Competition and Grocery Retail Formats: Empirical Evidence from a Horizontal Acquisition in Norway*

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Abstract

The second-largest company in the Norwegian grocery retail market acquired the fourth-largest company in 2015, resulting in a sharp change in ownership concentration and store format positioning. Several convenience discount stores and supermarkets were rebranded as soft discount stores, which have become increasingly dominant, with a total market share of 61 % in 2020. A store-level difference-in-differences analysis of one of the established soft discount chains shows that rival stores rebranding to a new soft discount format decreased sales by between 7 and 12.9 % and product variety by approximately 1 %. Consistent with uniform nationwide pricing, there was no differential price adjustment at the store level, but national real food prices declined by approximately 4-5 % compared to neighboring countries after the acquisition. The acquisition facilitated asset transfers that increased the competitive pressure in the soft discount segment and, subsequently, the industry at large.

Keywords: Competition, Mergers, Acquisitions, Ex-post evaluation, Grocery retail
JEL Codes: D22, D43, L13, L11, L41, L66, L81, C23

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1 Introduction

In Western grocery retail industries, ownership has been concentrated among a few vertically integrated companies since the 1980s.[1] This is particularly pronounced in Scandinavian countries, where three or four firms have dominated the market since the early 2000s. Furthermore, food prices in Scandinavia are higher than the European average, with Norway experiencing a particularly large gap of 50 % (Eurostat, 2022). Norway stands out even more after adjusting for Scandinavia's high value-added and excise taxes, which the Nordic Competition Authorities (2005) have attributed to import tariffs and restrictions not shared by Norway's neighbors in the European Union. Additionally, Norway lacks a competitive fringe of international retailers such as Aldi or Lidl that are present in other Scandinavian countries (Friberg et al., 2020b). Food and non-alcoholic beverages account for around 12 % of Norwegian household consumption (Statistics Norway, 2022), and policymakers have long been concerned about high concentration and insufficient competition causing high prices and limited product variety for consumers.

From 1994 to 2015, the ownership concentration in the industry remained stable with four multi-chain companies, commonly referred to as umbrella chains, accounting for approximately 96 % of total sales. However, in 2015, when the third largest umbrella chain, Coop, acquired the fourth, ICA, concerns about the lack of competition in the industry resurfaced. While rising national ownership concentration is commonly associated with a reduction in competition, mergers and acquisitions can also lead to changes in the market structure that are not captured by this metric. Firstly, travel costs limit store choices for consumers, creating local competition among stores, which may not be accurately reflected in national measures (see Smith and Ocampo, 2022). The number of competitors in a local market need not change even if the number of national companies is reduced. Secondly, the identity of the stores could change alongside their ownership, as inimitable assets such as store concepts, locations, business relations, and managerial expertise are reallocated. For example, the remaining stores could be more efficient (see Braguinsky et al., 2015; Demirer and Karaduman, 2022), but also more closely positioned in terms of prices, assortments, and formats, both of which could increase the competitive pressure in the market.

The aim of this article is to analyze the competitive effects of Coop's acquisition of ICA in 2015. The Norwegian Competition Authority (NCA) cleared the acquisition conditional on Coop divesting 93 of ICA's approximately 550 stores, leaving Coop with 29 % of the market by the end of 2016. Coop retained the existing store locations but replaced ICA's store concepts with their own, particularly the soft discount concept Extra, or closed them down. National market concentration, as measured by the

[1] The US is comparable to Europe at the state level (Ellickson, 2011).

Hirschman-Herfindahl index, rose sharply by 0.05 points, and the competitive landscape changed substantially as the market share of soft discounters rose by 8 percentage points. The main research question addressed in this article is: How do the rival store rebrandings and shutdowns following the acquisition affect the sales, prices, and product assortments of the soft discount competitor Kiwi? The sales diversion informs us about the competitive pressure of the different retail formats. In addition to studying local price and assortment responses, I also investigate what happened to food prices and product assortments at the national and chain levels, respectively.

The main research question can be addressed by observing that the stores of the acquired umbrella chains were not present in all local markets. Therefore, the store rebrandings that occurred after the acquisition differentially affected markets throughout Norway. The staggered rollout of the new store concepts enables us to compare affected stores with those that were unaffected at each point in time. This allows us to estimate the effects of different format rebrandings and store shutdowns on sales, prices, and product variety using difference-in-differences estimators that account for heterogeneous treatment effects.[2] To implement the identification strategy, I combine store locations and demographics with detailed transactional data to create a panel that tracks the sales, prices, assortments, and characteristics of grocery stores across Norway.

I find that the new soft discount chain Extra diverts between 7 and 12.9 % more sales from the established soft discount chain Kiwi compared to the previous formats. This indicates that the new stores are more direct competitors than their predecessors. Additionally, sales increase by between 2.4 % and 8.3 % when a rival store closes, showing that the previous formats also competed with Kiwi. Stores do not adjust prices locally in response to the rebrandings or shutdowns, which is consistent with the prevalence of uniform national prices in the Norwegian grocery market (Friberg et al., 2022; Meile, 2020). However, real food prices in Norway did decline by approximately 4-5 % after the acquisition compared to neighboring countries. Finally, the effective assortment size is reduced by approximately 1 % when a rival rebrands to the Extra format and remains unchanged otherwise. The small response might reflect retailers and suppliers negotiating assortment decisions centrally as assortment sizes increased by 25 % at the chain level from 2014 to 2016.

Literature. This articles relates to the large literature on the competitive effects of mergers. Merger evaluations can be classified based on two main methodological approaches: structural merger simulations and quasi-experimental designs like difference-in-differences using ex-post data. Notable examples of work using the former approach can be found in the industries of beer (Friberg and Romahn, 2015), analgesics (Björnerstedt and Verboven, 2016), newspapers (Fan, 2013), and groceries (Skrainka,

[2]See de Chaisemartin and D'Haultfœuille (2022) for a survey.

2012). The latter approach, to which this paper belongs, has been applied in a wide range of retail industries including books (Aguzzoni et al., 2016), gasoline (Hastings, 2004), and groceries (Allain et al., 2017; Pires and Trindade, 2018; Rickert et al., 2021). While price effects have been the primary focus of this literature, some attention has also been given to quality responses (Matsa, 2011; Trindade, 2012; Argentesi et al., 2021) and costs (Al-Sharkas et al., 2008; Ashenfelter et al., 2015; Schmitt, 2017).

The existing literature primarily focuses on the effects of ownership concentration on competitive outcomes. Most quasi-experimental merger evaluations define markets as affected by the merger if local ownership concentration changes. A notable exception is the study of Hastings (2004), which analyzes the effect of competing with an independent retailer in the gasoline market on prices. Using the sharp conversion of independent retailers to a vertically integrated gas company, she finds that competing with an independent retailer decreased gasoline prices by 5 %. The acquisition primarily affects price competition through the repositioning of firm characteristics, not ownership concentration.

Similarly, the ICA acquisition often did not change local ownership concentration as one umbrella chain replaced another, but many markets experienced a shift in their competitive environment in the form of rival stores rebranding their store concepts. Yet, contrary to the gasoline stations studied by Hastings (2004), chain-level uniform pricing inhibits Norwegian grocery stores from making unilateral price adjustments to their local environment.[3] This allows us to study how demand responds to the store rebrandings since prices are held fixed in the cross-section. I take the diversion of sales as a measure of the competitive pressure between store formats and show that repositioning across grocery retail segments — specifically toward the soft discount segment — can be pro-competitive. Insofar as these changes are facilitated by the acquisition, they belong in the calculus of merger control decisions.[4]

A consequence of national pricing is that comparisons between domestic stores do not identify the price effects of the acquisition.[5] By considering every market where one of the merging parties operates as affected, Allain et al. (2017) identify the price response of rival stores that price locally but not the price response of the merging parties that price nationally. Aguzzoni et al. (2016) uses domestic comparison groups that theoretically should have smaller price responses, i.e., competitors' books and top-selling titles, to identify the direction of national price responses but not the magnitude since the control group is affected by the merger. This article compares real food prices

[3]Friberg et al. (2022) establish that the prices of the largest retail group in Norway does not vary geographically.

[4]Fan (2013) study the welfare implications of mergers in the newspaper market, taking into account that the merging parties can adjust product characteristics following ownership consolidation. This article studies product characteristic changes that were facilitated by the merger itself.

[5]Generally, such comparisons only allow us to identify effects at the store level, and any effect that operates at the chain level, such as cost efficiencies or increased buyer power, would be differenced out.

in Norway and neighboring countries to overcome the lack of a domestic comparison group, which rules out common shocks to the grocery retail industry that coincide with the merger and provides suggestive evidence on the price effect of the acquisition.

In the next section, I provide an overview of the structure and segmentation of the Norwegian grocery retail market, as well as the ICA acquisition. Then, in Section 3, I present the data and some descriptive statistics. Section 4 describes the research design used to analyze the competitive effects of retail format rebrandings, while Section 5 presents the empirical results on sales, prices, and product variety. Section 6 discusses the validity of the identification assumptions and provides a set of robustness checks. Finally, Section 7 discusses the implications of the results, and Section 8 concludes.

2 The Norwegian Grocery Retail Market

2.1 Market Structure

Since 1994, the Norwegian grocery retail market has been dominated by four large umbrella chains — NorgesGruppen, Coop, Reitangruppen (Rema 1000), and ICA; until Coop acquired the latter in 2015. They are all vertically integrated with their own wholesalers and distribution, and all except Reitangruppen carry several chain concepts across different segments (see Table B.1 for an overview).[6] The evolution of market shares and ownership concentration in the last two decades is shown in Figure 2.1.[7] Before 2014, ICA was steadily losing market shares to the other chains (from 25 % in 2001 to 11 % in 2014), especially the market leader NorgesGruppen and Rema 1000, which grew by 11 and 7 percentage points respectively from 2001 to 2020. Coop had a slight decline before increasing by 7 percentage points following the acquisition. Bunnpris has maintained a small but growing presence (from 1.6 % in 2001 to 3.4 % in 2020), while the hard discounter Lidl exited the market in 2009 after failing to gain a foothold for five years (peaking at 1.7 % in 2007). From the early 2000s to 2020 we have moved from four to three large umbrella chains, with the survivors largely maintaining their relative standings.

The Herfindahl-Hirschman index (HHI) in Norway (0.25; $N^e = 4$) and other Scandinavian countries was already high in 2002 compared to other European countries such as Germany (0.16; $N^e = 6.25$) and the United Kingdom (0.15; $N^e = 6.67$) (Nordic Competition Authorities, 2005).[8] However, it grew only 3 percentage points in the 14

[6]Bunnpris is the largest retail chain outside the big umbrella chains, and shares distribution with NorgesGruppen

[7]Ownership concentration is measured as the Herfindahl-Hirschman index: $HHI = \sum_{i=1}^{N}(S_i)^2$ where S_i is the market share of firm i.

[8]The effective number of firms is defined as: $N^e = \frac{1}{HHI} \leq N$; holding with equality when the firms are of equal size. It can be interpreted as the hypothetical number of symmetric firms that would produce

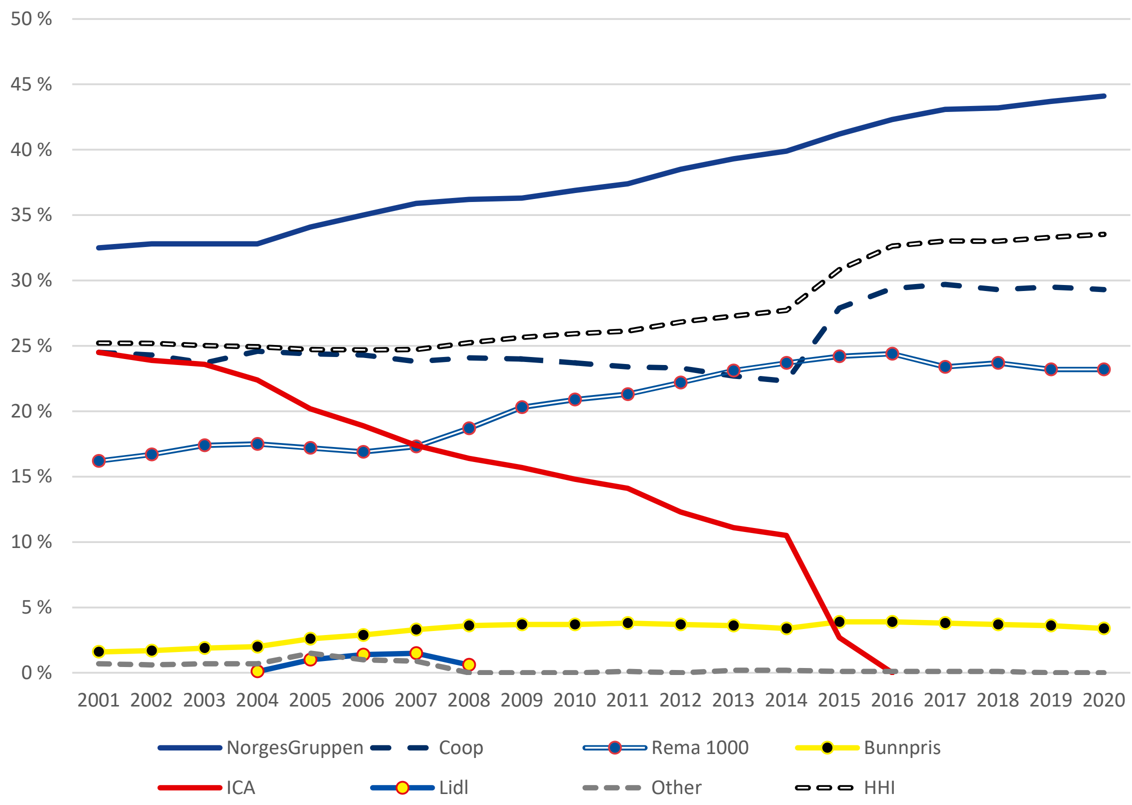

Figure 2.1: The evolution of market shares and the Herfindahl–Hirschman index at the umbrella chain level from 2001 to 2020. *Source:* AC Nielsen.

years leading up to the acquisition, before increasing a further 5 points by the end of 2016 ($HHI = 0.33$; $N^e = 3$). The acquisition revived concerns about the lack of competition and consequently reduced product variety and higher food prices (Dagens Næringsliv, 2015; e24, 2014), and as of 2022, the NCA still lists competition in the grocery retail market as one of their prioritized issues (Ministry of Trade, Industry and Fisheries, 2022).[9] Yet, transportation costs ensure that competition is local as consumers are unlikely to include distant stores in their consideration set. Even if strategic decisions such as pricing and base assortment are determined at the national level, they will nonetheless be a function of local market conditions.

Figure 2.2 plots the quartiles and extremas of local HHI at the postcode level. The distribution of local market concentration clearly displays bunching at the right endpoint ($HHI = 1$); the median local market is a monopoly. However, many rural markets are served by one small general store, and the sales raised in these markets likely constitute small shares of the umbrella chains' total sales. A more representative measure of the

the same HHI as the actual firms of unequal size.

[9]The U.S. Department of Justice & FTC, Horizontal Merger Guidelines consider an HHI in excess of 0.25 highly concentrated. Mergers involving an increase in HHI by more than 0.02 in highly concentrated industries are presumed likely to increase market power. Similarly, the European Commission cannot rule out competition concerns with a post-merger HHI above 0.2 and a change in HHI by more than 0.015. For a discussion on how HHI relates to the intensity of competition and social welfare; see Spiegel (2021)

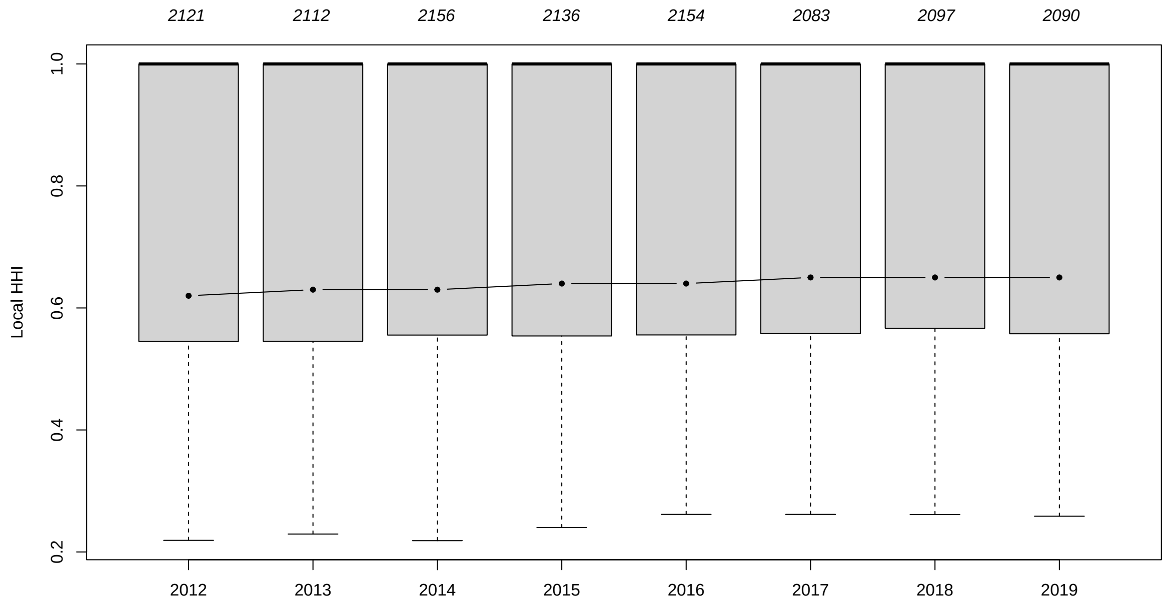

Figure 2.2: Box-plots of the Herfindahl-Hirschman Index at the postcode level from 2012 to 2019 using accounting revenues. The weighted mean using the postcode sales shares is shown as the line joined points. The number of local markets in the sample are displayed above the box-plots. *Source:* Geodata.

competitive pressure imposed on the umbrella chains is the weighted mean of HHI using local markets' share of nation wide sales, shown as the line joined points in Figure 2.2. Since national chains are not equally represented in any given market, local ownership concentration tends to be substantially higher than national. The sales-weighted mean HHI across postcode areas increased marginally from 0.63 ($N^e = 1.59$) in 2014 to 0.64 ($N^e = 1.56$) in 2016, a change of 0.01 points ($\Delta N^e = -0.03$). The reason is that the acquirer and acquiree did not compete in all local markets, and when they did, the Norwegian Competition Authority imposed divestment remedies to limit competition concerns (Konkurransetilsynet, 2015, Clause 1744).

Similar plots of local HHI for alternative geographical units such as Basic Statistical Units (BSU), postal areas, municipalities, and counties, are shown in Figures B.1, B.2, B.3, B.4 in appendix B. There are approximately 14000 BSUs in Norway, and they are too small to capture the relevant market as the vast majority of them contain one or no stores. As I consider increasingly large market delineations like postal areas, municipalities, and counties, the sales-weighted HHI decreases mechanically towards the national level depicted in Figure 2.1. However, the national increase in HHI following the acquisition is only clearly reflected at the county level. To the extent that the acquisition affected competition, it stands to reason that changes in local ownership concentration play a limited role.

2.2 Market Segmentation

The store concepts in the Norwegian grocery industry are traditionally categorized as general stores, discount stores, supermarkets, and hypermarkets (AC Nielsen).[10] General stores are typically small stores that offer a limited selection of goods and services to meet the basic needs of local communities.[11] Supermarkets are large, full-service grocery stores that offer a wide variety of products, including fresh produce. In comparison, discount chains offer fewer products, focusing on cost efficiency, low prices and more private labels. Hypermarkets are even larger than supermarkets and tend to stock articles other than food, such as clothes and electronics. They usually have lower prices due to economies of scale but are confined to the outskirts of cities and large shopping centers. Since the mid-2000s, the market share of discount chains has steadily grown at the expense of the other segments (from 47 % in 2005 to 68 % in 2020).

