$$

that can be written as:

$$t(d(h_j, v_j)) - t(d(h_j, v_{j+1})) = \Delta_j \tag{5}$$

Equations (5) implicitly define the indifferent consumers, denoted as $h_j(v_j, v_{j+1})$.

Lemma E.2 *For any $j = 1, ..., n-1$, $h_j(v_j, v_{j+1})$ is increasing both in v_j and in v_{j+1}.*

proof 2 *It is apparent that $h_j(v_j, v_{j+1}) \geq v_j$. Indeed, Δ_j is positive, as we assumed that $p_{j+1} > p_j$, and the expression $t(d(h_j, v_j)) - t(d(h_j, v_{j+1}))$ would be negative if $h_j(v_j, v_{j+1}) < v_j$, as $d(h_j, v_{j+1}) > d(h_j, v_j)$ and $t(\cdot)$ is an increasing function in $d(\cdot)$. Hence condition (5) cannot hold if $h_j(v_j, v_{j+1}) < v_j$. Given this and the assumption that $h_j(v_j, v_{j+1}) < v_{j+1}$, Lemma 2 is formally proved by the sign of the following derivatives:*

$$\frac{\partial h_j(v_{j+1}, v_j)}{\partial v_j} = -\frac{-\frac{\partial t}{\partial d}\frac{\partial d(h_j, v_j)}{\partial v_j}}{\frac{\partial t}{\partial d}\frac{\partial d(h_j, v_{j+1})}{\partial h_j} - \frac{\partial t}{\partial d}\frac{\partial d(h_j, v_j)}{\partial h_j}} > 0$$

as $\frac{\partial t}{\partial d} > 0$, $\frac{\partial d(h_j,v_j)}{\partial v_j} < 0$, $\frac{\partial d(h_j,v_{j+1})}{\partial h_j} < 0$ *and* $\frac{\partial d(h_j,v_j)}{\partial h_j} > 0$*; similarly*

$$\frac{\partial h_j\left(v_{j+1},v_j\right)}{\partial v_{j+1}} = -\frac{\frac{\partial t}{\partial d}\frac{\partial d(h_j,v_{j+1})}{\partial v_{j+1}}}{\frac{\partial t}{\partial d}\frac{\partial d(h_j,v_{j+1})}{\partial h_j} - \frac{\partial t}{\partial d}\frac{\partial d(h_j,v_j)}{\partial h_j}} > 0$$

as $\frac{\partial d(h_j,v_{j+1})}{\partial v_{j+1}} > 0$. *Again Lemma 2 can be intuitively explained. Let* h_j *be the consumer indifferent between* j *and* $j+1$*, suppose that store* $j+1$ *increases variety (i.e.* v_{j+1} *increases), consumer* h_j *is now more distant from store* $j+1$ *and is no longer indifferent between* j *and* $j+1$*; she now prefers buying from* j*. Hence, the new indifferent consumer is closer to the location of* $j+1$ *and, therefore,* $h_j\left(v_{j+1},v_j\right)$ *increases. Suppose that store* j *offers a higher level of variety (i.e.* v_j *increases). Now consumer* h_j *is closer to store* j *and is no longer indifferent between* j *and* $j+1$*; she prefers buying at* j*. In this case the new indifferent consumer is also closer to* $j+1$*; which explains why* $h_j\left(v_{j+1},v_j\right)$ *is increasing in* v_j*.*

All consumers with $v_h > h_j\left(v_{j+1},v_j\right)$ prefer buying from store $j+1$, and all those with $v_h < h_j\left(v_{j+1},v_j\right)$ prefer buying from store j. Hence, demand for store $j = 1,...,n$ stemming from h-consumers is:

$$q_{hj}\left(v\right) = \left(1-\alpha\right)\left[H\left(h_j\right) - H\left(h_{j-1}\right)\right].$$

Again, we assume that all h-consumers are served and, therefore, that $H\left(h_n\right) = 1$, and that $H\left(h_0\right) = 0$.

The profit function of store $j = 1,...,n$ is:

$$\pi_j\left(v\right) = p_j\left(q_{vj}\left(v\right) + q_{hj}\left(v\right)\right) - c\left(v_j\right).$$

Now suppose that stores j $(j = 1,..,n-k)$ and $j+k$ merge. Before proving the propositions stated in Section E.1, we prove that a merger between "distant competitors" (i.e. when $k \geq 2$) does not affect variety.