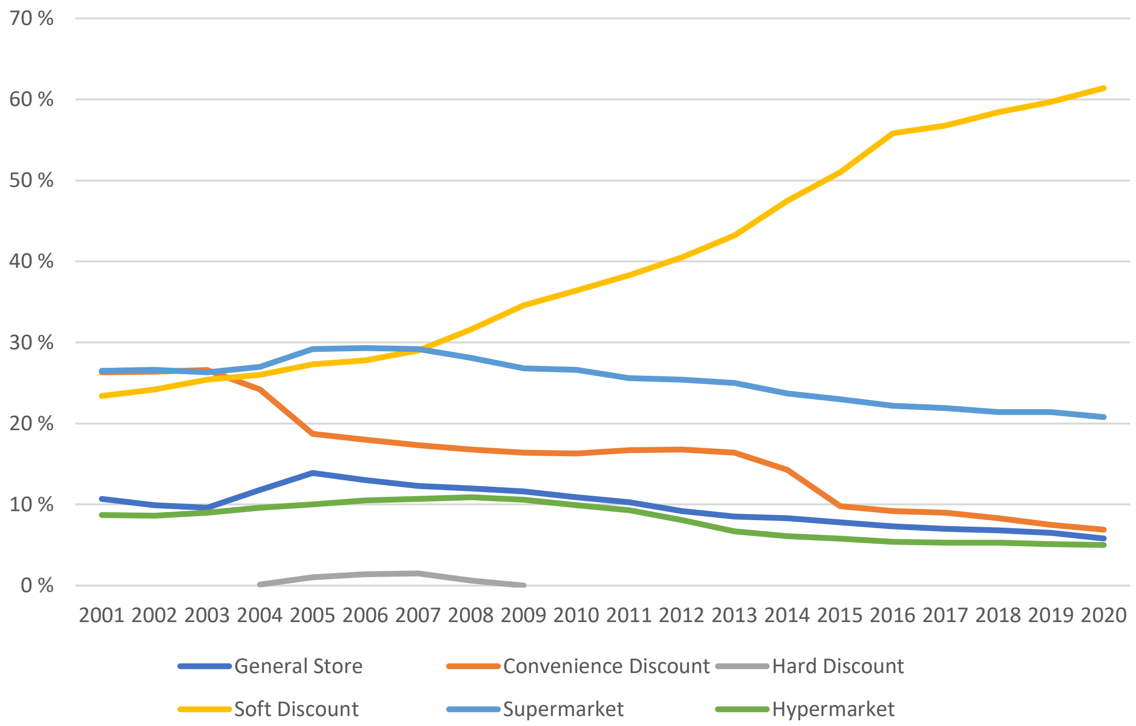

Figure 2.3: The evolution of market shares and the Herfindahl–Hirschman index at the retail segment level from 2001 to 2020. *Source:* AC Nielsen.

In the Norwegian context, it is useful to further segment the discount segment into hard, soft, and convenience discount. Hard discount stores are ”no-frills” stores that

[10]In Norwegian: Nærbutikk, lavpris, supermarked and hypermarked.

[11]”Nærbutikk” is sometimes translated to ”convenience store”, but it should not be confused with small stores, such as kiosks and petrol stations, which are often located in busy areas. These small stores typically offer a limited range of on-the-go products, such as prepared food, drinks, and tobacco, and have long opening hours.

carry a narrow set of essential items, predominantly private labels. This allows for high volumes of basic products, efficient operations, and subsequently very low prices.[12] In comparison, soft discounters are characterized by larger assortment sizes and more national brand names. Convenience discount stores are typically smaller and focus on quick and easy shopping, offering ready-to-eat meals, convenience foods, and on-the-go products like salad bars, while still providing the basics at low cost.

Figure 2.3 shows the evolution of market shares across retail segments. The soft discount segment has grown tremendously over the last two decades, increasing from 23 % in 2001 to 61 % in 2020, at the expense of all other formats. The convenience discount segment shrank the most from 26 % in 2001 to 7 % in 2020. It experienced a sharp decline when ICA's convenience discounter Rimi was discontinued following the acquisition. Engelund and Eimind (2018) find that the share of consumers reporting discount chains as their preferred store format has been increasing steadily from 2008 to 2016. Furthermore, consumers report that accessibility, assortment size, and low prices are the most important store attributes, with the latter increasing in importance over time. The soft discounters provide a mix of large assortment sizes, accessibility, and low prices that shoppers seem to prefer.[13] Urbanization might also help explain their success as the share of people living in urban areas has increased from 77 % in 2001 to 83 % in 2020 (Statistics Norway), allowing for larger stores and more efficient distribution. Given their burgeoning presence, effective competition in the soft discount segment is paramount to ensure consumers access to high-quality groceries at low prices.

Rema 1000, inspired by the German hard discounter Aldi, spearheaded the soft discount segment in Norway. As displayed in Figure 2.4, they dominated throughout the 2000s and early 2010s, but the segment has become more crowded over time. Extra grew quickly after entering the market in 2006 — particularly from the ICA acquisition — and Kiwi has improved its position. In 2001, Rema 1000 and Kiwi had market shares of 70 % and 30 % respectively, and the soft discount HHI was 0.57 ($N^e = 1.75$). By 2020, there was a triopoly of Rema 1000, Kiwi, and Extra with market shares of 38 %, 37 %, and 25 % respectively, and an HHI of 0.34 ($N^e = 2.94$). The ICA acquisition was an integral part of this development, and in this article I will study the competitive effects of the resulting infusion of soft discounters in the market.

[12]Examples of quintessential hard discount chains are Aldi and Lidl, with the latter having a brief spell in Norway from 2004 to 2008. Import restrictions, low population density, and the lack of national brands are commonly put forward as likely culprits for Lidl's exit.

[13]The three soft discounters dominate VGs matbørs, a recurring blind test orchestrated by Norway's leading newspaper. See https://www.vg.no/spesial/matborsen/.

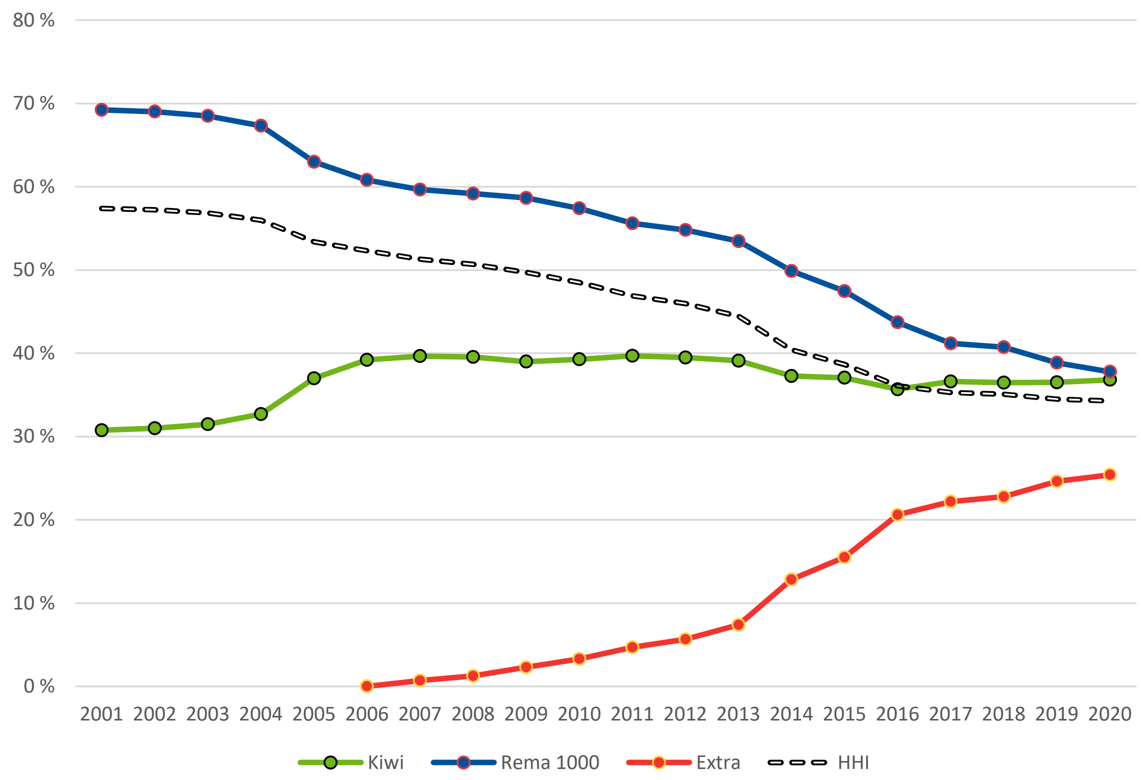

Figure 2.4: The evolution of market shares and the Herfindahl–Hirschman index in the soft discount segment from 2001 to 2020. *Source:* AC Nielsen.

2.3 Coop Acquires ICA

The ICA group, with the chain concepts Rimi (convenience discount), ICA Supermarked, and Matkroken (general store), steadily lost market share throughout the 2000s and early 2010s, struggling with low profits. The NCA blocked a purchasing and distribution agreement with NorgesGruppen aimed at improving ICA's profitability through lower wholesale prices and more efficient distribution in 2014. Consequently, ICA instead sought to sell their 554 Norwegian stores to Coop, which the NCA accepted conditional on divestment remedies — 43 stores were sold to Bunnpris and 50 to NorgesGruppen.

The NCA employed a sequential screening process to select these stores: First, the NCA filtered out 227 ICA stores that, if acquired by Coop, were unlikely to limit competition purely based on the number of competing umbrella chains and their market shares. Secondly, 93 of the remaining stores were identified as problematic based on a high degree of competition (as measured by diversion ratios) between the merging parties and post-acquisition incentives to raise quality-adjusted prices. The NCA considered acquisition-specific efficiency gains but concluded that they were insufficient to compensate for the costs of adjustment and loss of competition (Konkurransetilsynet, 2015, Clause 1733). Furthermore, the likelihood of disciplining future entry was deemed low due to significant barriers to entry such as import restrictions, irreversible investments, economies of scale, and vertical integration (Konkurransetilsynet, 2015, Clause 156).[14] Finally, the competitive effects of store format rebranding on non-merging stores were not considered. The NCA concluded that the proposed divestment remedies would mitigate the anti-competitive effects of the acquisition, but pro-competitive outcomes were not considered (Konkurransetilsynet, 2015, Clause 1753).

3 Data Sources and Descriptive Statistics

I draw on several sources of data to analyze the effects of store rebrandings on local competition. The first dataset is a yearly panel from Geodata[15] tracking characteristics such as geographical location, size, retail format, ownership, accounting revenues, and opening hours of Norwegian grocery stores. It also includes demographic variables like population, average earnings, and education at various levels of geographical aggregation such as basic statistical units (BSU), municipalities, and counties. The second data source is the schedule of staggered store rebrandings and shutdowns provided by the acquirer. It tracks which format replaced each store at what time following the acquisition.[16]

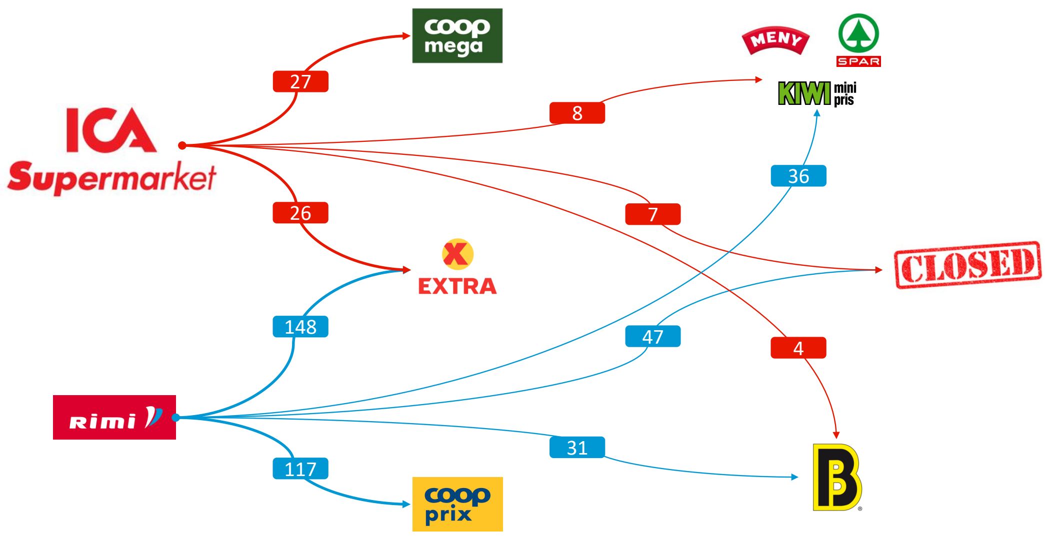

Figure 3.1: The number of ICA Supermarket and Rimi rebrandings across target formats and closings. General store concepts like ICA's Matkroken and NorgesGruppen's Joker are omitted.

Figure 3.1 shows the frequency of the various format rebrandings that transpired during 2015 and 2016. The store rebrandings rolled out between April 2015 and July 2016, concentrating around late 2015 and early 2016. Figure 3.2 shows accumulated store rebrandings. Roughly half of the 385 total rebrandings took place in September

[14]The details of the proposed efficiency gains of the merging parties are withheld from the public.
[15]See https://geodata.no/
[16]For most stores, I have the exact date of reopening provided by the acquirer. For others I determine the month of reopening by studying local newspaper articles.

2015. With the exception of 27 rebrandings in the five months leading up to September 2015, the remainder occurred gradually until July 2016. Combined with store locations, the schedule allows us to determine whether a store experienced one of their rivals rebranding in their vicinity.

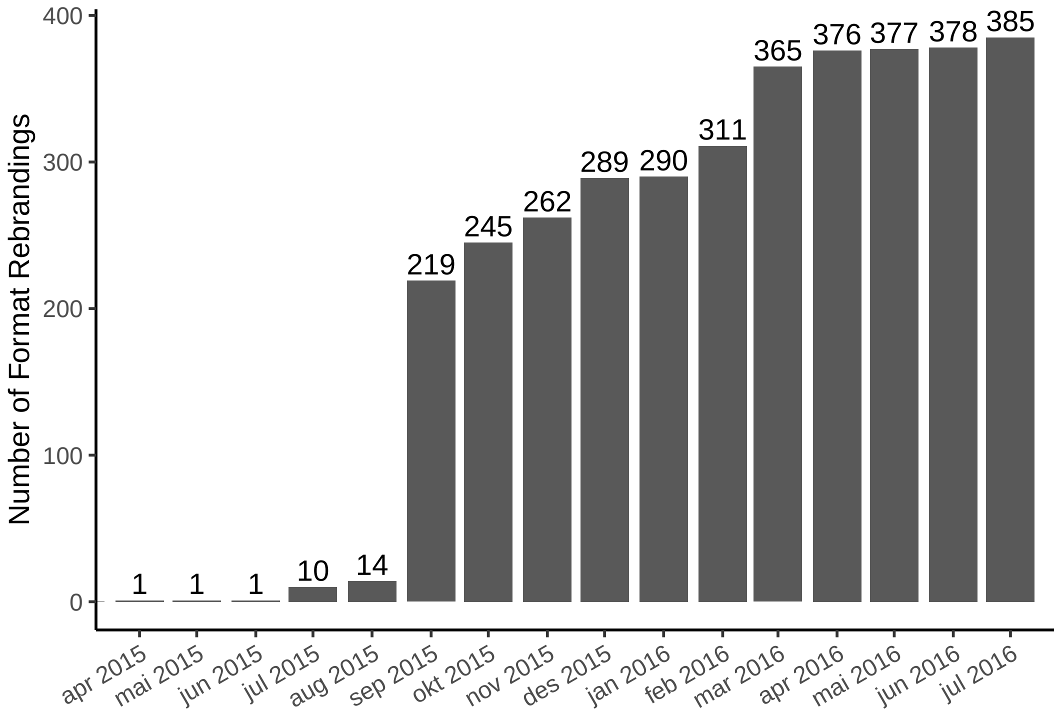

Figure 3.2: The Accumulated Number of Store Rebrandings from January 2014 to December 2016. The first rebranding takes place in April 2015 and by July 2016 every store has been transformed.

The third data source consists of high-frequency transaction data that allow us to measure product sales, prices and product assortment sizes for each store under the NorgesGruppen umbrella. The product categories represented in the sample are listed in Table B.3 in Appendix B alongside their expenditure shares. Combined with the location data, we are left with a panel of stores observed at monthly intervals from 2014 to 2016, with a rich set of store and product characteristics. In the following analysis, I will focus on the soft discount chain Kiwi which averaged a 19 % market share in the sample period.

4 Empirical Strategy

I use a difference-in-differences approach to estimate the competitive effects of the format rebrandings following the ICA acquisition. The staggered roll out of format rebrandings necessitates a *staggered adoption design* (Athey and Imbens, 2021) and the use of heterogeneous treatment effect robust estimators (see de Chaisemartin and

D'Haultfœuille (2022) for a survey). The empirical strategy is to exploit the fact that ICA's stores were not present in all local markets, which allows me to impute the counterfactual outcome of the affected stores never experiencing a rival rebranding by comparing affected and unaffected stores before and after the rebrandings. Figure B.5 in Appendix B maps the geographical distribution of the Kiwi and ICA stores before the acquisition. Both chains are represented in all counties, although Kiwi has a stronger presence in the south and ICA in the north. There are clear instances of Kiwi and ICA stores competing and not competing with each other. Under the assumptions of common trends in unaffected potential outcomes across store, and no anticipatory behavior prior to the rebranding, we can identify the Average Treatment Effect on the Treated (ATT). Section 6 explores the validity of the identifying assumptions through various robustness checks.

4.1 Local Market Definition

One way to categorize affected and unaffected stores is to define the local market or catchment area of a store as the radius around it. Stores located sufficiently close to each other are assumed to compete for customers, whereas stores located far apart do not. This approach is prevalent in retail applications in the ex-post merger evaluation literature. Although distance is not the sole factor determining whether a consumer will consider shopping at a store, I aim to select a radius that is large enough to include most relevant competitors and small enough to avoid diluting the market with non-competitors. Additionally, the ideal size of the market likely varies across geographical areas and markets. For example, Hastings (2004) considers gasoline retailers within a one-mile radius (~ 1.6 km), Choné and Linnemer (2012) considers parking lots within the range of 650-1000 m, and Allain et al. (2017) considers grocery retailers within 10 km (20 km for hypermarkets) of the city center where the store is located.

A few factors suggest a smaller market size for Norwegian grocery stores. Allain et al. (2017) determine the market size based on the French competition authority's assumption that consumers are willing to drive 10 to 15 minutes on average to reach a supermarket or a discount store. They also find similar results using a 5 km radius (10 km for hypermarkets). In the case of the ICA acquisition in Norway, the competition authority used similar driving times for most areas, except for the largest cities and most remote areas, where they used 5 and 20 minutes, respectively (Konkurransetilsynet, 2015, Clause 90). However, they note that survey evidence suggests that local markets are smaller than this, especially in urban areas (Konkurransetilsynet, 2015, Clause 93). Norwegian topography and infrastructure make travel costly, and a sparse population of shoppers tends to favor smaller and more dispersed stores. Indeed, there is a high store density in Nordic countries, and consumers do not have to travel far to shop (Friberg et al., 2020a, p. 37).[17] Hence, I consider market sizes in the range of 0.5-10 km based on previous literature and competition authority practices.

The catchment area of a store should depend on the density of stores in its neighborhood. In an area with a uniform distribution of stores and consumers, as store density increases, fewer consumers need to travel far to reach a store. These consumers are the ones who create competition between stores located far apart, as their geographical consideration sets are necessarily large. Therefore, local markets are likely to be smaller when there is high store density and accessibility. For example, a market radius that is appropriate in rural areas where consumers have to travel long distances by car would be inappropriate in large cities where walking is a viable option. I categorize stores according to the 6 quantiles of BSU population density to proxy for the varying store accessibility and subsequent catchment areas across Norway.[18] I consider the specifications in Table 4.1 where stores in low population density BSUs are generally granted larger catchment areas.

Table 4.1: Market Sizes Across BSU Population Density Quantiles

	Quantiles					
Specifications	1	2	3	4	5	6
10-1.5 km	10 km	7 km	5 km	4 km	2 km	1.5 km
10-1 km	10 km	7 km	5 km	3 km	1.5 km	1 km
10-0.5 km	10 km	7 km	5 km	2 km	1 km	0.5 km
6-1.5 km	6 km	5 km	4 km	3 km	2 km	1.5 km
5-0.5 km	5 km	4 km	3 km	2 km	1 km	0.5 km

Notes: Catchment area radiuses across 6 quantiles and 5 specifications.

Other applications in the literature (e.g. Aguzzoni et al. (2016), Pires and Trindade (2018) and Argentesi et al. (2021)) use pre-defined geographical areas such as cities. Similarly, I include a specification using postcode areas to define local markets. Postcodes indicate the geographic location of cities, districts and townships, and large cities are often divided into several postcodes. They tend to be smaller in densely populated areas in line with the reasoning of the previous paragraph.

[17]This is particularly true in the capital Oslo, where the average consumer has access to 137 stores within 10 minutes of travel (Friberg et al., 2020a, p. 50).

[18]I do not use the more direct measure of store density at the BSU or municipality level. BSUs are too small to capture the variation in catchment areas across Norway, as most of them contain only one or no stores. On the other hand, using municipalities as the level of aggregation is not ideal because store accessibility can vary significantly between cities and their outskirts. Densely populated BSUs, however, are likely to have better store accessibility in and around them. It is reassuring that municipalities housing the big cities are over-represented among high population dense BSUs but still appear among low population BSUs as expected for stores in the outskirts.

4.2 Affected and Unaffected Markets

Stores can be labeled as affected or unaffected based on the local market definition. Affected stores competed locally with an ICA store before the acquisition while the unaffected stores did not. Within the affected group, I further differentiate between different types of format rebrandings to define separate treatment arms: format rebrandings into Coop Extra, Coop Prix, or Bunnpris, and permanent store closings.[19] To ensure that changes in local ownership concentration do not contaminate the effect of format rebrandings, I focus on the local markets where the umbrella group of the target store format was not already present. Cases where multiple format transformations occurred in the same market are also excluded.

Using the postcode market definition, Table B.2 in Appendix B displays the mean values of the outcome and control variables before and after the acquisition across treatment groups, along with their percentage change. The number of stores used in the analysis is indicated in parentheses next to the names of each group. There is an increasing trend in sales across groups, except for the Extra group which remained constant on average. As expected, the average number of competitors only changed for the stores experiencing a rival closing down. Affected stores started out with higher sales and more competitors, which is consistent with the likelihood of competing with another store increasing in the market size. The market share of private label products, assortment sizes, and the price level increased in the sample period, but in roughly similar amounts across groups.[20] Note that the initial price levels, assortment sizes, and private label shares are very similar across groups despite differences in sales and market concentration, which might suggest limited discretion for stores to adjust these variables locally.

4.3 Staggered Adoption Design

To estimate the average treatment effect on the treated (ATT) of an event, I estimate equations in the following form:

$$Y_{it} = \gamma_i + \lambda_t + \beta T_{it} + \delta^{'} \boldsymbol{Z_{it}} + \epsilon_{it} \tag{4.1}$$

where $\beta = E[\beta_{it}] = ATT$. Here, T_{it} indicates whether store i experienced the event at time t, Y_{it} is the outcome variable, Z_{it} is a vector of covariates, and ϵ_{it} represents the unobserved regression error. Additionally, γ_i and λ_t are store and time fixed effects,

[19]A few irregular cases of rebranded stores closing down or rebranding a second time during the sample period of 2014-2016 are excluded.

[20]The price indices are explained in Section 5.2.

respectively, while β's and δ' are the parameters to be estimated. I allow treatment effects to vary arbitrarily across stores i and time t.

As recently shown in methodological papers such as Goodman-Bacon (2021), Sun and Abraham (2021), Borusyak et al. (2021), Callaway and Sant'Anna (2021), and de Chaisemartin and D'Haultfœuille (2020), estimating equation 4.1 with ordinary least squares does not yield consistent estimates of the ATT if treatment effects are heterogeneous across units or time and treatment is staggered.[21] Instead, I use the estimator proposed by both Sun and Abraham (2021) (SA) and Callaway and Sant'Anna (2021).[22] Imputation estimators proposed by Gardner (2021) and Borusyak et al. (2021) often yield similar results but are more sensitive to violations of the parallel trends assumption (see Roth et al., 2022). The SA-estimator is more sensitive to anticipation effects, but this can be diagnosed and adjusted for by shifting the timing of the event and excluding affected periods (see section 6). The SA-estimator also allows for easily interpretable event study plots because the coefficients measure the mean differences between the ever and never affected stores relative to a reference period, which is here the last period before the event. Finally, I cluster the standard errors at the municipality level to allow for correlation in the error term ϵ_{it} caused by within-store persistency or common shocks within municipalities.

5 The Competitive Effects of Retail Format Rebrandings

5.1 Sales Diversion

The costs of high prices, small assortment sizes, or low-quality service are determined by the level of competition between rival stores, as the availability of close substitutes allows dissatisfied shoppers to seek alternatives elsewhere. Therefore, a decrease in the number or market share of competitors raises concerns as it restricts consumer choice. However, alterations in rival characteristics can also impact stores' pricing and quality incentives. In the subsequent analysis, I will examine the relative competitive pressure exerted by previous and new formats by estimating the effects of rivals rebranding or closing down on sales.

I report the estimated effects of Equation 4.1 with the natural logarithm of total monthly sales as the outcome variable in Table 5.1. It includes six different local market definitions, and I use the natural logarithms of municipality population and median income as controls to account for potentially different demographic trends across affected and unaffected stores.[23] A rival rebranding to the soft discount format

[21]Treatment effects could, for example, be heterogeneous due to variation in market concentration or seasonal variation coinciding with the time of rebranding.

[22]The implementation is made possible by the R Package *fixest* Bergé (2018).

[23]The estimators of Sun and Abraham (2021) and Callaway and Sant'Anna (2021) currently do not

Table 5.1: Effect of Rival Rebrandings on Sales

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Extra}	-0.093***	-0.101***	-0.126***	-0.070***	-0.129***	-0.117***
	(0.016)	(0.018)	(0.014)	(0.015)	(0.015)	(0.021)
T_{Prix}	-0.010	-0.008	-0.015	-0.025	-0.025	-0.033*
	(0.017)	(0.018)	(0.022)	(0.018)	(0.021)	(0.018)
T_{Bunnpris}	0.081***	0.023	0.025	0.037	-0.001	-0.045
	(0.030)	(0.035)	(0.044)	(0.032)	(0.053)	(0.039)
T_{Closed}	0.078***	0.083***	0.076***	0.082***	0.073***	0.024
	(0.019)	(0.023)	(0.021)	(0.022)	(0.025)	(0.019)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode

$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$

Notes: Each Column reports the reports the estimated ATT using the estimator of sun and Abraham (2021) for different local market definitions and events. The data span all months of 2014 - 2016, and the standard errors shown in parentheses are clustered by municipality. Each ATT is retrieved from separate regressions reported fully in Tables C.1, C.2, C.3, and C.4 in appendix C. Controls for municipality level population and income are included.

Extra is estimated to decrease sales by 7 % to 12.9 %, and the finding that Extra is a tougher competitor than ICA-owned stores, predominantly Rimi, remains robust regardless of the chosen market definition. The estimated effect of a rival rebranding to the convenience discount format Prix is small and statistically insignificant across specifications, except for the postcode specification, where it is 3.3 % and statistically significant at the 10 % level. This suggests that convenience discount stores like Rimi and Prix are not able to compete as effectively in the soft discount segment as Extra.[24] The lack of a significant difference between Coop Prix and ICA-owned stores also indicates that Coop's larger scale alone is not sufficient to be more competitive than ICA in the short run.

The ICA acquisition was approved by the Norwegian Competition Authority conditional on Coop selling off 43 stores to Bunnpris, a convenience discount chain, and 50 stores to NorgesGruppen. These remedies were meant to alleviate weakened competition due to increased market concentration. The estimated competitive effect of Bunnpris is on average positive across specifications, but only statistically significant at the 1 % level for the 10-1.5 km specification. There is no evidence that the Bunnpris format is more competitive than the ICA or Coop formats. The estimated effect of a

implement multiple treatment variables in one estimation procedure in either STATA or R. Hence, I run separate regressions for each treatment variable and exclude the stores that are affected by other treatments.

[24]Comparing ATTs across treatment groups requires careful consideration of potential selection into them. See section 7.1 for a discussion.

rival ICA store permanently closing down is between 7.3 % and 8.3 % and statistically significant across specifications, except for the postcode specification, where it is positive but smaller and not significant. Considering the selection of which stores to close, it is likely that this effect pertains to stores that were performing worse than average and thus exerted less competitive pressure in the market. If so, it should be interpreted as a lower bound on the overall average treatment effect. Taken together with the format rebranding effects, it is clear that the convenience discount formats exert some competitive pressure on Kiwi, but the new soft discount chain Extra is more competitive. The fact that 148 stores rebranded to Extra and only 35 stores closed down suggests that the overall competitive pressure increased.

5.2 Food Prices

We should expect increased competitive pressure from rivals to incentivize stores to lower their prices as their residual demand becomes more sensitive to price differences between competitors. However, the way competitive pressure translates into pricing is complicated by centralized pricing decisions and the degree to which individual stores have the freedom to price to their local market. The next section mirrors the sales diversion analysis and establishes that stores do not make local price adjustments to changes in the identities of their competitors. In the following section, I then study the evolution of national food prices to provide some suggestive evidence of the price effects of the acquisition.

5.2.1 Local Price Responses to Format Rebrandings

Using product-level sales data, we can calculate the average unit price of product j in store i at time t as:

$$P_{ijt} = \frac{\text{Sales}_{ijt}}{\text{Quantity}_{ijt}}$$

These prices can be aggregated into a price index that summarizes the overall price level of the store using index weights w_{ijt}, calculated as product j's sales share of total store-level sales at time t.[25] I consider several indices, the simplest being the log-transformed sales-weighted average of every product price:

$$\hat{P}^1_{it} = \ln(\sum_j w_{ijt}[P_{ijt}])$$

After taking the natural logarithm, changes in the index can be interpreted as a percentage change in the price level. However, groceries are measured in different

[25] I could perform the analysis at the store-product level as well, but it is very computationally demanding.

units, i.e., grams, liters, or packages of various sizes. To account for this, we can divide store-level product prices by the cross-sectional average across stores and take logs:

$$\hat{P}^2_{it} = \sum_j w_{ijt}[\ln(\frac{P_{ijt}}{\overline{P_{jt}}})] = \sum_j w_{ijt}[\ln(P_{ijt}) - \ln(\overline{P_{jt}})]$$

Now, each product contributes to the index its approximate percentage deviation from the cross-sectional average across stores, eliminating the issue of differing units of measurement. Finally, I also calculate an average store price by dividing total store-level sales over total volumes, as in Argentesi et al. (2021):

$$\hat{P}^3_{it} = \frac{\sum_j \text{Sales}_{ijt}}{\sum_j \text{Quantity}_{ijt}}$$

Note that $\hat{P}^1_{it}$ and $\hat{P}^2_{it}$ can change either due to changes in individual prices P_{ijt} or changes in the local product sales weights w_{ijt}. So, even in the absence of local product price deviations, the indices can change if consumers substitute to, on average, higher or lower-priced products.

Table 5.2: Effect of Rival Rebrandings on Prices

	$\hat{P}^1_{it}$ (1)	$\hat{P}^2_{it}$ (2)	$\hat{P}^3_{it}$ (3)	$\hat{P}^1_{it}$ (4)	$\hat{P}^2_{it}$ (5)	$\hat{P}^3_{it}$ (6)
T_{Extra}	0.005	-0.001*	0.001	0.002	-0.000	-0.001
	(0.004)	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)
T_{Prix}	0.006	0.000	-0.001	0.004	0.000	0.001
	(0.011)	(0.001)	(0.003)	(0.008)	(0.001)	(0.002)
T_{Bunnpris}	0.015	0.002*	-0.001	0.013	0.000	0.000
	(0.013)	(0.001)	(0.003)	(0.009)	(0.001)	(0.003)
T_{Closed}	0.015	0.001	0.007**	0.005	-0.000	-0.002
	(0.010)	(0.001)	(0.003)	(0.008)	(0.001)	(0.002)
Market Definition	10-1 km	10-1 km	10-1 km	Postcode	Postcode	Postcode

∗ $p < 0.1$, ∗∗ $p < 0.05$, ∗ ∗ ∗ $p < 0.01$
Notes: Each Column reports the reports the estimated ATT using the estimator of sun and Abraham (2021) for different price indices and market definitions and events. The data span all months of 2014 - 2016, and the standard errors shown in parentheses are clustered by municipality. Each ATT is retrieved from separate regressions reported fully in Tables C.5, C.6, C.7, and C.8 in appendix C. Controls for municipality level population and income are included.

The estimated price effects of rival rebrandings are shown in Table 5.2. The effective local price responses are very small across price indices and format transformations, and the largest detected price response, at the 5 % level, is a 0.7 % increase across indices and specifications. This is consistent with uniform national prices, and consumers substituting from Kiwi to Extra without changing the composition of low- and high-price products. This also means that the estimated sales effects must be driven by consumers buying fewer items since overall prices do not adjust locally.

5.2.2 National Food Prices After the Acquisition

Given national pricing, the previous analysis cannot provide any insights into the price effects of the format rebrandings or the acquisition in general. Any price response would be absorbed by the time fixed effects, since the prices of both the affected and unaffected stores would move in lockstep. However, we can explore what happened to national food prices after the acquisition. In that regard, I utilize the monthly Harmonized Index of Consumer Prices (HICP) for Norway and neighboring countries from 2005 to 2020, provided by Eurostat.[26] It is derived from a national basket of representative consumer products chosen by the national statistical institutes.

The HICP for Food and Non-Alcoholic Beverages (F&B) increased by ~ 5.5 % from 2014 to 2017. However, the All-item HICP rose by ~ 8 % in the same period. To measure the evolution of real food prices, I deflate food prices with overall prices and take logarithms: $\ln(P_t^{Food}) - \ln(P_t^{All})$. Now, we have a normalized index of real food prices that can be interpreted as the approximate percentage deviation in food prices from overall prices. Figure 5.1 plots F&B and All-Item HICP, as well as normalized food prices in Norway from 2005 to 2021. There appears to be a negative shift in the trend of real food prices after ICA exited the market in 2016. A formal structural break analysis can be found in Appendix A.1.

Figure 5.2 illustrates the best linear fits of real food prices in Norway before and after the ICA acquisition from 2011 to 2020. The transition period, during which only some ICA stores were rebranded, is excluded. The annualized trend growth rate of real food prices in Norway was 0.24 % since 2011 before changing to -1.19 % after the acquisition. By the end of 2019, the trend of real food prices had declined by 5.85 % compared to the trajectory predicted by the pre-acquisition trend.

Of course, the shift in real food prices following the acquisition could be due to other factors such as changes in global commodity prices, supply-chain shocks, or changes in consumer purchasing power. Yet, such changes should manifest themselves in food price changes in neighboring countries exposed to the same underlying factors, while the domestic ICA acquisition should not. If comparable countries did not experience a structural break in conjunction with Norway, the acquisition provides a viable explanation.

Figures A.1 and A.2 in Appendix A.2 plots F&B and All-Item HICP as well as

[26] https://ec.europa.eu/eurostat/web/hicp/data/database

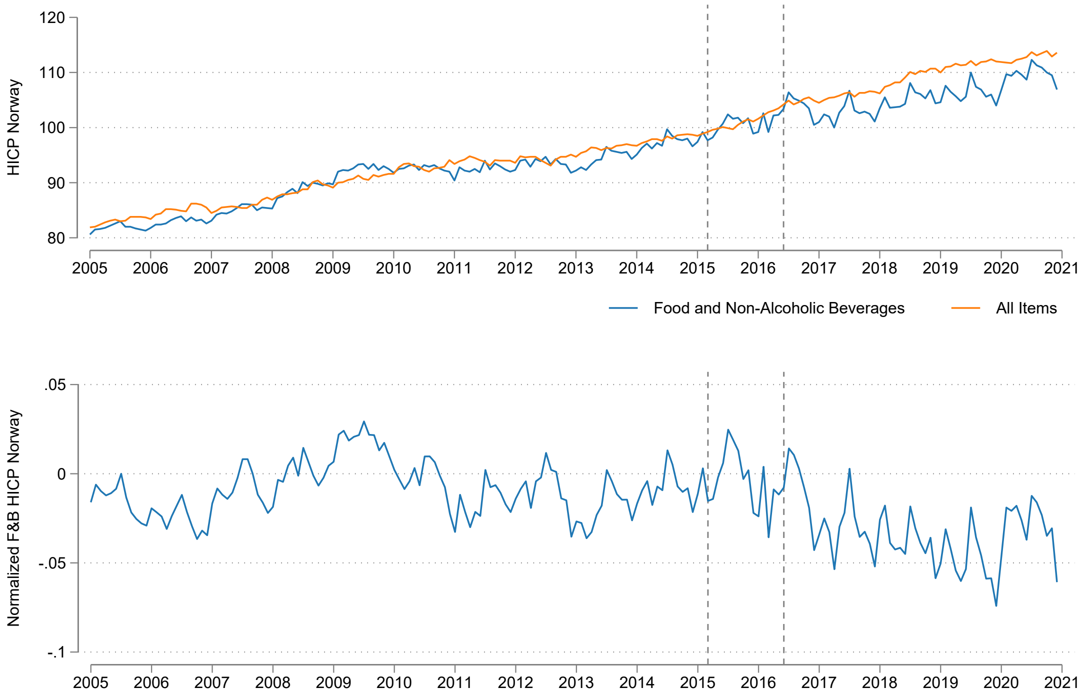

Figure 5.1: The top figure shows F&B and All-Item HICP in Norway with mean index values of 2015 = 100. The bottom figure shows the normalized F&B HICP in Norway; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$. The two vertical lines span the transition period from right before the first (2015m3) to right before the final (2016m6) store rebranding. *Source:* Eurostat.

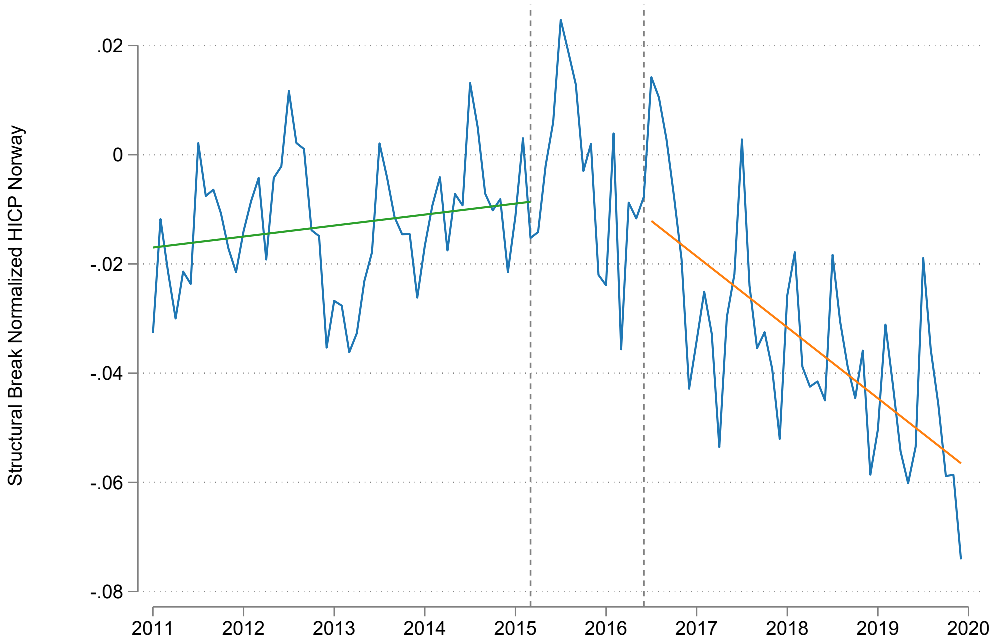

Figure 5.2: The best linear fit of normalized F&B HICP; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$, from 2011 to 2019 before and after the acquisition. The transition period (2015m4 - 2016m6) is excluded. *Source:* Eurostat.

normalized food prices for a set of candidate comparison countries. By inspection, it seems that Sweden, Denmark, Germany, and Iceland plausibly follow common linear trends with Norway from the Great Recession until the acquisition. Figure 5.3 shows that real food prices in these countries, including Norway, indeed follow similar paths prior to the acquisition, and that Norway experiences a negative trend shift while the other countries remain on trend. Formal difference-in-differences analysis (see Appendix A.2) suggests that real food prices fell by an average og 5.1 % after the acquisition. Under the assumptions of common trends or deviations from linear trends, the structural break in Norwegian real food prices cannot be explained by factors that are common across the comparison countries.