Proposition E.2 *A merger between two distant competitors does not affect the level of variety offered in the market.*

proof 3 *Post-merger the new entity maximizes the following profit function:*

$$\pi_m\left(v\right) = p_j q_j\left(v\right) + p_{j+k}q_{j+k}\left(v\right) - c\left(v_j\right) - c\left(v_{j+k}\right)$$

The FOCs of this maximization problem are:

$$\frac{\partial \pi_m(v)}{\partial v_j} = p_j \frac{\partial q_j(v)}{\partial v_j} - \frac{\partial c(v_j)}{\partial v_j} + \frac{\partial q_{j+k}}{\partial v_j} = 0; \tag{6}$$

$$\frac{\partial \pi_m(v)}{\partial v_{j+k}} = p_{j+k} \frac{\partial q_{j+k}(v)}{\partial v_{j+k}} - \frac{\partial c(v_{j+k})}{\partial v_{j+k}} + \frac{\partial q_j}{\partial v_{j+k}} = 0. \tag{7}$$

If $k \geq 2$, we have that

$$\frac{\partial q_{j+k}}{\partial v_j} = 0 \text{ and } \frac{\partial q_j}{\partial v_{j+k}} = 0.$$

Hence the v_j and v_{j+1} that solve the new entity's maximization problem are the same as the one that solve the maximization problem faced by the two stores pre-merger. Since the other store's maximization problem is not directly affected by the merger, it follows that the pre-merger equilibrium profile remains an equilibrium post-merger.

Intuitively, the consequence of the merger is to internalize the effect that the decision concerning variety has on the other merging party. Since the demand obtained by a store j depends only on the level of variety set in the same store and in the two closest stores, $j+1$ and $j-1$, a merger between two distant competitors does not alter the merging parties' incentives as the effects of a change in variety remain external effects.

We can now prove the proposition in the Section E.1 that is reported here for the sake of exposition.

Proposition E.3 *After a merger between two close competitors, the new entity decreases variety in the low-variety store. The new entity decreases variety in the high-variety store only if there are "many" v-consumers.*

proof 4 *The new entity maximization problem and the FOCs are those described in the proof of Proposition E1. However, in this case $k = 1$. The low-variety store, j , has an incentive to decrease variety if the FOC (6) is negative at the pre-merger equilibrium profile. We know that, by definition, at the pre-merger equilibrium*

$$p_j \frac{\partial q_j(v)}{\partial v_j} - \frac{\partial c(v_j)}{\partial v_j} = 0.$$

Hence, the sign of the derivative depends on the sign of $\frac{\partial q_{j+1}}{\partial v_j}$, where we have replaced k with 1. Computing this derivative we get:

$$\frac{\partial q_{j+1}}{\partial v_j} = -\alpha \frac{\partial G}{\partial w_j} \frac{\partial w_j}{\partial v_j} - (1-\alpha) \frac{\partial H}{\partial h_j} \frac{\partial h_j}{\partial v_j}.$$

Both G and H are increasing function by definition. Moreover from Lemmas 1 and 2 we know that $\frac{\partial w_j}{\partial v_j} > 0$ and that $\frac{\partial h_j}{\partial v_j} > 0$. This proves that $\frac{\partial q_{j+1}}{\partial v_j} < 0$ and, therefore, that the low-variety store has an incentive to decrease variety post-merger. We can repeat the same reasoning for the high-variety store. In this case, the relevant FOC is (7) and the relevant sign is the sign of $\frac{\partial q_j}{\partial v_{j+1}}$. We have that:

$$\frac{\partial q_j}{\partial v_{j+1}} = \alpha \frac{\partial G}{\partial w_j} \frac{\partial w_j}{\partial v_{j+1}} + (1-\alpha) \frac{\partial H}{\partial h_j} \frac{\partial h_j}{\partial v_{j+1}}. \tag{8}$$

Again we know that G and H are increasing functions; however from Lemmas 1 and 2 we know that $\frac{\partial w_j}{\partial v_{j+1}} < 0$ and that $\frac{\partial h_j}{\partial v_{j+1}} > 0$. Hence the sign of (8) is not unambiguously determined. The post-merger choice on variety of the high-variety store depends on the relative strength of the two effects just identified. In any case, we can define a threshold value of α, denoted with α^*, such that:

$$\frac{\alpha^*}{1-\alpha^*} = \frac{\partial H}{\partial h_j} \frac{\partial h_j}{\partial v_{j+1}} \Big/ \frac{\partial G}{\partial w_j} \frac{\partial w_j}{\partial v_{j+1}}$$

and we say that there are "many" v-consumers if $\alpha > \alpha^*$. From all of the above it stems that if there are many v-consumers the sign of (8) is negative and the high-variety store will decrease variety after the merger. If $\alpha = \alpha^*$ the merger will have no impact on the variety offered in the high-variety store. Finally if there are few v-consumers (i.e. $\alpha < \alpha^*$) the high-variety store increases variety post-merger.