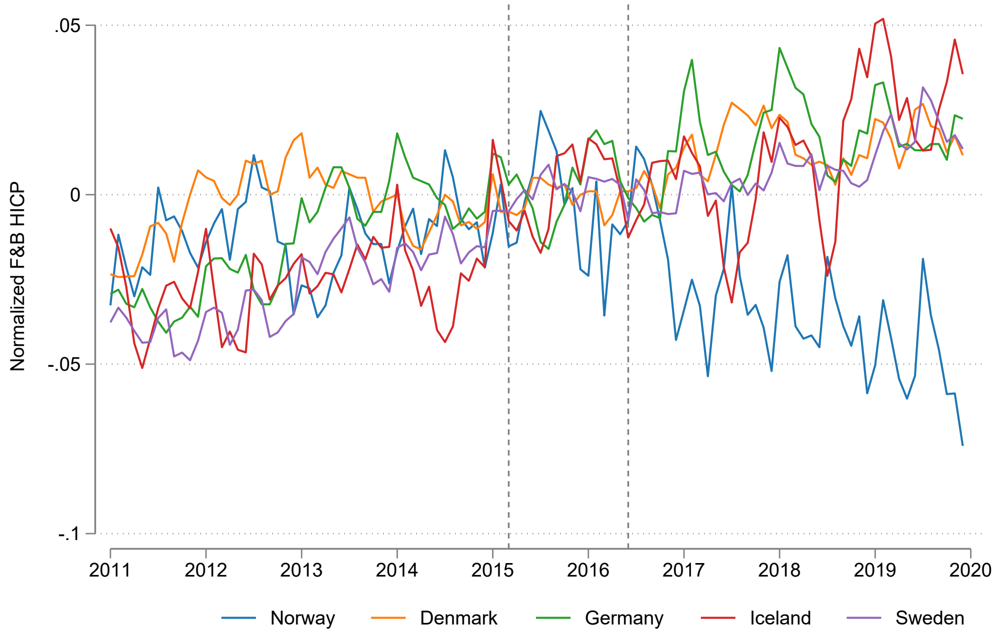

Figure 5.3: Normalized F&B HICP for Norway and comparison countries; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$. The transition period (2015m4 - 2016m6) is indicated by the vertical dashed lines. *Source:* Eurostat.

I also employ the synthetic control method proposed by Abadie and Gardeazabal (2003) to relax the assumptions of common or linear trends. I extend the time series back to 2005 and construct a synthetic comparison country consisting of a weighted average of Scandinavian countries. The deseasonalized real food prices of Norway, the synthetic control, and their difference are shown in Figure A.3 in Appendix A.3. The synthetic comparison country closely mirrors Norway until the acquisition, after which a gap emerges as real food prices begin to decline in Norway. Consistent with the difference-in-differences analysis, Norwegian food prices are imputed to fall by an average of 5.2 % compared to the synthetic control. For additional details and alternative specifications, please see Appendix A.3.

A priori, we might be concerned that Norwegian food prices do not follow similar trajectories to neighboring countries, particularly due to non-membership in the European Union. Therefore, it is reassuring that a weighted average of neighboring countries can replicate their evolution before the acquisition. This suggests that we have captured the underlying factors that drive them. However, there could be structural breaks in the data-generating process that coincide with the acquisition. For example, Norway protects its agricultural sector through trade restrictions and tariffs, and changes in protectionist policies could partly explain the downward trend-shift in real food prices. However, Steen and Pettersen (2020) find that protection support in Norway, compared to the European Union increased in the period under study, which contrarily should have pushed Norwegian food prices upwards relative to neighboring EU members.

5.3 Product Variety

Although stores are unable to change prices in response to changes in their competitive environment, they could make quality adjustments. A key component of customer satisfaction in the grocery retail market is product variety and accessibility. Previous studies find that shocks in market structure, such as the advent of Walmart, can have significant effects on product stock shortfalls. Matsa (2011) argues that the increased risk of losing customers incentivized supermarkets to limit stock shortfalls by about a third. However, considering assortment size more generally, increased competitive pressure can also disincentivize the addition of a new product in the line if there are fixed costs associated with doing so. The business-stealing effect of a fiercer competitor might render a large product assortment unprofitable.

To investigate how stores adjust assortment sizes in response to rival rebranding, we must overcome the measurement error that stems from not directly observing assortment but rather the number of unique products that are purchased. In a given month, some products might be offered but not purchased and subsequently not observed in the data. By only counting products that sold at least 100 units n ationally in every period of the sample, we obtain a measure that should only change if the store indeed changes its assortment offering. The absolute and percentage effects of a rival rebranding to Extra on assortment size are reported in Table 5.3. All specifications predict that Kiwi responded to rivals rebranding to Extra by reducing its product assortment, but only by approximately 1 %. There is no evidence that rival rebrandings into Prix or Bunnpris resulted in Kiwi locally adjusting its assortment size. A rival closing down is associated with a slightly larger assortment size.

Counting the number of unique products offered provides an intuitive measure of product variety, but it does not account for the importance of each individual product. Consider a store offering a large set of marginal products together with a few very

Table 5.3: Effect of Rival Rebrandings on Assortment Size

	Variety	ln(Variety)	Variety	ln(Variety)	Variety	ln(Variety)
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Extra}	-17.400**	-0.009**	-6.484	-0.007*	-10.105	-0.007**
	(8.143)	(0.003)	(8.707)	(0.004)	(6.732)	(0.003)
T_{Prix}	-16.013	-0.007	-1.786	-0.002	-4.105	-0.000
	(11.358)	(0.004)	(9.812)	(0.004)	(9.838)	(0.004)
T_{Bunnpris}	-4.002	-0.003	-1.217	-0.002	3.035	0.001
	(6.406)	(0.003)	(13.583)	(0.005)	(9.566)	(0.005)
T_{Closed}	7.373	0.006*	7.785	0.007**	10.278**	0.004**
	(7.608)	(0.004)	(6.927)	(0.003)	(4.687)	(0.002)
Market Definition	10-1	10-1 km	6-1.5 km	6-1.5 km	Postcode	Postcode

* p < 0.1, ** p < 0.05, * * * p < 0.01

Notes: Each Column reports the reports the estimated ATT using the estimator of sun and Abraham (2021) in levels and logs for different local market definitions and events. The data span all months of 2014 - 2016, and the standard errors shown in parentheses are clustered by municipality. Each ATT is retrieved from separate regressions reported fully in Tables C.9, C.10, C.11, and C.12 in appendix C. Controls for municipality level population and income are included.

popular ones, and compare it to a store with a large offering of products with similar sales shares. The latter kind of variety is more valuable to consumers as revealed by the expenditure shares. Alexander (1997) proposes measuring product variety as entropy (Shannon, 1948):

$$E_{it} = -\sum_{j=1}^{J_{it}} w_{ijt} \ln(w_{ijt})$$

where w_{ijt} is the sales share, and J_{it} is the assortment size of store i at time t. This measure increases with the assortment size J_{it}, but it is largest for a given J_{it} when $w_{ijt} = 1/J_{it}$, resulting in $E_{it} = \ln(J_{it})$. If one product gains all the sales, i.e., $w_{1it} = 1$ and $w_{ijt} = 0$ for every other $2 \leq j \leq J_{it}$, the measure becomes $E_{it} = 0$. In the intermediate case when sales shares are asymmetric but strictly positive for more than one product, we have: $0 \leq E_{it} \leq \ln(J_{it})$. This notion of product variety also does not suffer from the unobservability of offered but not sold products, as they do not contribute to the entropy measure.

The estimated effects of rival rebrandings on variety entropy are shown in Table 5.4. All specifications find a decrease in the entropy measure between 0.6 % and 2 % following a rival rebranding to Extra, but only the 10-0.5 km, 5-0.5 km, and postcode specifications are statistically significant at the 5 % level. For rivals rebranding to Prix, there is no evidence of an effect across specifications. This is also the case for Bunnpris, except for a 2 % effect for the 10-1.5 km specification, which is statistically significant at

Table 5.4: Effect of Rival Rebrandings on Variety Entropy

	E_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Extra}	-0.007	-0.006	-0.016***	-0.007	-0.020***	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
T_{Prix}	0.003	0.004	0.005	0.003	0.008	0.005
	(0.007)	(0.006)	(0.004)	(0.007)	(0.005)	(0.007)
T_{Bunnpris}	0.020***	-0.002	-0.007	-0.002	-0.009	-0.005
	(0.006)	(0.009)	(0.009)	(0.011)	(0.010)	(0.008)
T_{Closed}	0.002	0.003	0.001	0.002	-0.002	-0.007
	(0.006)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode

$*$ p < 0.1, $**$ p < 0.05, $***$ p < 0.01

Notes: Each Column reports the reports the estimated ATT using the estimator of sun and Abraham (2021) for different local market definitions and events. The data span all months of 2014 - 2016, and the standard errors shown in parentheses are clustered by municipality. Each ATT is retrieved from separate regressions reported fully in Tables C.13, C.14, C.15, and C.16 in appendix C. Controls for municipality level population and income are included.

the 1 % level. There is no statistically significant effect of rivals closing down. In light of the stronger sales effect of Extra relative to other formats, the findings in Tables 5.3 and 5.4 could be explained by the competitive pressure of Extra rendering certain products unprofitable. It could also be that the migrating customers were the ones that used to purchase niche products, leaving them unsold. However, from Table B.2, it is clear that assortment sizes and entropy have been increasing over time, perhaps in response to increased competition in the soft discount segment and the risk of losing customers. The limited local adjustments compared to national adjustments might suggest that most of the decisions relating to product assortment are made centrally.

6 Robustness Checks

6.1 Dynamic Event Study Design

The identifying assumptions that allow us to interpret our results causally are the parallel trends and no anticipation assumptions. To investigate their validity, it is useful to consider a variant of Equation 4.1 where the treatment effects are allowed to vary non-parametrically over time, often referred to as the dynamic event study design. Firstly, it allows us to diagnose if there are significant deviations in trends across affected and unaffected markets prior to the rebrandings. Secondly, we can look for anticipatory effects in the lead-up to rival rebrandings. The dynamic version has the following form:

$$Y_{it} = \gamma_i + \lambda_t + \sum_{l \neq \{-1,-\infty\}} \mu_l \mathbb{1}\{t - E_i = l\} + \delta' \boldsymbol{Z_{it}} + \epsilon_{it} \tag{6.1}$$

where $\mu_l = E[\mu_{itl}] = ATT_l$ and $\mathbb{1}\{\cdot\}$ is the indicator function. E_i is the time of rebranding in store i's market and $t - E_i = l$ is the time passed since the rebranding. Now the parameters of interest are the average treatment effects of the treated l periods after the initial treatment μ_l. To avoid perfect collinearity of the relative time indicators, I exclude one relative time period that serves as a reference point. As is customary, I use the time before treatment $l = -1$. Markets in the unaffected group are indicated with $l = -\infty$. If the parallel trends and no anticipation assumptions hold, we should expect no difference in trajectory, as captured by $\mu_l \; \forall \; l < -1$, between affected and unaffected stores prior to treatment. The event study plots for the 10-1 km specification are shown in Figure 6.1 whereas the complete set of specifications can be found in Figures C.1, C.2, C.3, and C.4 in Appendix C.

Event Study Plots 10-1 km - ln(Sales)

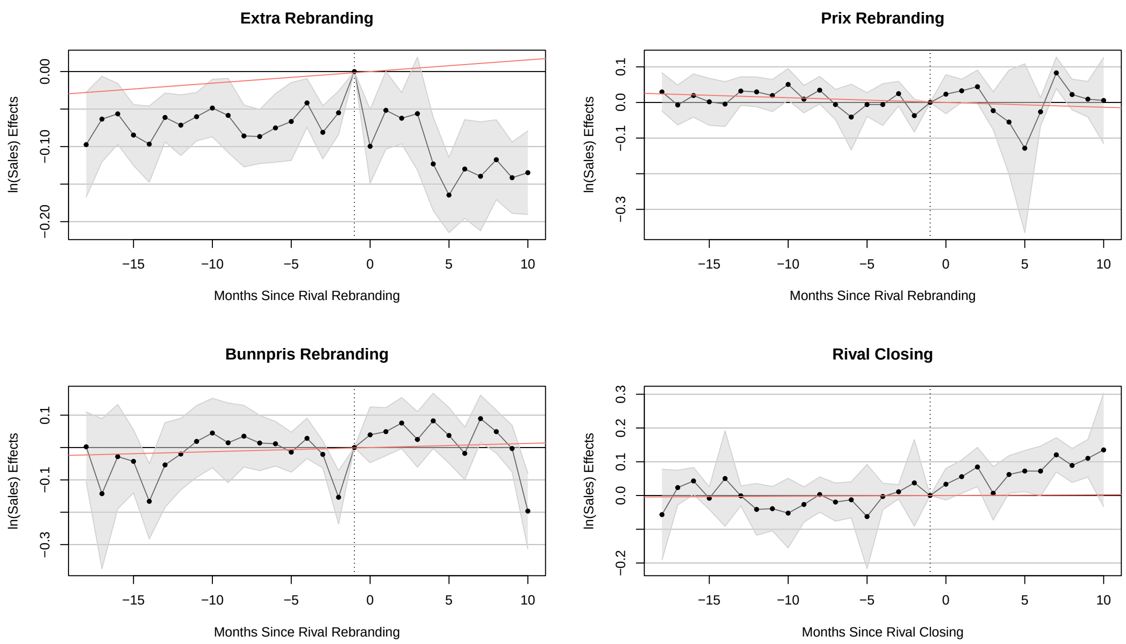

Figure 6.1: The percentage sales effects of a rival rebranding or closing as a function of the time since the event. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs. The linear pretrend is extrapolated into the post period.

Figure C.1 in Appendix C shows the results of Equation 6.1 for ln(sales) and rivals rebranding to Extra. Upon inspection, none of the specifications indicate trend differences in the pre-period that can explain the post-rebranding effects, but there is a tendency for sales to increase right before the rebranding. For the Prix estimates, depicted in Figure C.2, it is hard to imagine significant effects being masked by pretrends, but there is some noise right before the rebranding that would make the estimates sensitive to the exact reference period. The event study plots for Bunnpris, illustrated in Figure C.3, show increasing pre-trends that could bias the effects upward, although the magnitudes differ across specifications. It is important to note that there are not many instances of rivals rebranding to Bunnpris, so we should be careful when inferring trends and effects that could be attributed to sampling noise. In Figure C.4, most specifications display no clear pretrends although there is some variability. The postcode specification exhibits a lot of noise in the pre-period, making the estimated effects very sensitive to the chosen reference period. For example, sales were higher in the post-period than 5 periods before the rival closings, but lower than 2 or 14 before. However, there is a clear tendency of sales increasing after a rival closes down in most specifications.

The event study plots of $\hat{P}^1_{it}$ for Extra, Prix, Bunnpris, and closings are shown in Figures C.5, C.6, C.7, and C.8 in Appendix C. None of them indicate clear pretrends or anticipation effects that would invalidate the general conclusions in Section 5. The percentage assortment size and variety entropy effects of Extra are reported in Figures C.9 and C.13, respectively. The pretrends are fairly flat across specifications but exhibit a lot of variation. The assortment size and variety entropy pretrends for Prix, Bunnpris, and closings are depicted in Figures C.9, C.14, C.11, C.15, C.12, and C.16. They appear erratic, but it is important to note that the effect sizes are quite small.

6.2 Adjusting for Anticipation and Linear Pre-trends

In this section I account for potential violations of the no anticipation and parallel trends assumptions. The former might arise naturally in this setting if there is an adjustment period as stores are rebranded and not operating as normal. To avoid this problem, I exclude the last month before the event and use the second to last as a reference when estimating Equations 4.1 and 6.1. The estimated ATTs are shown in Table 6.1 and Figure 6.2 depicts the event study plots for the 10-1 km specification. The complete set of specifications can be found in Figures C.17, C.18, C.19, and C.20 in Appendix C.

The effect of a rival rebranding to Extra is now between -5.1 % and -9.6 % across specifications. As expected, given the high sales right before the event, the estimates are smaller than the unadjusted specification but still economically and statistically significant. The ATTs for Prix do not change much. The estimates for Bunnpris become very large because of a negative outlier two periods before the event, and the effect of a rival closing becomes smaller and not statistically significant because of a higher reference point. The S&A estimator is clearly sensitive to the chosen reference point, which the next robustness check addresses.

The parallel trends assumption is not directly testable, but a long history of pre-

Table 6.1: Effect of Rival Rebrandings on Sales - Last Period Before Event Excluded

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Extra}	-0.072***	-0.051***	-0.096***	-0.053***	-0.091***	-0.094***
	(0.017)	(0.018)	(0.015)	(0.018)	(0.013)	(0.022)
T_{Prix}	0.034	0.019	-0.030	0.007	-0.045	-0.065**
	(0.031)	(0.026)	(0.026)	(0.033)	(0.036)	(0.030)
T_{Bunnpris}	0.255***	0.176***	0.132***	0.223***	0.136***	0.019
	(0.061)	(0.040)	(0.032)	(0.063)	(0.041)	(0.056)
T_{Closed}	0.044	0.046	0.056	0.044	0.051	-0.061
	(0.064)	(0.079)	(0.061)	(0.071)	(0.078)	(0.068)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode

$* \, p < 0.1$, $** \, p < 0.05$, $*** \, p < 0.01$

Notes: Each Column reports the reports the estimated ATTs using the estimator of sun and Abraham (2021) for different local market definitions and events. The data span all months of 2014 - 2016 except the last period before the event, and the standard errors shown in parentheses are clustered by municipality. Each ATT is retrieved from separate regressions reported fully in Tables C.17, C.19, C.21, and C.23 in appendix C. Controls for municipality level population and income are included.

Event Study Plots 10-1 km - ln(Sales) - Last Period Before Event Excluded

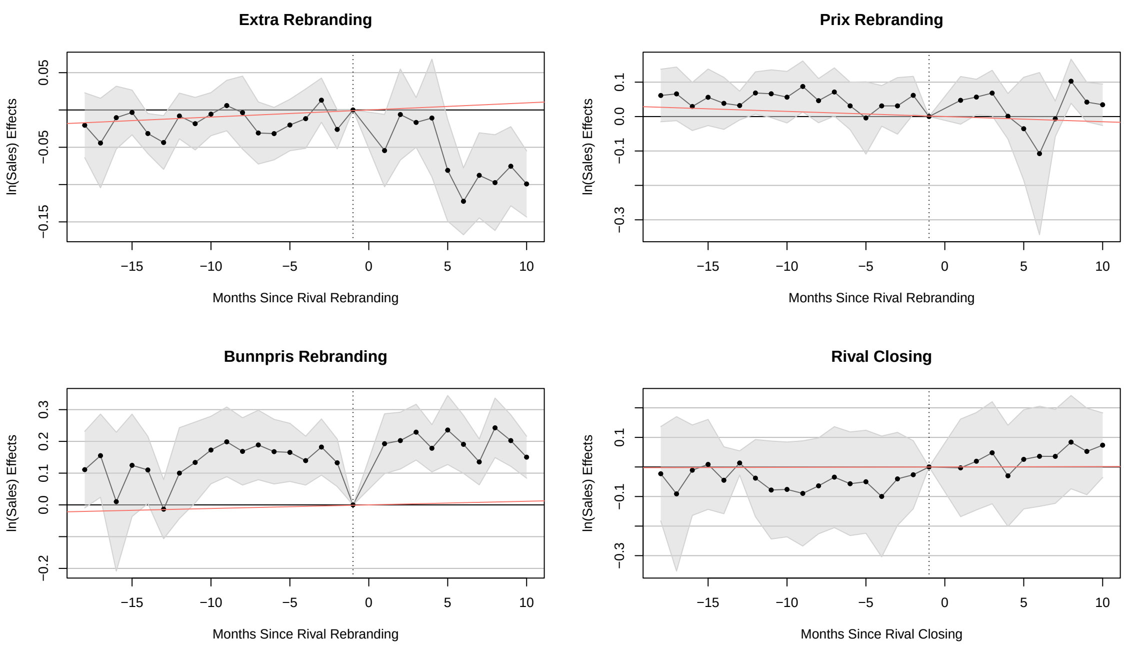

Figure 6.2: The percentage sales effects of a rival rebranding or closing as a function of the time since the event. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The last period before the rival rebranding is excluded and the linear pretrend is extrapolated into the post rebranding period. The first vertical line indicates two periods before the event and the second line indicates the first period after the event.

event observations allows us to check for pretrends that could reasonably explain the observed post-event evolution. Furthermore, by invoking parametric restrictions on the pretrends one can extrapolate them into the post-period and estimate the ATTs under the assumption of common deviations from trends (Angrist and Pischke, 2015). Including linear trends represents a weakening of the identifying assumptions in the sense that if trends are indeed parallel, it should not introduce bias, but if there are close to linear trend differences the bias could be mitigated. Hence, I consider an augmented version of Equation 6.1:

$$Y_{it} = \gamma_i + \lambda_t + \text{Affected} \times \text{Trend} + \sum_{l>=0} \mu_l \mathbb{1}\{t - E_i = l\} + \delta' \boldsymbol{Z_{it}} + \epsilon_{it} \tag{6.2}$$

This equation includes an affected store-specific linear time trend and no lead indicators. Now the linear pretrend of all the pre-event observations replaces the last pre-period as the baseline outcome, which makes the results less sensitive to variability leading up to the event.