F. Additional Heterogenous Effects and Robustness Checks

Table 11: Interaction with high concentration: Variety

	(1)	(2)	(3)	(4)
	Full sample	C1000	Jumbo	Competitors
Overlap × Post	0.052***	-0.158***	0.299***	0.022***
	(0.011)	(0.008)	(0.026)	(0.006)
Overlap × Post × HHI $\geq$ 4000	-0.041***	0.175***	-0.097***	-0.022*
	(0.013)	(0.012)	(0.018)	(0.013)
Population	4.919***	3.302***	11.480***	-0.183
	(0.360)	(0.284)	(0.898)	(0.204)
Average Income	-1.281***	0.066	-3.309***	-0.881***
	(0.187)	(0.195)	(0.369)	(0.193)
Discounters Market Shares	1.792***	0.247**	2.803***	0.019
	(0.125)	(0.121)	(0.234)	(0.079)
Net Sales Floor	-0.019***	0.014***	-0.085***	-0.001
	(0.003)	(0.001)	(0.007)	(0.001)
House Value	0.369***	-0.796***	1.034***	-0.009
	(0.069)	(0.073)	(0.118)	(0.059)
HHI >4000	0.138***	0.039***	0.114***	-0.008
	(0.012)	(0.007)	(0.016)	(0.010)
Observations	183,994	73,669	58,854	51,471
R-squared	0.892	0.941	0.856	0.940
FE	Store-Time × Category	Store-Time × Category	Store-Time × Category	Store-Time × Category
Cluster	StoreCategory	StoreCategory	StoreCategory	StoreCategory

The dependent variable is $ln(variety)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors are clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 12: Interaction with high concentration: Average Category Price

	(1) Full sample	(2) C1000	(3) Jumbo	(4) Competitors
Overlap × Post	0.034***	0.005	0.089***	3.76e-04
	(0.003)	(0.004)	(0.007)	(0.002)
Overlap × Post × HHI ≥ 4000	-0.033***	-0.007	0.002	-0.008
	(0.005)	(0.007)	(0.007)	(0.005)
Population	1.080***	0.101	2.878***	0.139***
	(0.107)	(0.142)	(0.241)	(0.051)
Average Income	-0.314***	0.263**	-1.133***	-0.039
	(0.060)	(0.106)	(0.103)	(0.044)
Discounters Market Shares	0.276***	0.065	0.520***	-0.009
	(0.039)	(0.060)	(0.067)	(0.022)
Net Sales Floor	-0.010***	-0.001*	-0.025***	2.88e-04
	(0.001)	(0.001)	(0.002)	(0.000)
House Value	0.214***	0.024	0.368***	0.013
	(0.021)	(0.034)	(0.033)	(0.022)
HHI ≥ 4000	0.026***	0.001	-0.008	0.003
	(0.004)	(0.005)	(0.006)	(0.004)
Observations	176,442	63,461	58,774	54,207
R-squared	0.852	0.865	0.849	0.944
FE	Store-Time × Category	Store-Time × Category	Store-Time × Category	Store-Time × Category
Cluster	StoreCategory	StoreCategory	StoreCategory	StoreCategory

The dependent variable is $ln(categoryprices)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors are clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 13: Interaction with divestiture: Variety

	(1) Full sample	(2) C1000	(3) Jumbo	(4) Competitors
Overlap × Post	0.111***	-0.128***	0.513***	0.040***
	(0.014)	(0.008)	(0.040)	(0.010)
Overlap × Post × Divestiture	-0.131***	0.152***	-0.503***	-0.041***
	(0.018)	(0.009)	(0.036)	(0.009)
Population	4.965***	2.797***	12.52***	-0.204
	(0.380)	(0.296)	(0.923)	(0.220)
Average Income	-1.912***	0.0136	-4.879***	-0.944***
	(0.225)	(0.218)	(0.460)	(0.213)
Discounters Market Shares	1.552***	0.320***	2.243***	-0.178**
	(0.126)	(0.117)	(0.213)	(0.085)
HHI	-0.003***	-0.007***	0.006***	-0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
Net Sales Floor	-0.037***	0.015***	-0.130***	-0.001
	(0.004)	(0.002)	(0.009)	(0.001)
House Value	0.574***	-0.952***	1.007***	0.067
	(0.073)	(0.089)	(0.113)	(0.055)
Divestiture	0.065***	-0.075***	0.250***	0.020***
	(0.009)	(0.005)	(0.018)	(0.005)
Observations	140,491	56,706	45,052	38,733
R-squared	0.892	0.940	0.869	0.941
FE	Store-Time × Category	Store-Time × Category	Store-Time × Category	Store-Time × Category
Cluster	StoreCategory	StoreCategory	StoreCategory	StoreCategory