The ATTs and affected group specific trends estimated from Equation 6.2 with one pre-period excluded are shown in 6.2. None of the affected groups display statistically significant trends, although some are large enough in magnitude to meaningfully shift the baseline outcome over time, as can be seen in the event study plots. The estimated ATTs for Prix and Bunnpris are qualitatively similar to the unadjusted specification in Table 5.1. In comparison, the Extra ATT ranges between -4.4 % and -10.8 % across specifications; somewhat smaller in magnitude. The estimated ATT of a rival closing largely mirrors the unadjusted estimates, although they are slightly larger across specifications. The main conclusions of Section 5 are robust to the inclusion of affected group-specific trends and the removal of the last period before the event.

7 Discussion

7.1 Heterogeneous Effects across Treatment Arms

Although the common trends and no-anticipation assumptions identify the average treatment effect on the treated for each treatment arm, we must be careful when comparing the effects of different treatments estimated from different samples. Identifying differences in ATTs for a given treatment group requires assuming that treatment effects are common across treatment arms since we do not observe the potential outcomes associated with a different treatment (Callaway et al., 2021). If there is selection into treatment arms, differences in ATT estimates might reflect heterogeneous treatment effects for a given treatment across treatment groups.

Table 6.2: Effect of Rival Rebrandings on Sales
- Group Specific Linear Trends and the Last Period Before Event Excluded

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
Trend - Extra	0.001	0.001	0.002	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T_{Extra}	-0.069**	-0.055*	-0.108***	-0.044	-0.081***	-0.089***
	(0.029)	(0.030)	(0.022)	(0.032)	(0.023)	(0.030)
Trend - Prix	-0.002	-0.002	-0.001	-0.001	-0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
T_{Prix}	-0.003	-0.009	0.015	-0.012	0.028	-0.022
	(0.029)	(0.032)	(0.036)	(0.032)	(0.038)	(0.026)
Trend - Bunnpris	0.002	0.001	0.005	0.005	0.007	0.005
	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.004)
T_{Bunnpris}	0.058*	0.026	-0.015	-0.016	-0.049	-0.062
	(0.032)	(0.036)	(0.035)	(0.047)	(0.049)	(0.040)
Trend - Closed	0.000	0.000	0.001	-0.001	-0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
T_{Closed}	0.073*	0.091**	0.083*	0.092**	0.111	0.037
	(0.037)	(0.041)	(0.047)	(0.038)	(0.075)	(0.043)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$
Notes: Each Column reports the estimated ATTs and trends of Equation 6.2 for different local market definitions and events. The data span all months of 2014 - 2016 except the last period before the event, and the standard errors shown in parentheses are clustered by municipality. Each ATT and trend is retrieved from separate regressions reported fully in Tables C.18, C.20, C.22, and C.24 in appendix C. Controls for municipality level population and income are included.

As can be seen from Figure 7.1, which depicts the size distributions of Coop's formats Prix, Extra and Mega, Extra stores are routinely larger than Prix, which probably limits the scope for Coop to select its target format based on differences in their expected profitability. However, this makes it clear that differences in the ATT for Extra and Prix could be partially due to differences in the store sizes of rebranding rivals. For example, it could be that if the stores that rebranded to Prix were instead rebranded to Extra, they would not produce as strong business-stealing effects as the ATT estimated in this paper because smaller Extra stores would not capture as many consumers.

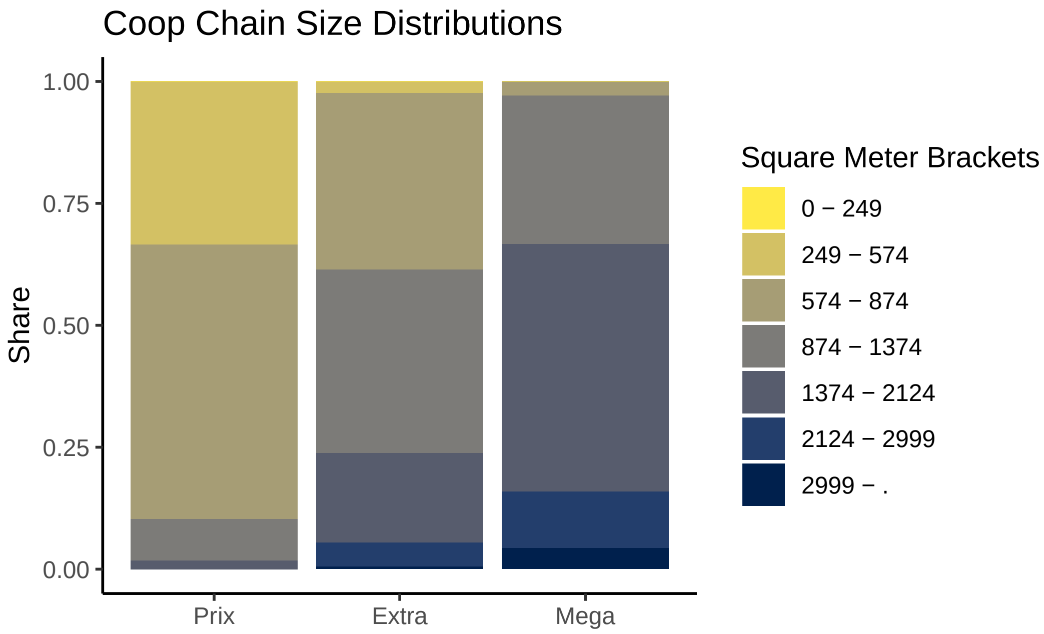

Figure 7.1: The share of stores within each square meter bracket for each of Coop's target formats in 2019. Prix and Extra are overlapping, but routinely Extra stores are larger than Prix stores.

For markets where the NCA intervened or Coop chose to close the store, we need to consider what motivated them. The markets where Bunnpris was allowed to buy stores were chosen based on the risk of anti-competitive effects (Konkurransetilsynet, 2015, Clause 218), which means that Coop was present in these markets, but also that there were no more than 2 umbrella chains present post-merger. The effect of a rival rebranding could be muted in already competitive markets, but whether these markets were particularly competitive is not clear a priori since at least the Coop Extra format is a close competitor to Kiwi. As discussed in the main analysis, it is reasonable to assume that the stores that closed down were under performing and that the effect of closing them understates the overall effect of closing a rival ICA store.

7.2 How the Sales Diversions Relate to the Price and Assortment Effects

[[TBA]]

7.3 Limitations

[[TBA]]

8 Conclusion

This article empirically assesses the competitive effects of an acquisition in the Norwegian grocery retail industry. Local ownership concentration did not increase on average, but the identity of several stores changed. I find that Coop's soft discount format, Extra, which is the most prevalent new format, is more competitive than the previous convenience discount formats in the market. This suggests that the aggregate effect of the store rebrandings is a more competitive industry despite increasing ownership concentration at the national level. However, stores do not adjust prices locally in response to changes in rival identities, which is consistent with a national pricing policy. Hence, it is not feasible to learn about the price effects of the acquisition using domestic stores as controls. Instead, I study real food prices at the national level by making comparisons to neighboring countries. I find that the acquisition was followed by a nationwide decline in real food prices, but it is not possible to rule out other shocks in Norway that could have contributed to it. Still, it cannot be explained by underlying factors shared with the grocery retail industries of neighboring countries. Finally, I find a small effect of the new soft discount chain on product assortment, but most of the variation happens over time, not in the cross-section. The fact that chain-level assortment sizes increased in the sample period without local adjustments is consistent with most of the assortment decisions being made centrally.

This study illustrates the importance of considering the heterogeneous characteristics of firms in merger evaluations. Competition agencies often weigh the anti-competitive effects of increased ownership concentration against potential efficiency gains from synergies, economies of scale or scope, or the disciplining threat of entry. However, the transfer of inimitable assets facilitated by mergers and acquisitions can enable product characteristics repositioning that changes the degree of competition between incumbent firms. This mechanism is distinct from the allocative efficiency and productivity gains from mergers established in studies like Braguinsky et al. (2015) and Demirer and Karaduman (2022); which are synergistic effects. The shift towards more soft discount stores following the ICA acquisition necessarily crowds the segment and leads to stores being closer competitors. The findings in this paper indicate that this effect could dominate the anti-competitive effects of ownership concentration and should be carefully considered in merger cases where there is potential for the repositioning of product characteristics.

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Appendix

A Analysis of National Real Food Prices

A.1 Structural Break Analysis

I test if there is a structural break in the evolution of real food prices around the time of the acquisition by estimating the following equation:[27]

$$\ln\left(\frac{P_t^{Food}}{P_t^{All}}\right) = \beta_0 + \beta_1 t + \beta_2(\text{Post Acquisition}) + \beta_3(t \times \text{Post Acquisition}) + \beta_4(\text{Month}) + \epsilon_t \tag{A.1}$$

where "Post Acquisition" is an indicator for the time after the acquisition (April 2015), and "Month" is the vector of monthly dummies. The time trend t is normalized to indicate the number of months after the acquisition so that β_2 can be interpreted as the shift in real food prices at the time of the acquisition. However, I restrict the sample period to 2011 - 2019 as the great recession and the C-19 pandemic could represent structural breaks themselves. We also need to consider that the ICA takeover transpired in the course of April 2015 - July 2016 during which only some ICA stores were rebranded.

Specification (1) in Table A.1 excludes the transition period of April 2015 - June 2016 for which we cannot expect a stable trend. Specification (2) replaces "Post Acquisition" with the variable "Rebranding Share" which measures the share of total store rebrandings that have occurred (as depicted in 3.2) and moves from 0 to 1 during the transition period. I can then include the full sample period and measure the change in real food prices associated with the total 385 format rebrandings, assuming a constant marginal effect. For specification (1), I find that real food prices were trending slightly upward prior to the acquisition ($\beta_1 = 0.02$ %), before the trend shifted downward ($\beta_3 = -0.12$ %) without a significant initial shift in levels ($\beta_2 = 0.87$ %).[28] The annualized growth rate was 0.24 % before the acquisition and decreased by 1.43 % after.[29]. Specification (2) produce very similar results with an annualized growth rate of 0.36 % before and a reduction of 1.55 % after. Both specifications find an annualized post acquisition growth rate of -1.19 %. Specification (1) is represented graphically in figure 5.2.

[27]The structural break model is also called the Interrupted Time Series design (Reichardt, 2019).

[28]In Norway, grocery retailers and wholesalers negotiate prices and terms biannually; in February and July, which typically entails price hikes. This could mask instantaneous effects of the acquisition.

[29]Calculated as $(1 + \text{monthly grwoth rate})^{12} - 1$

Table A.1: Structural Break Analysis - Normalized F&B HICP 2011 - 2019

$\ln(P_t^{Food}) - \ln(P_t^{All})$	(1)	(2)
Trend	0.0002**	0.0003***
	(0.0001)	(0.0001)
Post Acquisition	0.0087	
	(0.0068)	
Trend × Post Acquisition	-0.0012***	
	(0.0002)	
Rebranding Share		0.0071
		(0.0047)
Trend × Rebranding Share		-0.0013***
		(0.0001)
Constant	-0.0144***	-0.0128***
	(0.0031)	(0.0032)
Monthly Dummies	Yes	Yes
Observations	93	108

∗ p < 0.1, ∗∗ p < 0.05, ∗ ∗ ∗ p < 0.01
Notes: The time series starts in January 2011 and ends in December 2019. Driscoll-Kraay standard errors are shown in parentheses. The transition period (2015m4 - 2016m6) is excluded in model (1).

A.2 Comparative Structural Break Analysis

The difference-in-differences approach typically takes the form of a standard two-way fixed effects regression:

$$\ln\left(\frac{P_{it}^{Food}}{P_{it}^{All}}\right) = \alpha_i + \lambda_t + \alpha_5(\text{Post Acquisition} \times \text{Norway}) + \epsilon_{it}$$

where α_i and λ_t are fixed effects and "Norway" is an indicator function. The results of this regression is shown in column 3 of Table A.1. It suggests that Norwegian food prices on average fell by 5.1 % after the acquisition relative to comparison countries. The time fixed effects allow for each country's trend to take any non-parametric form so long as it is common to them, but without a large cross section of units, each fixed effect is estimated using very few observations. The specification in column 2 of Table A.1 alleviates this problem by exchanging time fixed effects with the before-after indicator "Post Acquisition", and finds a similar average decline in food prices of 5.23 %. It allows for a differential shift in food prices between Norway and comparison countries at the time of the acquisition, but assumes that there is no trend component.

An alternative approach is to instead include linear time trends that can be

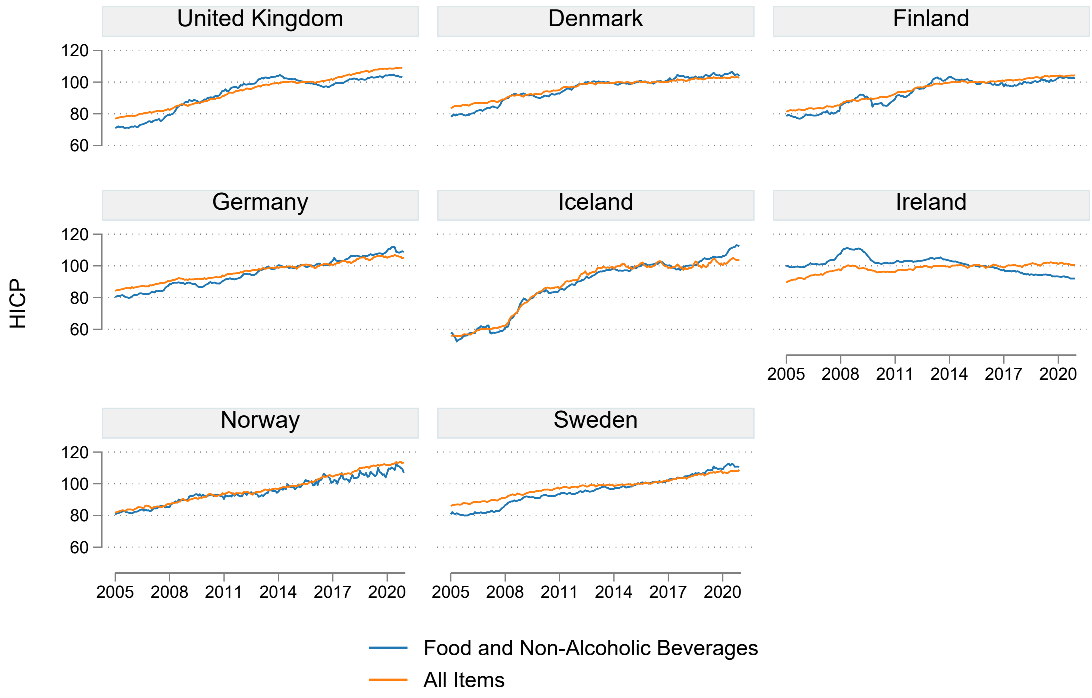


Figure A.1: Food and Non-Alcoholic Beverages, and All-Item HICP. Mean index values of 2015 = 100. *Source:* Eurostat.

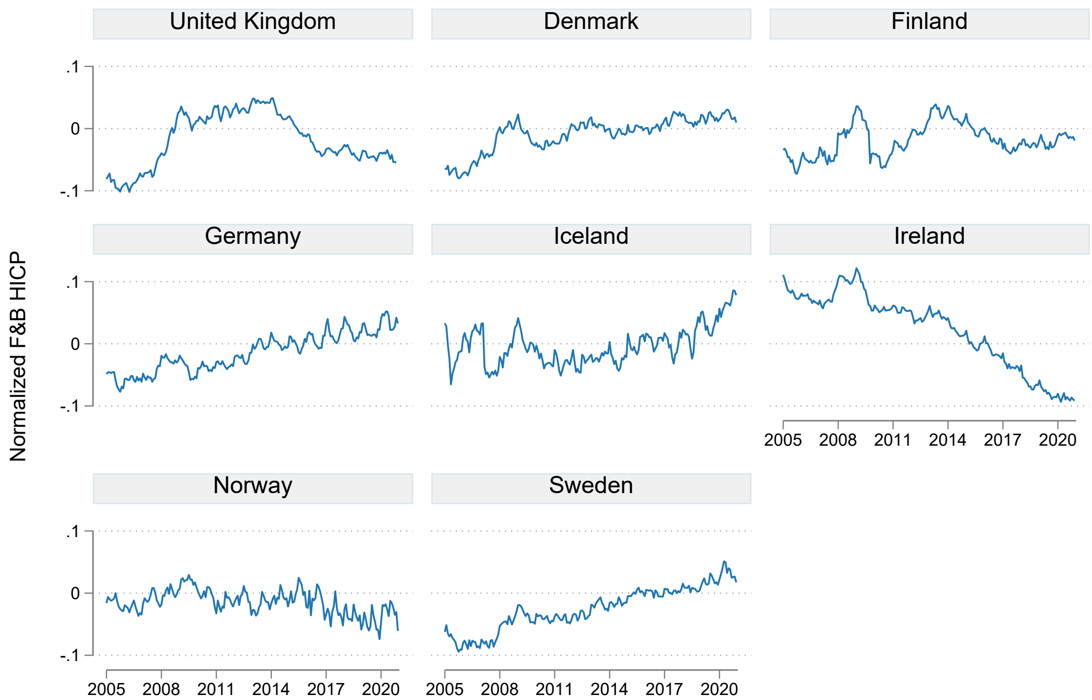


Figure A.2: Percentage F&B price deviations from overall prices by country; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$. *Source:* Eurostat.

consistently estimated due to the longer time series under the assumption that trends are indeed linear. In fact, by introducing country specific linear trends we can dispense with the assumption of common trends in favor of common deviations from trends (Angrist and Pischke, 2015). See Øivind A. Nilsen et al. (2016) for an application of this approach in the evaluation of an upstream merger in the market for eggs in Norway.[30] I estimate the following equation to learn how real food prices evolved in Norway compared to neighboring countries:

$$\begin{aligned}\ln\left(\frac{P_{it}^{Food}}{P_{it}^{All}}\right) = \alpha_i + \alpha_1 t + \alpha_2(\text{Post Acquisition}) + \alpha_3(t \times \text{Post Acquisition}) \\ + \alpha_4(t \times \text{Norway}) + \alpha_5(\text{Post Acquisition} \times \text{Norway}) \\ + \alpha_6(t \times \text{Post Acquisition} \times \text{Norway}) + \alpha_7(\text{Month} \times \text{Country}) + \epsilon_{it}\end{aligned}$$

where α_i are country specific intercepts and "Country" is the vector of country indicators. I allow for separate trends and levels between Norway and the control group, before and after the acquisition.[31] Seasonal effects are country specific. In other words, I test for structural breaks in both groups to validate the findings in Table A.1. The results are shown in column 1 of Table A.2.

[30]The approach is also called the Comparative Interrupted Time Series design.

[31]Allowing for country specific trends and structural breaks in the control group and comparing Norway with the average control country yield virtually the same results, so common trends and breaks are assumed within the control group for simplicity.

Table A.2: DiD Analysis - Normalized F&B HICP 2011 - 2019

$\ln(P_t^{Food}) - \ln(P_t^{All})$	(1)	(2)	(3)	(4)	(5)	(6)
Trend	0.0005***			0.0006***		
	(0.0001)			(0.0000)		
Trend × Norway	-0.0004***			-0.0003***		
	(0.0001)			(0.0001)		
Post Acquisition	-0.0022	0.0301***				
	(0.0030)	(0.0034)				
Post Acquisition × Norway	0.0109	-0.0523***	-0.0510***			
	(0.0081)	(0.0065)	(0.0084)			
Post Acquisition × Trend	-0.0000					
	(0.0001)					
Post Acquisition × Trend × Norway	-0.0012***					
	(0.0002)					
Rebranding Share				-0.0008	0.0279***	
				(0.0026)	(0.0037)	
Rebranding Share × Norway				0.0079	-0.0481***	-0.0483***
				(0.0058)	(0.0074)	(0.0088)
Rebranding Share × Trend				-0.0001		
				(0.0001)		
Rebranding Share × Trend × Norway				-0.0012***		
				(0.0001)		
Constant	-0.0144***	-0.0181***	-0.0028	-0.0128***	-0.0177***	0.0156***
	(0.0031)	(0.0038)	(0.0032)	(0.0031)	(0.0038)	(0.0044)
Monthly Dummies	Yes	Yes	No	Yes	Yes	No
Time Fixed Effects	No	No	Yes	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	465	465	465	540	540	540

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: The panel includes Norway, Sweden, Denmark, Germany and Iceland, starting January 2011 and ending December 2019. Driscoll-Kraay standard errors are shown in parentheses. The transition period (2015m4 - 2016m6) is excluded in model (1) through (3).

In fact, the results in column 1 of Table A.1 can be derived from the structural break regression in Table A.2.[32] The difference is that the difference-in-differences analysis allows us to moderate the changes in the trend and level in Norway with those of the comparison countries. If Norway would have experienced a common structural break without the merger, this is identified by the other countries. Coefficient α_5 measures the difference in level shifts after the acquisition between Norway and the comparison group. Neither Norway or the control countries experienced level-shifts significantly different from zero or each other. Coefficient α_6 measures the difference in trend shifts after the acquisition. There was no change in trajectory for the control countries around the acquisition, suggesting that the trend shift of Norwegian real food prices was not caused by factors that are common across neighboring countries ($\beta_3 = \alpha_6 = -0.0012$). However, coefficient $\alpha_4 = -0.0004$ also shows that Norway and the comparison countries have slightly different average trends prior to the acquisition (~ 0.5 % annualized growth) violating the common trends assumption and confirming that differing pre-trends should be accounted for.

Columns 4-6 mirror the hitherto analysis, but replaces the "Post Acquisition" indicator with the variable "Rebranding Share". The results are similar, but the effect sizes in columns 5 and 6 are slightly smaller than their counterparts in columns 2 and 3 at approximately -4.8%.

A.3 Synthetic Control Analysis

The previous analysis rests on the assumption that real food prices trend linearly or that the comparison countries share common trends on average. However, real food prices have exhibited deviations from linear trends in the past, and the unweighted average of comparison countries does not exactly follow parallel trends with Norway before the acquisition. The synthetic control method of Abadie and Gardeazabal (2003) accommodates both non-linear and non-parallel trends by constructing a weighted average of comparison countries that do share a common trend with Norway. The idea is that while the outcome is driven by a set of common factors, different factor loadings can cause non-parallel trends. These factor loadings are not observable, but only a synthetic control that matches the factor loadings of Norway is likely to reproduce its history. This is especially true if there is a long past history and little volatility in the data (see Abadie (2021) for an in depth discussion).

The aim is to identify the possibly time-varying effects of an intervention: $\tau_{1t} = Y_{1t}^I - Y_{1t}^N$, where unit 1 is the affected unit and Y_{1t}^I and Y_{1t}^N are the potential outcomes with and without the intervention respectively. The counterfactual of no intervention

[32] Coefficients $\beta_1 = 0.0002 \approx 0.0005 - 0.0004 = \alpha_1 + \alpha_4$, $\beta_2 = 0.0087 \approx (-0.0022) + 0.0109 = \alpha_2 + \alpha_5$ and $\beta_3 = -0.0012 \approx (-0.0000) - 0.0012 = \alpha_3 + \alpha_6$.

is not observed, but rather imputed by a weighted combination of control units. The synthetic control estimator is then:

$$\hat{\tau}_{1t} = Y_{1t} - \Sigma_{j=2}^{J+1} w_j Y_{jt}$$

where the weights w_j are non-negative and sum to one. In the following analysis, the weights are chosen to best approximate the pre-acquisition history of Norwegian food prices.

The credibility of the synthetic control as a comparison is strengthened by a long past of reproducing the outcomes of Norway in the absence of the merger, so I extend the pre-period back to 2005. As pointed out by Abadie (2021), it is advisable to apply filters to volatile time series to avoid overfitting the trend. I present specifications that simply difference out country specific monthly effects and specifications that apply the Hodric-Prescott filter tuned at $\lambda = 14400$ (Hodrick and Prescott, 1997).[33] Without loss of generality, the levels of the time series are normalized to be mean zero in the pre-acquisition period, effectively controlling for level differences akin to unit fixed effects in the difference-in-differences model. Finally, the comparison pool is restricted to Nordic countries to avoid the interpolation bias that can occur if there are too large discrepancies between the characteristics of individual countries and norway.[34]

Figure A.3 plots the deseasonalized real food prices of Norway and the synthetic control along with their difference. The average real food price decline after the acquisition is imputed to be -5.2 %. The synthetic control is able to capture the tendencies of Norwegian real food prices quite well, but the fit is not perfect because of significant volatility. The fit is improved when I use an HP-filter tuned at $\lambda = 14400$; shown in figure A.4. The imputed real food price decline is now 4.7 %. The country weights of the synthetic control are shown in Table A.3. If I restrict the sample period to 2011 - 2019, I find an almost perfect fit; as is not surprising given the steady linear trends of the control countries and in Norway before the acquisition. The imputed real food price decline is -3.8 % for both time series transformations. The post acquisition predictions of all specifications are largely consistent with the previous analysis: Norwegian real food prices experienced a downward trend shift not experienced by neighboring countries.

[33]This is a common value for the tuning parameter on monthly data, and it seems to fit well for the application at hand in the sense that the cyclicality in food prices is smoothed out while larger price shifts are preserved.

[34]If I include Ireland, which has a very different trend from Norway, it can slightly improve the pre-acquisition fit because it counterweights some of the other countries with slightly more increasing trends with Norway. However, it is unlikely that Irish real food prices are driven by the same underlying factors as Norway given the very different trajectories.

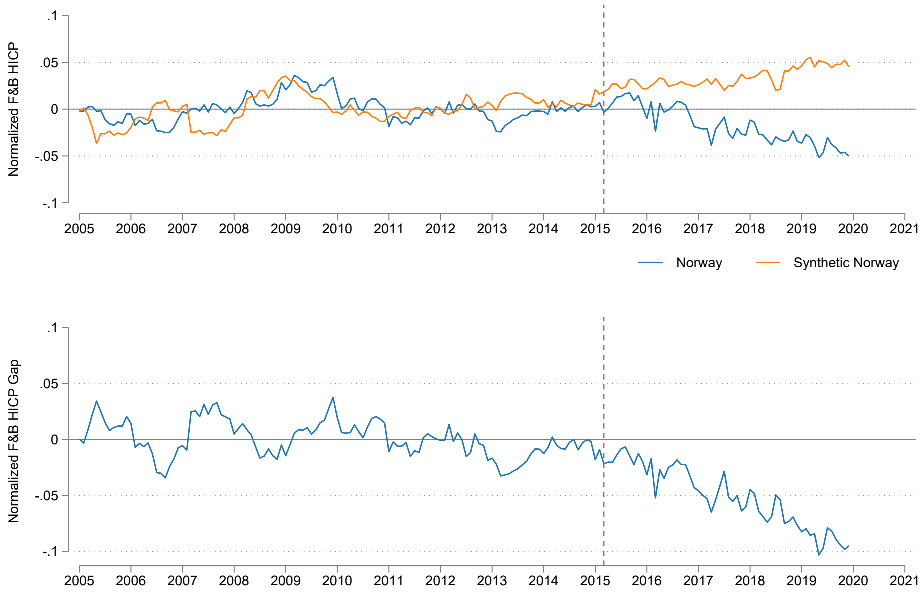


Figure A.3: The top figure shows percentage F&B price deviations from overall prices for Norway and a synthetic control; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$ after differencing out monthly fixed effects (deseasoning). The bottom figure shows the gap between Norway and the synthetic control. The vertical line marks the period right before the first store rebranding (2015m3). The country weights used to form the synthetic control are chosen to minimize the pre-acquisition differences from Norway and are displayed in column (1) of table A.3. Only Nordic countries are in the donor pool to avoid interpolation biases due to large pairwise trend discrepancies between Norway and the control units. *Source:* Eurostat.

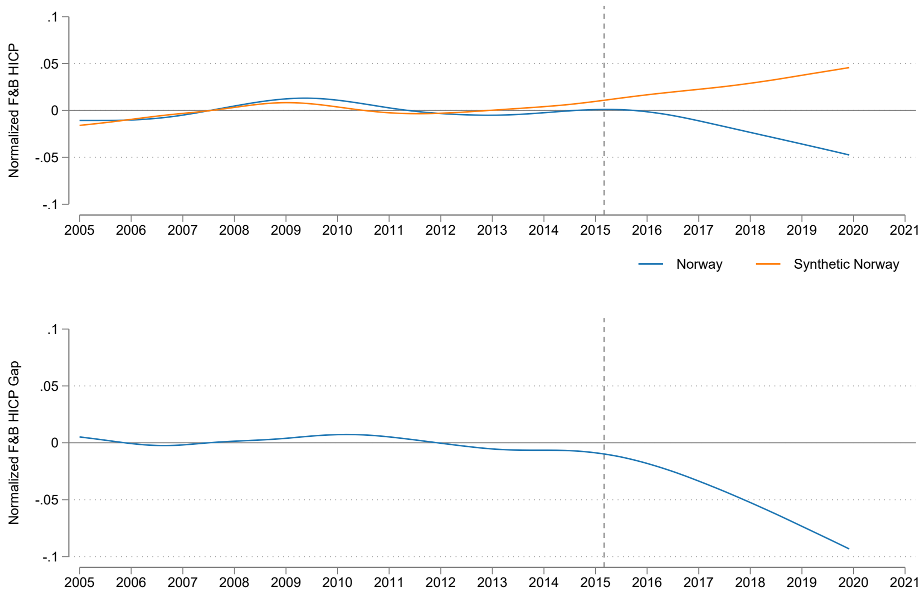
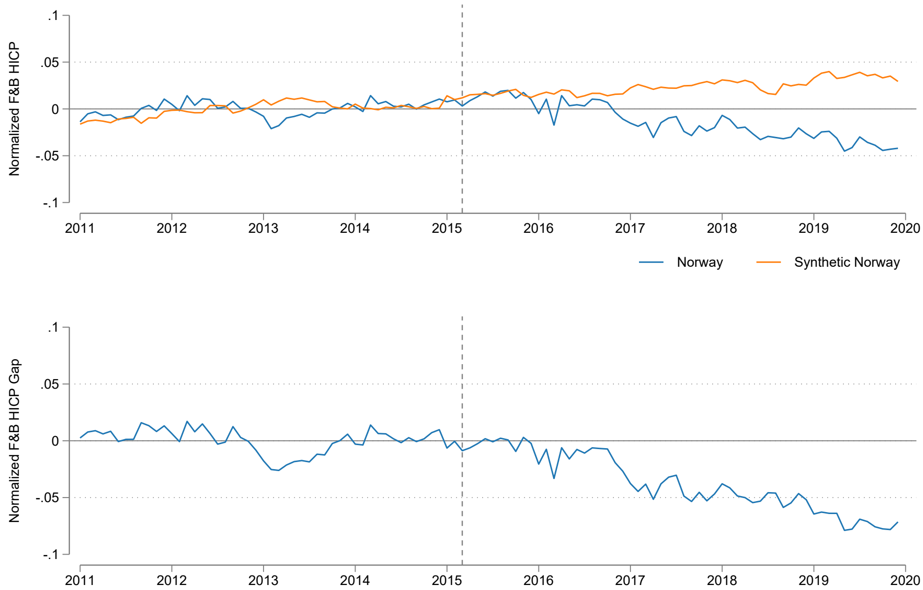
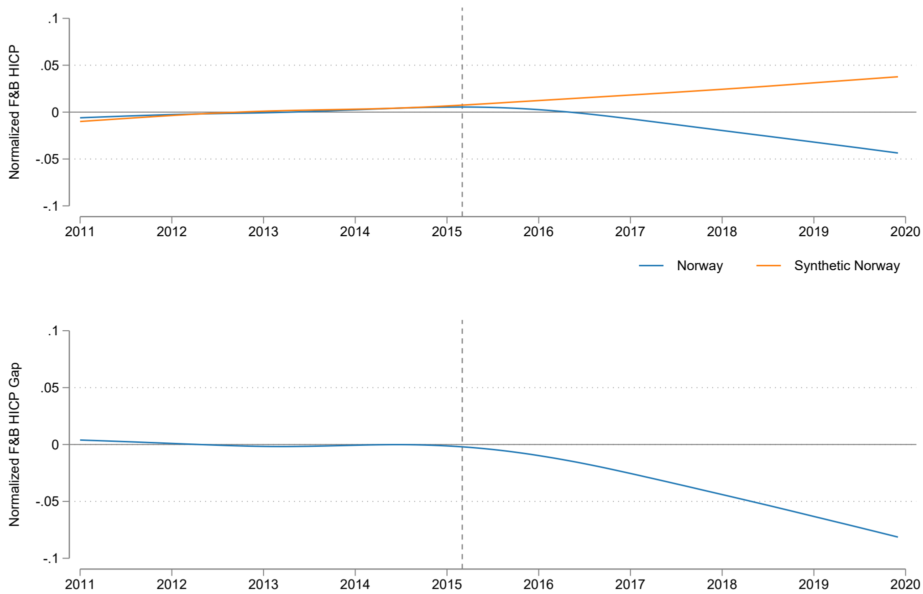


Figure A.4: The top figure shows percentage F&B price deviations from overall prices for Norway and a synthetic control; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$ after removing seasonality using an HP-Filter ($\lambda = 14400$). The bottom figure shows the gap between Norway and the synthetic control. The vertical line marks the period right before the first store rebranding (2015m3). The country weights used to form the synthetic control are chosen to minimize the pre-acquisition differences from Norway and are displayed in column (2) of table A.3. Only Nordic countries are in the donor pool to avoid interpolation biases due to large pairwise trend discrepancies between Norway and the control units. *Source:* Eurostat.



The top figure shows percentage F&B price deviations from overall prices for Norway and a synthetic control; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$ after differencing out monthly fixed effects (deseasoning). The bottom figure shows the gap between Norway and the synthetic control. The vertical line marks the period right before the first store rebranding (2015m3). The country weights used to form the synthetic control are chosen to minimize the pre-acquisition differences from Norway and are displayed in column (3) of table A.3. Only Nordic countries are in the donor pool to avoid interpolation biases due to large pairwise trend discrepancies between Norway and the control units. *Source:* Eurostat.



The top figure shows percentage F&B price deviations from overall prices for Norway and a synthetic control; calculated as $\ln(P_t^{Food}) - \ln(P_t^{All})$ after removing seasonality using an HP-Filter ($\lambda = 14400$). The bottom figure shows the gap between Norway and the synthetic control. The vertical line marks the period right before the first store rebranding (2015m3). The country weights used to form the synthetic control are chosen to minimize the pre-acquisition differences from Norway and are displayed in column (4) of table A.3. Only Nordic countries are in the donor pool to avoid interpolation biases due to large pairwise trend discrepancies between Norway and the control units. *Source:* Eurostat.

Table A.3: Synthetic Control Weights

	Deseasonalized 2005 - 2019	HP-Filter 2005 - 2019	Deseasonalized 2011 - 2019	HP-Filter 2011 - 2019
Country	Weight	Weight	Weight	Weight
Denmark	.279	.313	.477	.538
Finland	0	0	0	0
Iceland	.511	.687	.143	.462
Sweden	.21	0	.38	0

B Tables & Figures

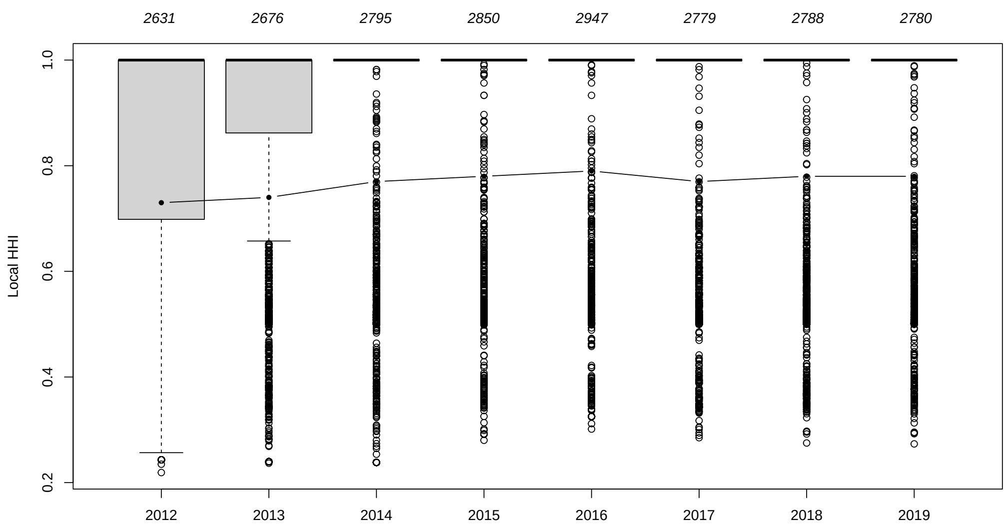


Figure B.1: Box-plots of the Herfindahl–Hirschman Index at the Basic Statistical Unit (BSU) level from 2012 to 2019 using accounting revenues. The weighted mean using the BSU sales shares is shown as the line joined points. The number of local markets in the sample are displayed above the box-plots. *Source:* Geodata.

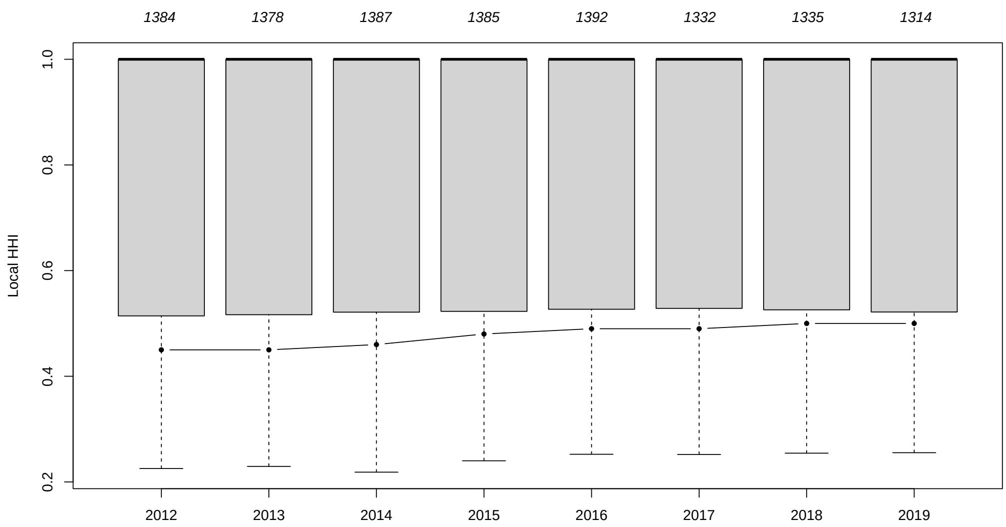


Figure B.2: Box-plots of the Herfindahl–Hirschman Index at the postal area level from 2012 to 2019 using accounting revenues. The weighted mean using the postal area sales shares is shown as the line joined points. The number of local markets in the sample are displayed above the box-plots. *Source:* Geodata.

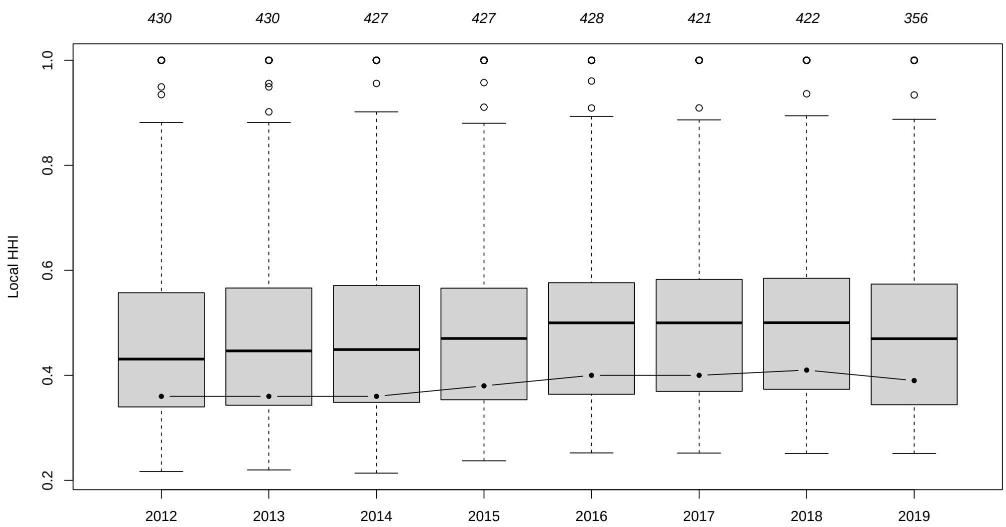
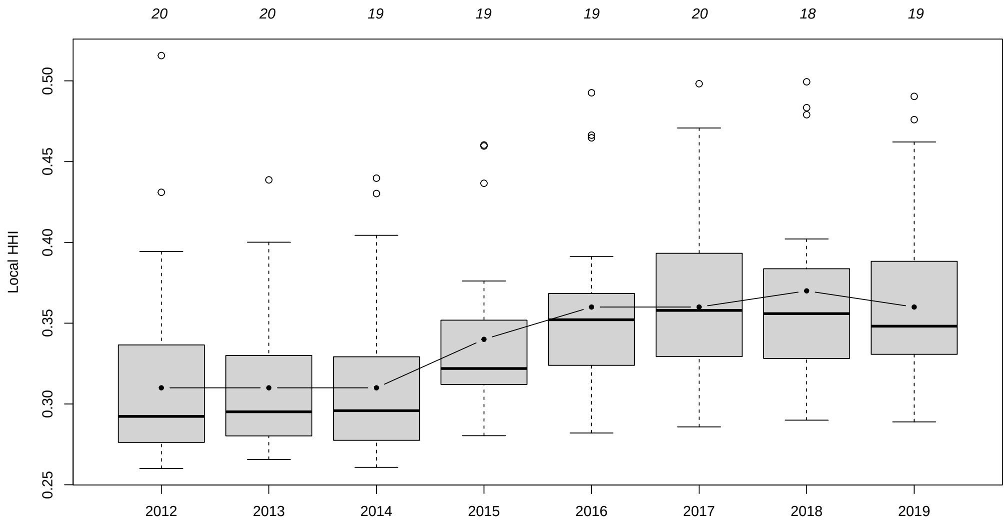


Figure B.3: Box-plots of the Herfindahl–Hirschman Index at the municipality level from 2012 to 2019 using accounting revenues. The weighted mean using the municipality sales shares is shown as the line joined points. The number of local markets in the sample are displayed above the box-plots. *Source:* Geodata.