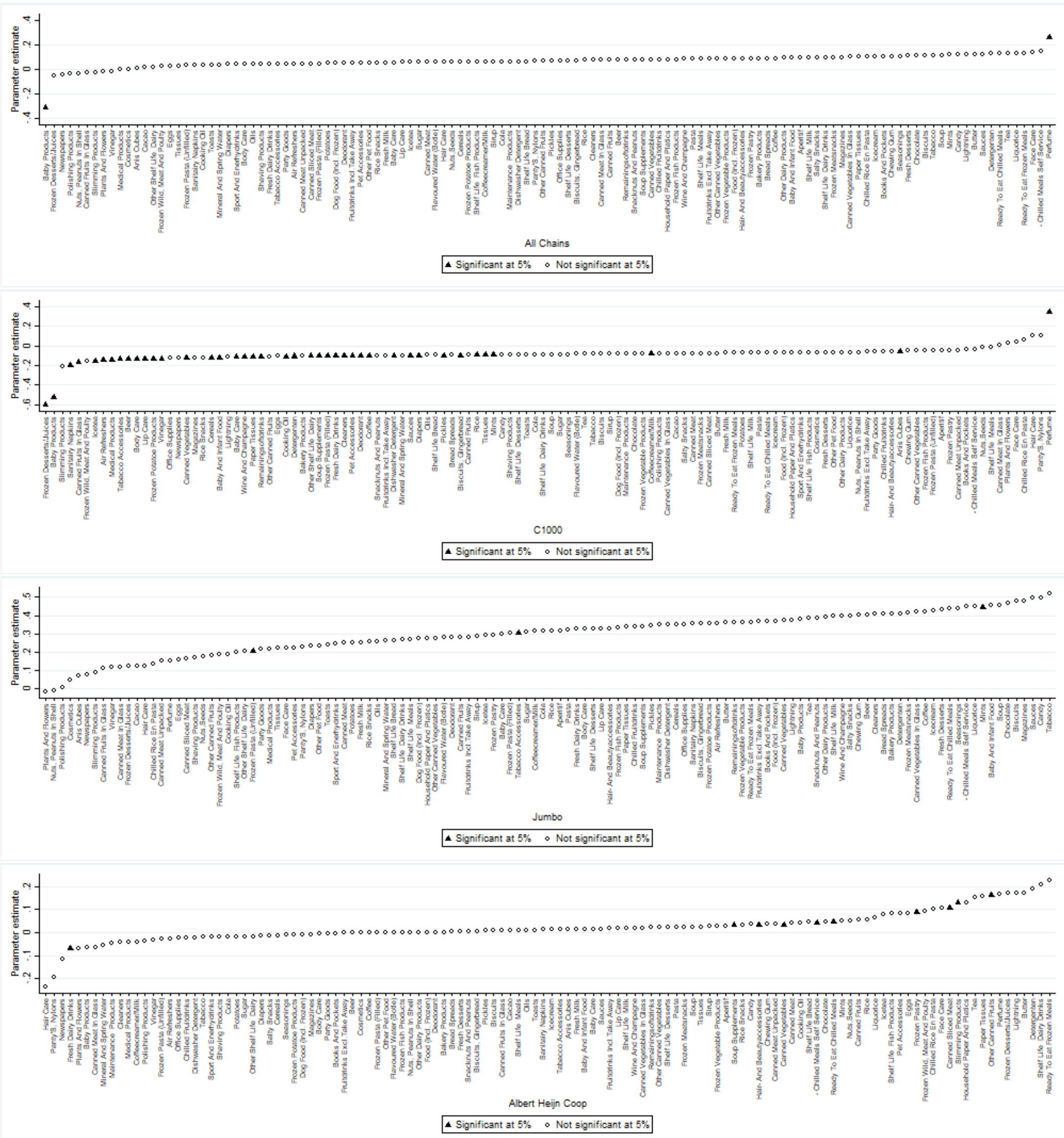
The dependent variable is $ln(variety)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors are clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 14: Interaction with divestiture: Average Category Price