Figure B.4: Local Herfindahl–Hirschman Index



Box-plots of the Herfindahl–Hirschman Index at the county level from 2012 to 2019 using accounting revenues. The weighted mean using the county sales shares is shown as the line joined points. The number of local markets in the sample are displayed above the box-plots. *Source:* Geodata.

Table B.1: Retail Chain Segmentation

Retail Chain	Umbrella Group	Market Segment
Joker	NorgesGruppen	General Store
Coop Marked	Coop	General Store
Nærbutikken	NorgesGruppen	General Store
Matkroken	ICA (then Coop)	General Store
Prix	Coop	Convenience Discount
Bunnpris	Bunnpris	Convenience Discount
Rimi	ICA	Convenience Discount
Lidl	Lidl	Hard Discount
Kiwi	NorgesGruppen	Soft Discount
Rema 1000	Reitangruppen	Soft Discount
Extra	Coop	Soft Discount
Eurospar	NorgesGruppen	Supermarket
Meny	NorgesGruppen	Supermarket
Coop Mega	Coop	Supermarket
ICA Supermarked	ICA	Supermarket
Spar	NorgesGruppen	Local Supermarket
obs!	Coop	Hypermarket

Notes: This table shows Norwegian retail chains, their ownership, and market segmentation.

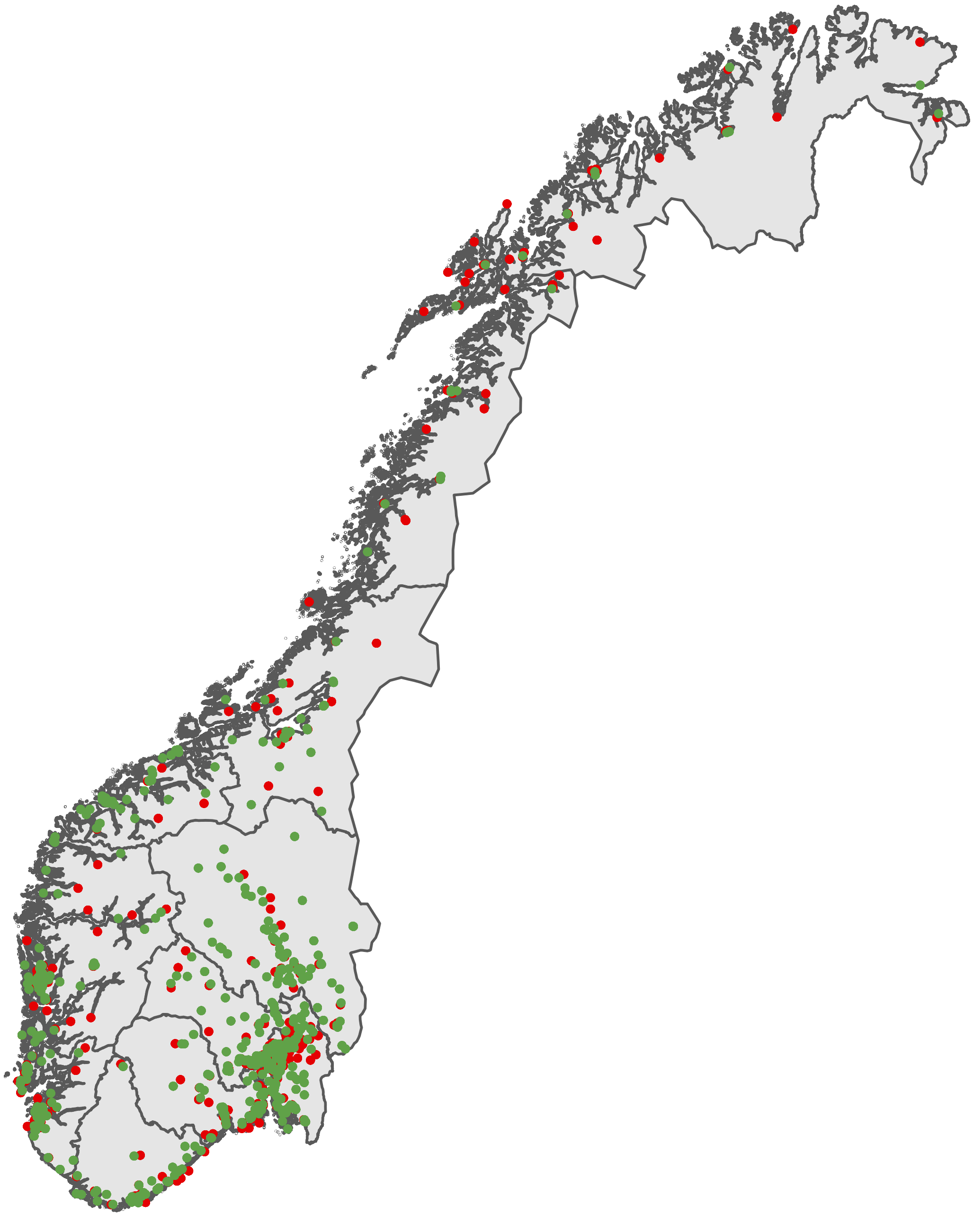


Figure B.5: Map of Kiwi and ICA stores operating in 2014 across Norway. The green dots indicate Kiwi (605) and the red dots indicate ICA (385).

Table B.2: Descriptive Statistics - Control & Format Groups

	Unaffected (484)			Extra (38)			Prix (20)			Bunnpris (12)			Closed (26)		
	Before	After	%	Before	After	%	Before	After	%	Before	After	%	Before	After	%
Sales (millions NOK)	2.68	2.97	10.82%	3.19	3.19	0.00%	2.81	3.27	16.37%	2.63	3.16	20.15%	2.76	3.28	18.84%
Private Label Sales (thousands NOK)	188.3	236.1	25.39%	223.9	258.4	15.41%	208.7	272.8	30.71%	189.2	251.4	32.88%	189.9	254.8	34.18%
Private Label Sales Share	0.07	0.08	14.29%	0.07	0.08	14.29%	0.08	0.08	0.00%	0.07	0.08	14.29%	0.07	0.08	14.29%
Assortment Size	1427	1944	36.23%	1427	1965	37.70%	1383	1945	40.64%	1388	1971	42.00%	1465	1990	35.84%
Variable Assortment Size	1248	1699	36.14%	1246	1720	38.04%	1202	1700	41.43%	1206	1725	43.03%	1286	1744	35.61%
Private Label Assortment Size	138	170	23.19%	138	171	23.91%	137	169	23.36%	137	171	24.82%	140	172	22.86%
Variable Private Label Assortment Size	109	140	28.44%	109	140	28.44%	107	139	29.91%	108	141	30.56%	111	141	27.03%
Assortment Entropy	6.818	6.835	0.25%	6.861	6.864	0.04%	6.805	6.825	0.29%	6.828	6.851	0.34%	6.806	6.816	0.15%
Price Index 1	48.6	51.9	6.79%	47.6	51.2	7.56%	47.8	51.3	7.32%	48.9	52.5	7.36%	49.6	53.3	7.46%
Price Index 3	27.9	29.7	6.45%	27.6	29.5	6.88%	27.7	29.6	6.86%	27.9	30	7.53%	28.1	30	6.76%
Number of Competitors	1.5	1.4	-6.67%	2.6	2.6	0.00%	2.2	2.1	-4.55%	2.8	2.8	0.00%	4.3	3.2	-25.58%
Herfindahl-Hirschman Index	0.62	0.62	0.00%	0.36	0.37	2.78%	0.39	0.41	5.13%	0.34	0.36	5.88%	0.28	0.33	17.86%
Population (in thousands)	124.9	128.2	2.64%	119.6	122.2	2.17%	151.2	130.5	-13.69%	114.1	142.9	25.24%	44	43.2	-1.82%
Population (per square km)	406.1	417.7	2.86%	453.7	443.7	-2.20%	390.4	358	-8.30%	334.9	401.1	19.77%	169.5	170.3	0.47%
Median Income (thousands NOK)	488	500.6	2.58%	494.5	503.5	1.82%	466.2	483.8	3.78%	474.2	488.2	2.95%	509.8	518.5	1.71%
High Education Share	0.31	0.32	3.23%	0.35	0.35	0.00%	0.29	0.31	6.90%	0.28	0.31	10.71%	0.27	0.28	3.70%
Employees	20.8	19.7	-5.29%	27.8	22.7	-18.35%	24.7	20.6	-16.60%	22.4	21.4	-4.46%	20.4	20.2	-0.98%
Postal Office Present Share	0.28	0.28	0.00%	0.16	0.15	-6.25%	0.27	0.31	14.81%	0	0	NaN%	0.21	0.19	-9.52%

Notes: This table reports mean values of outcome and control variables measured at the store-month level. The values are calculated by affected and unaffected stores before the first (2015m6) and after the last (2016m7) store rebranding in the vicinity of Kiwi. Stores are affected if they shared postcode with ICA in 2014 and are categorized by the rival format rebranding they experienced. I exclude 32 stores that either experienced multiple format rebrandings or a change in local market concentration. The number of stores is indicated in parenthesis behind the names of each group. Assortment size is measured as the number of observed unique products with at least 100 units sold every period. Variable assortment excludes products that are sold in every store (fixed assortment). Price Index 1 is the expenditure weighted average product price. Price Index 3 is store sales divided by total store quantities. The Herfindahl-Hirschman Index is calculated using accounting sales. Demographics are measured at the municipality level.

Table B.3: In Sample Product Category Expenditure Shares

Product Categories	Expenditure Share
Beverages	23.5 %
Frozen Food	5.3 %
Fresh Pastries	5.1 %
Ready-to-eat Meals	11.7 %
Fresh Fish and Shellfish	1.4 %
Fresh Meat	7.2 %
Home Supplies	4.0 %
Kiosk Goods	10.9 %
Dairy Products	19.9 %
Cosmetics	3.8 %
Other	7.3 %

Notes: This table shows the product categories included in the main analysis.

C Regressions and Event Study Plots

Table C.1: Effect of Extra on Sales

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Extra}	-0.093***	-0.101***	-0.126***	-0.070***	-0.129***	-0.117***
	(0.016)	(0.018)	(0.014)	(0.015)	(0.015)	(0.021)
ln(Population)	-0.109	-0.000	-0.108	0.002	-0.149	-0.043
	(0.389)	(0.401)	(0.395)	(0.400)	(0.461)	(0.069)
ln(Median Income)	0.574	0.472	0.164	0.561	0.120	0.357
	(0.351)	(0.335)	(0.308)	(0.342)	(0.320)	(0.271)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	348	396	468	372	492	529
Observations	10,808	12,371	14,955	11,662	15,893	17,351
R^2	0.83	0.84	0.84	0.83	0.84	0.85

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

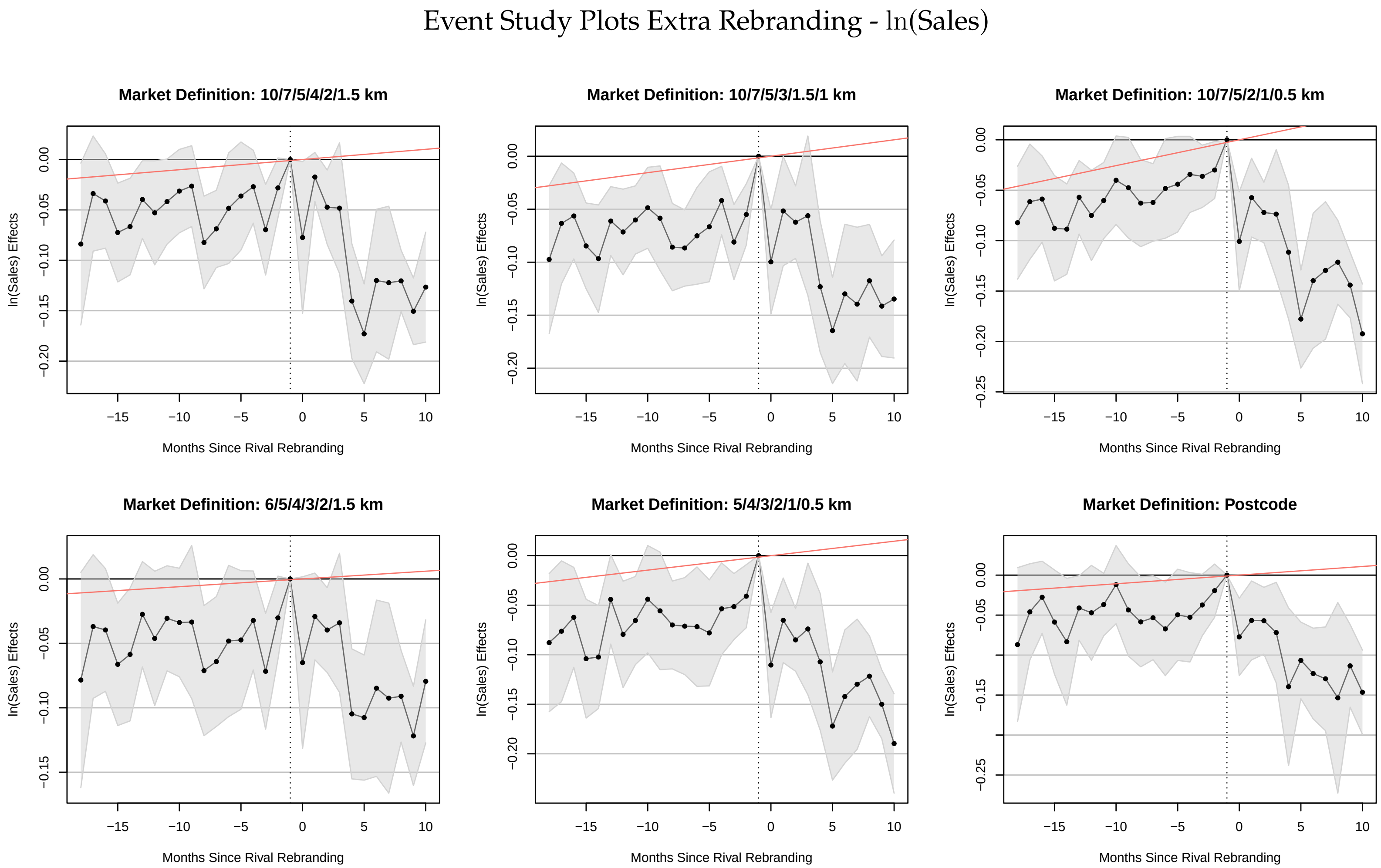


Figure C.1: The percentage sales effects of a rival rebranding to Extra as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs. The linear pretrend is extrapolated into the post rebranding period.

Table C.2: Effect of Prix on Sales

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Prix}	-0.010	-0.008	-0.015	-0.025	-0.025	-0.033*
	(0.017)	(0.018)	(0.022)	(0.018)	(0.021)	(0.018)
ln(Population)	0.105	0.181	-0.007	0.185	-0.124	-0.003
	(0.378)	(0.383)	(0.407)	(0.391)	(0.471)	(0.057)
ln(Median Income)	0.532	0.429	0.059	0.541	0.058	0.437*
	(0.344)	(0.330)	(0.311)	(0.339)	(0.324)	(0.262)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	327	372	449	350	479	512
Observations	10,060	11,615	14,365	10,889	15,521	16,705
R^2	0.83	0.84	0.84	0.83	0.84	0.85

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Prix Rebranding - ln(Sales)

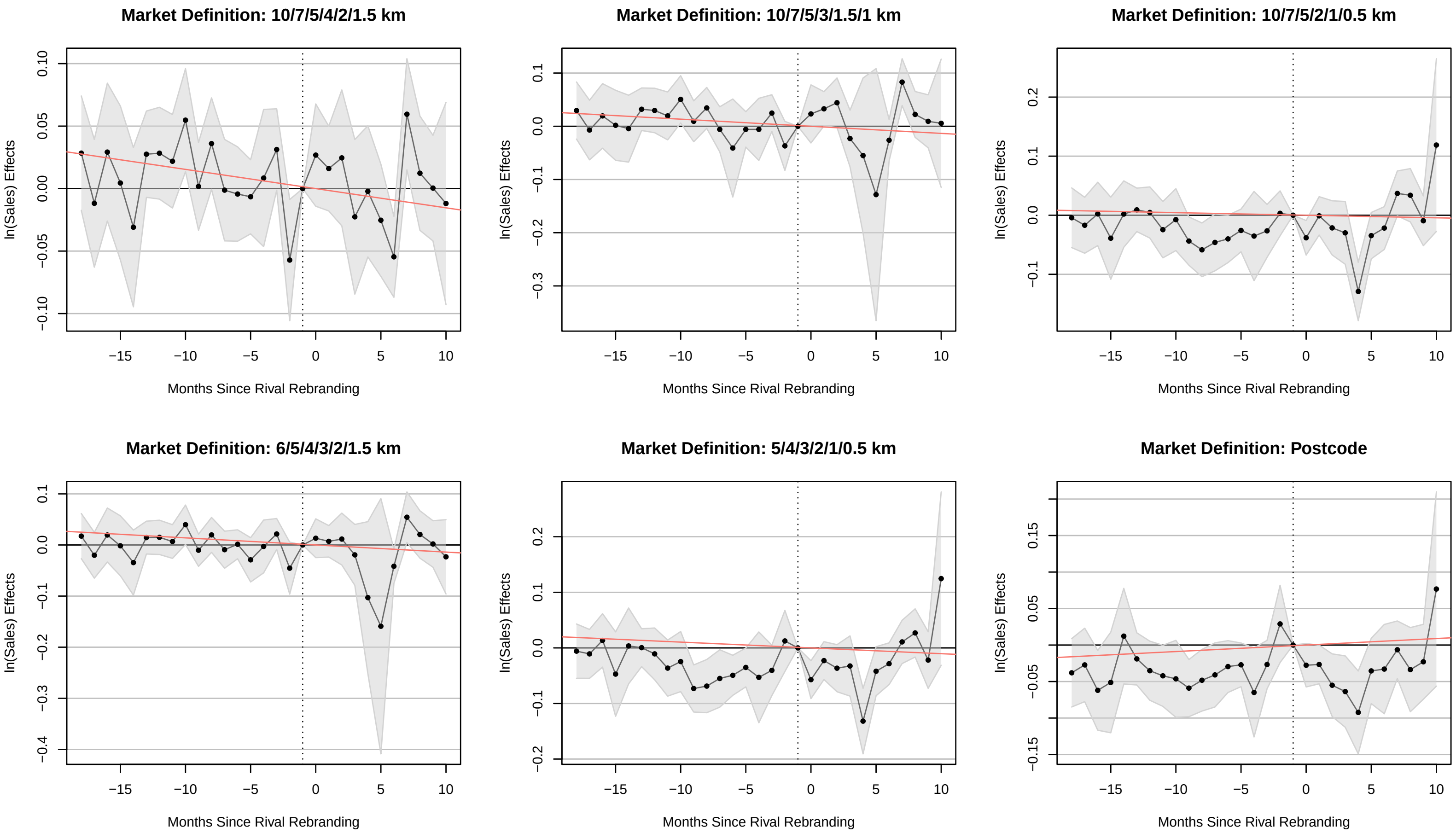


Figure C.2: The percentage sales effects of a rival rebranding to Prix as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs. The linear pretrend is extrapolated into the post rebranding period.