	(1)	(2)	(3)	(4)
	Full sample	C1000	Jumbo	Competitors
Overlap × Post	0.043***	0.003	0.142***	-0.001
	(0.004)	(0.003)	(0.011)	(0.002)
Overlap × Post × Divestiture	-0.056***	-0.004	-0.134***	-0.011**
	(0.005)	(0.004)	(0.010)	(0.004)
Population	1.172***	0.127	3.037***	0.132**
	(0.113)	(0.147)	(0.245)	(0.052)
Average Income	-0.448***	0.272**	-1.348***	0.016
	(0.069)	(0.115)	(0.123)	(0.049)
Discounters Market Shares	0.294***	0.078	0.535***	-0.022
	(0.041)	(0.063)	(0.064)	(0.025)
HHI	6.32e-04***	2.25e-04	2.38e-04***	1.62e-05
	(0.000)	(0.001)	(0.000)	(0.000)
Net Sales Floor	-0.015***	-0.001	-0.038***	-2.56e-04
	(0.001)	(0.001)	(0.002)	(0.000)
House Value	0.203***	0.008	0.293***	0.008
	(0.022)	(0.040)	(0.032)	(0.022)
Divestiture	0.029***	0.004	0.067***	0.005**
	(0.003)	(0.003)	(0.005)	(0.002)
Observations	134,660	48,835	44,988	40,837
R-squared	0.852	0.861	0.856	0.945
FE	Store-Time × Category	Store-Time × Category	Store-Time × Category	Store-Time × Category
Cluster	StoreCategory	StoreCategory	StoreCategory	StoreCategory

The dependent variable is $ln(categoryprices)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors are clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Figure 23: Estimated average effects by category



The dependent variable is $ln(variety)$. We report the point estimates for the coefficients α from equation 2 separately estimated for each category. The dependent variable is $ln(variety)$. We control for fixed effects at the store as well at the quarter level. Standard errors clustered at the store level. Coefficients significant at the 5% level are represented by a bold triangle.

Table 15: Robustness: Interactions with the quartiles of the variety distribution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample	Full sample	Base - C1000	Base - C1000	Base - Jumbo	Base - Jumbo	Base - AH_Coop	Base - AH_Coop
Overlap × Post	0.067***	0.031***	-0.084***	-0.091***	0.296***	0.181***	0.023***	0.024
	(0.009)	(0.012)	(0.007)	(0.016)	(0.025)	(0.021)	(0.007)	(0.017)
Overlap × Post × 2nd quartile		0.043**		0.007		0.102***		0.032
		(0.017)		(0.023)		(0.025)		(0.030)
Overlap × Post × 3rd quartile		0.045***		0.014		0.155***		-0.013
		(0.015)		(0.019)		(0.029)		(0.022)
Overlap × Post × 4th quartile		0.054***		0.009		0.206***		-0.023
		(0.018)		(0.020)		(0.039)		(0.022)
Population	4.532***	4.532***	2.606***	2.607***	11.732***	11.732***	-0.128	-0.127
	(0.354)	(0.354)	(0.275)	(0.275)	(0.907)	(0.903)	(0.198)	(0.197)
Average Income	-1.386***	-1.387***	0.381**	0.381**	-3.843***	-3.844***	-0.965***	-0.965***
	(0.193)	(0.193)	(0.192)	(0.192)	(0.389)	(0.388)	(0.192)	(0.192)
Discounters Market Shares	1.699***	1.698***	0.426***	0.425***	2.650***	2.652***	-0.004	-0.004
	(0.128)	(0.128)	(0.121)	(0.121)	(0.233)	(0.232)	(0.079)	(0.079)
HHI	-0.003***	-0.003***	-0.007***	-0.007***	-0.002***	-0.002***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Net Sales Floor	-0.020***	-0.020***	0.011***	0.011***	-0.087***	-0.087***	-0.001	-0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.007)	(0.007)	(0.001)	(0.001)
House Value	0.438***	0.438***	-0.638***	-0.638***	1.052***	1.053***	-0.021	-0.021
	(0.065)	(0.065)	(0.072)	(0.072)	(0.119)	(0.119)	(0.053)	(0.054)
Observations	225,667	225,667	90,484	90,484	72,056	72,056	63,127	63,127
R-squared	*0.735*	*0.735*	0.785	0.785	0.689	0.690	0.881	0.882
	0.891	0.894	0.939	0.938	0.858	0.870	0.941	0.943
FE	Store-Time × Category							
Cluster	StoreCategory							

The dependent variable is $ln(variety)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors are clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 16: Robustness: Variety

	Full sample		C1000		Jumbo		Competitors	
	3months	6months	3months	6months	3months	6months	3months	6months
Overlap × Post	0.083***	0.105***	-0.126***	-0.134***	0.402***	0.468***	0.041***	0.050***
	(0.012)	(0.014)	(0.008)	(0.009)	(0.035)	(0.041)	(0.010)	(0.011)
Population	4.541***	4.448***	3.148***	3.389***	12.110***	11.700***	-0.127	-0.049
	(0.365)	(0.353)	(0.293)	(0.300)	(0.955)	(0.921)	(0.213)	(0.199)
Average Income	-2.071***	-2.034***	0.556**	0.617***	-5.364***	-5.393***	-1.177***	-1.393***
	(0.221)	(0.217)	(0.220)	(0.223)	(0.479)	(0.488)	(0.235)	(0.287)
Discounters Market Shares	1.161***	1.484***	0.045	0.194	1.793***	2.386***	-0.145	-0.252**
	(0.096)	(0.113)	(0.120)	(0.122)	(0.161)	(0.211)	(0.095)	(0.109)
HHI	-0.003***	-0.003***	-0.008***	-0.007***	0.002***	0.003***	-0.003**	-0.003***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Net Sales Floor	-0.015***	-0.026***	0.014***	0.018***	-0.068***	-0.097***	-0.004***	-0.003**
	(0.003)	(0.004)	(0.002)	(0.002)	(0.006)	(0.008)	(0.001)	(0.001)
House Value	0.561***	0.630***	-0.716***	-0.779***	1.096***	1.120***	0.00954	0.031
	(0.068)	(0.070)	(0.084)	(0.092)	(0.115)	(0.117)	(0.054)	(0.057)
Observations	140,744	112,015	56,344	45,069	45,180	36,095	39,220	30,851
R-squared	0.891	0.894	0.939	0.938	0.858	0.870	0.941	0.943
FE	Store-Time×Category							
Cluster	Store×Category							

The dependent variable is $ln(variety)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors are clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.

Table 17: Robustness: Average Category price

	Full sample		C1000		Jumbo		Competitors	
	3months	6months	3months	6months	3months	6months	3months	6months
Overlap × Post	0.036***	0.043***	0.003	0.003	0.118***	0.139***	1.38e-04	3.80e-04
	(0.004)	(0.004)	(0.003)	(0.004)	(0.009)	(0.011)	(0.002)	(0.002)
Population	1.136***	1.082***	0.142	0.0915	3.049***	2.923***	0.162***	0.166***
	(0.110)	(0.106)	(0.150)	(0.151)	(0.258)	(0.247)	(0.051)	(0.052)
Average Income	-0.447***	-0.462***	0.258**	0.225*	-1.380***	-1.425***	-0.0186	-0.011
	(0.070)	(0.069)	(0.114)	(0.116)	(0.130)	(0.131)	(0.048)	(0.053)
Discounters Market Shares	0.191***	0.198***	0.0817	0.0973	0.337***	0.361***	-0.0117	-0.010
	(0.034)	(0.039)	(0.066)	(0.076)	(0.051)	(0.062)	(0.027)	(0.028)
HHI	4.10e-04***	0.001***	2.01e-04	2.61e-04	0.001***	0.002***	-1.26e-04	-6.01e-05
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Net Sales Floor	-0.009***	-0.012***	-0.002*	-4.17e-04	-0.022***	-0.032***	1.62e-04	-2.67e-04
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
House Value	0.194***	0.195***	0.009	0.015	0.334***	0.324***	0.011	0.011
	(0.021)	(0.022)	(0.040)	(0.044)	(0.033)	(0.034)	(0.022)	(0.023)
Observations	135,019	107,486	48,595	38,924	45,108	36,039	41,316	32,523
R-squared	*0.848*	*0.850*	0.858	0.853	0.845	0.857	0.943	0.945
FE	Store-Time×Category							
Cluster	Store×Category							

The dependent variable is $ln(categoryprices)$. We control for fixed effects at the store level as well at the category-quarter level. Standard errors are clustered at the store-category level. The symbols ***, **, * denote significance level at the 1%, 5%, and 10% significance level, respectively.