Table C.3: Effect of Bunnpris on Sales

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Bunnpris}	0.081***	0.023	0.025	0.037	-0.001	-0.045
	(0.030)	(0.035)	(0.044)	(0.032)	(0.053)	(0.039)
ln(Population)	0.011	0.110	-0.113	0.107	-0.199	-0.011
	(0.391)	(0.394)	(0.399)	(0.400)	(0.469)	(0.058)
ln(Median Income)	0.660*	0.453	0.057	0.559	0.058	0.420
	(0.351)	(0.328)	(0.296)	(0.348)	(0.313)	(0.268)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	291	342	424	317	456	489
Observations	9,277	10,951	13,781	10,158	14,903	16,112
R^2	0.82	0.83	0.83	0.82	0.84	0.85

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Bunnpris Rebranding - ln(Sales)

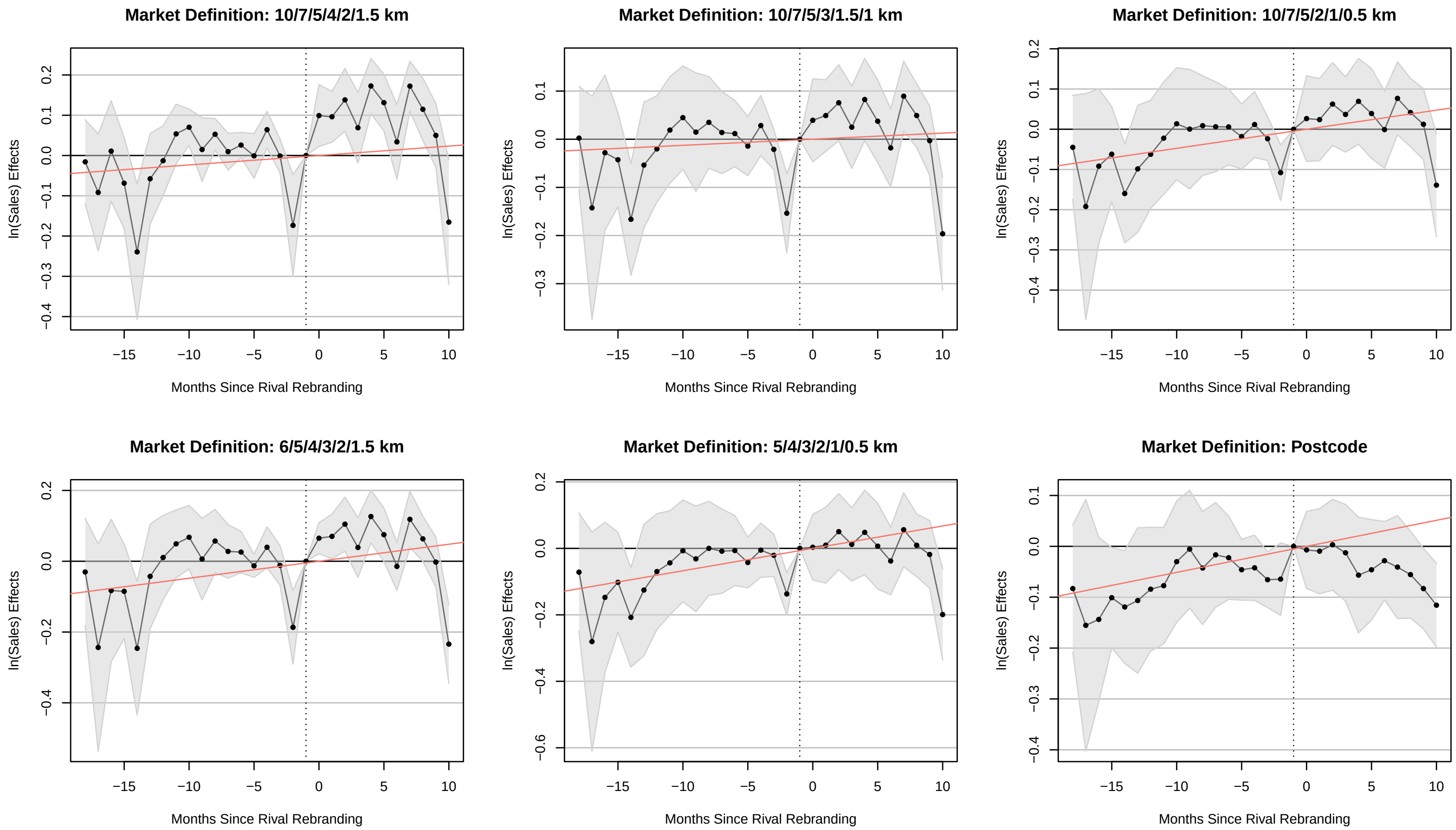


Figure C.3: The percentage sales effects a rival rebranding to Bunnpris as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs. The linear pretrend is extrapolated into the post rebranding period.

Table C.4: Effect of Store Closings on Sales

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Closed}	0.078***	0.083***	0.076***	0.082***	0.073***	0.024
	(0.019)	(0.023)	(0.021)	(0.022)	(0.025)	(0.019)
ln(Population)	-0.064	0.063	-0.121	0.011	-0.170	-0.008
	(0.390)	(0.394)	(0.413)	(0.394)	(0.479)	(0.068)
ln(Median Income)	0.558	0.490	0.016	0.531	0.002	0.528*
	(0.355)	(0.341)	(0.319)	(0.346)	(0.329)	(0.273)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	314	355	434	337	463	504
Observations	10,040	11,363	14,127	10,815	15,141	16,626
R^2	0.81	0.83	0.83	0.82	0.84	0.85

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Rival Closing - ln(Sales)

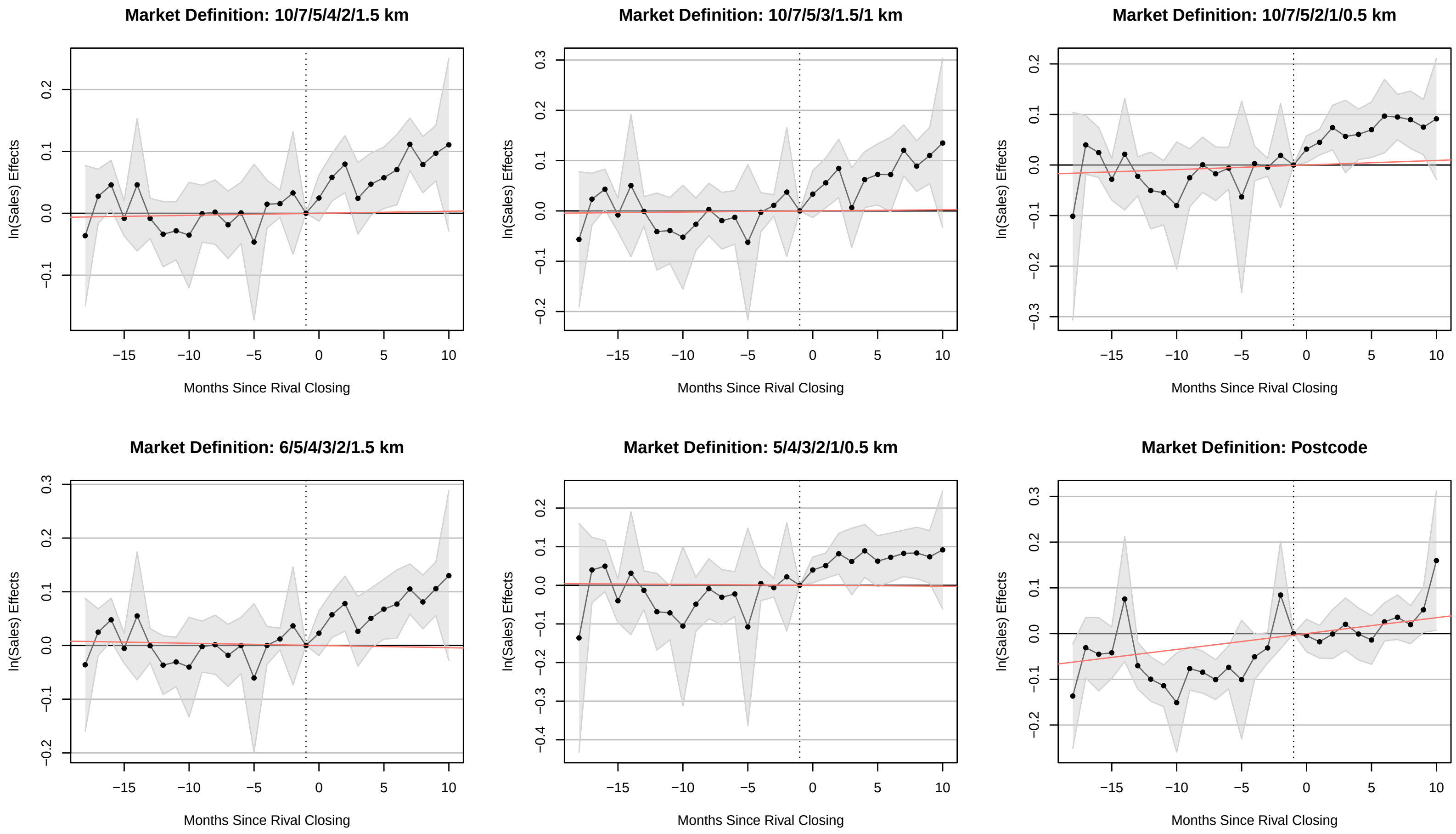


Figure C.4: The percentage sales effects of a rival closing as a function of the time since shutdown. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs. The linear pretrend is extrapolated into the post closing period.

Table C.5: Effect of Extra on Local Prices

	$\hat{P}^1_{it}$ (1)	$\hat{P}^2_{it}$ (2)	$\hat{P}^3_{it}$ (3)	$\hat{P}^1_{it}$ (4)	$\hat{P}^2_{it}$ (5)	$\hat{P}^3_{it}$ (6)
T_{Extra}	0.005	-0.001*	0.001	0.002	-0.000	-0.001
	(0.004)	(0.000)	(0.002)	(0.003)	(0.000)	(0.002)
ln(Population)	-0.067	0.045***	-0.086**	-0.052**	0.009	-0.015
	(0.066)	(0.012)	(0.039)	(0.020)	(0.007)	(0.011)
ln(Median Income)	0.050	0.007	0.040	-0.030	0.011	0.012
	(0.067)	(0.011)	(0.032)	(0.067)	(0.017)	(0.033)
Market Definition	10-1 km	10-1 km	10-1 km	Postcode	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	396	396	396	529	529	529
Observations	12,371	12,371	12,371	17,351	17,351	17,351
R^2	0.81	0.17	0.93	0.84	0.18	0.93

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with the different Price indices and local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Extra Rebranding - Price Index 1

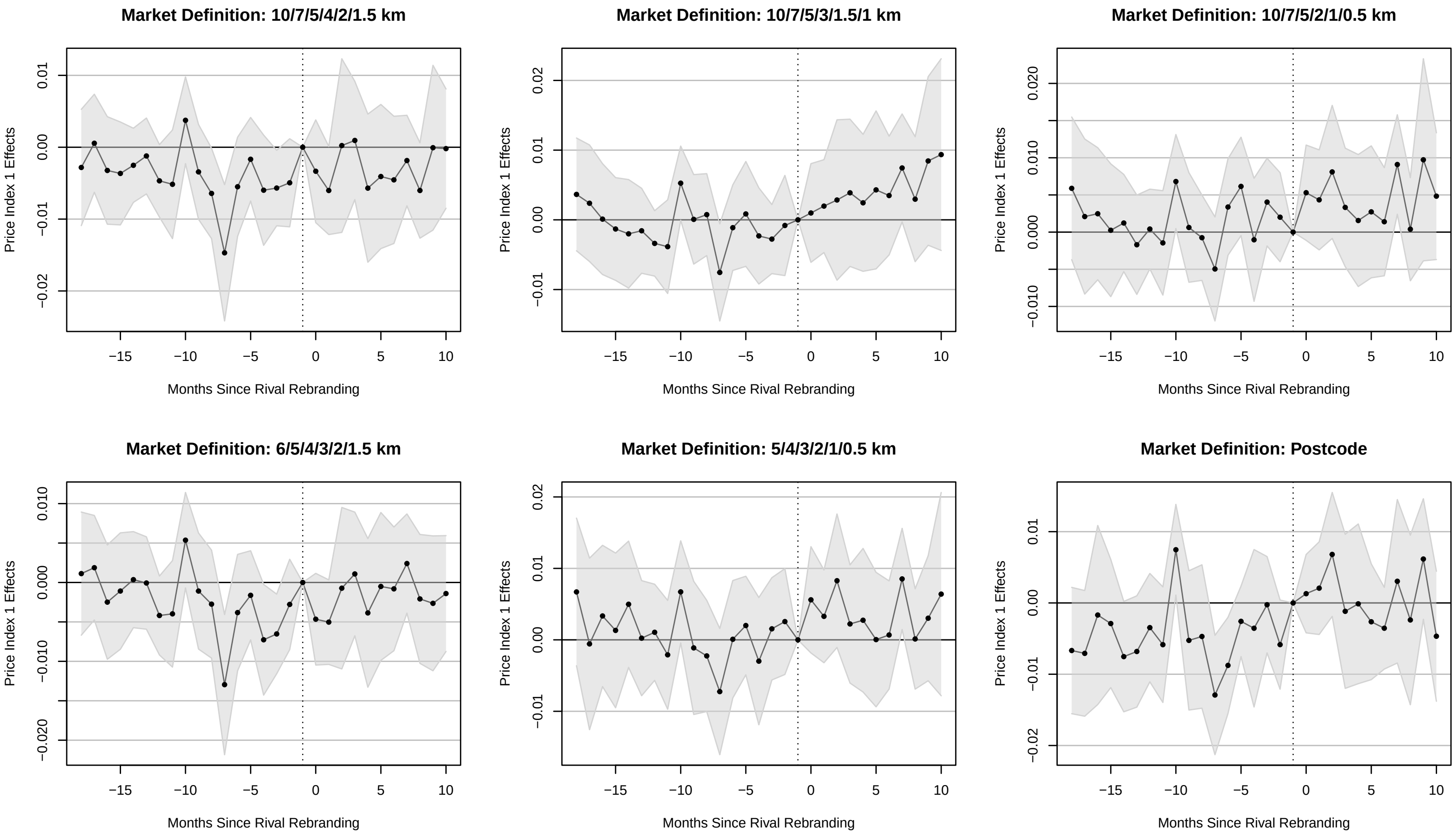


Figure C.5: The percentage price effects of a rival rebranding to Extra as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.6: Effect of Prix on Local Prices

	$\hat{P}^1_{it}$ (1)	$\hat{P}^2_{it}$ (2)	$\hat{P}^3_{it}$ (3)	$\hat{P}^1_{it}$ (4)	$\hat{P}^2_{it}$ (5)	$\hat{P}^3_{it}$ (6)
T_{Prix}	0.006	0.000	-0.001	0.004	0.000	0.001
	(0.011)	(0.001)	(0.003)	(0.008)	(0.001)	(0.002)
ln(Population)	-0.035	0.047***	-0.068*	-0.049**	0.009	-0.013
	(0.062)	(0.013)	(0.037)	(0.019)	(0.007)	(0.010)
ln(Median Income)	0.033	0.007	0.029	-0.019	0.013	0.013
	(0.063)	(0.011)	(0.032)	(0.064)	(0.017)	(0.032)
Market Definition	10-1 km	10-1 km	10-1 km	Postcode	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	372	372	372	512	512	512
Observations	11,615	11,615	11,615	16,705	16,705	16,705
R^2	0.79	0.16	0.92	0.83	0.17	0.93

$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with the different Price indices and local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Prix Rebranding - Price Index 1

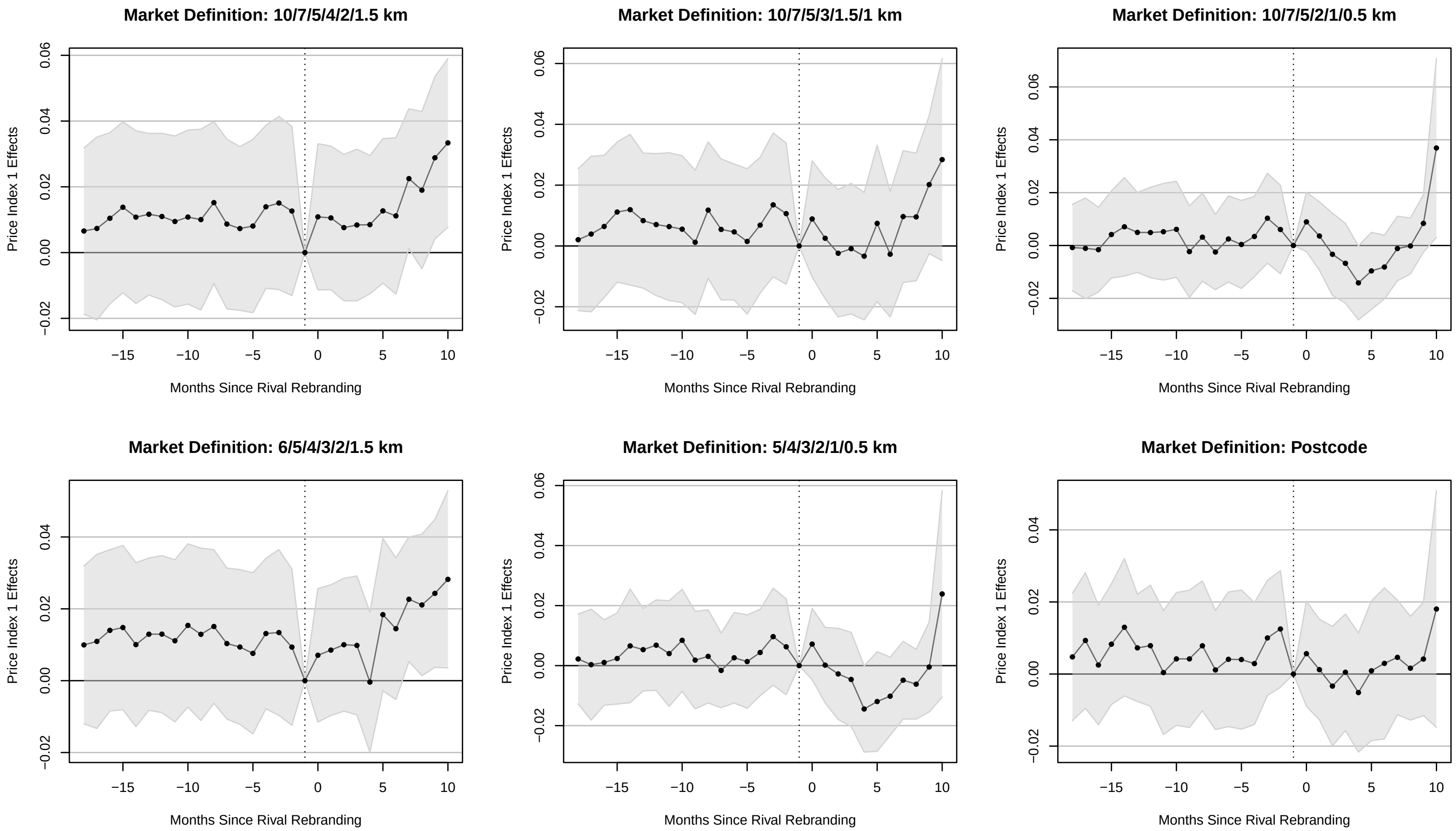


Figure C.6: The percentage price effects of a rival rebranding to Prix as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.7: Effect of Bunnpris on Local Prices

	$\hat{P}^1_{it}$ (1)	$\hat{P}^2_{it}$ (2)	$\hat{P}^3_{it}$ (3)	$\hat{P}^1_{it}$ (4)	$\hat{P}^2_{it}$ (5)	$\hat{P}^3_{it}$ (6)
T_{Bunnpris}	0.015	0.002*	-0.001	0.013	0.000	0.000
	(0.013)	(0.001)	(0.003)	(0.009)	(0.001)	(0.003)
ln(Population)	-0.028	0.049***	-0.067*	-0.048***	0.008	-0.014
	(0.064)	(0.014)	(0.037)	(0.017)	(0.008)	(0.009)
ln(Median Income)	0.023	-0.002	0.025	-0.040	0.006	0.002
	(0.065)	(0.013)	(0.034)	(0.063)	(0.018)	(0.033)
Market Definition	10-1 km	10-1 km	10-1 km	Postcode	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	342	342	342	489	489	489
Observations	10,951	10,951	10,951	16,112	16,112	16,112
R^2	0.78	0.16	0.91	0.83	0.16	0.93

$*$ p < 0.1, ** p < 0.05, $* * *$ p < 0.01

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with the different Price indices and local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Bunnpris Rebranding Rebranding - Price Index 1

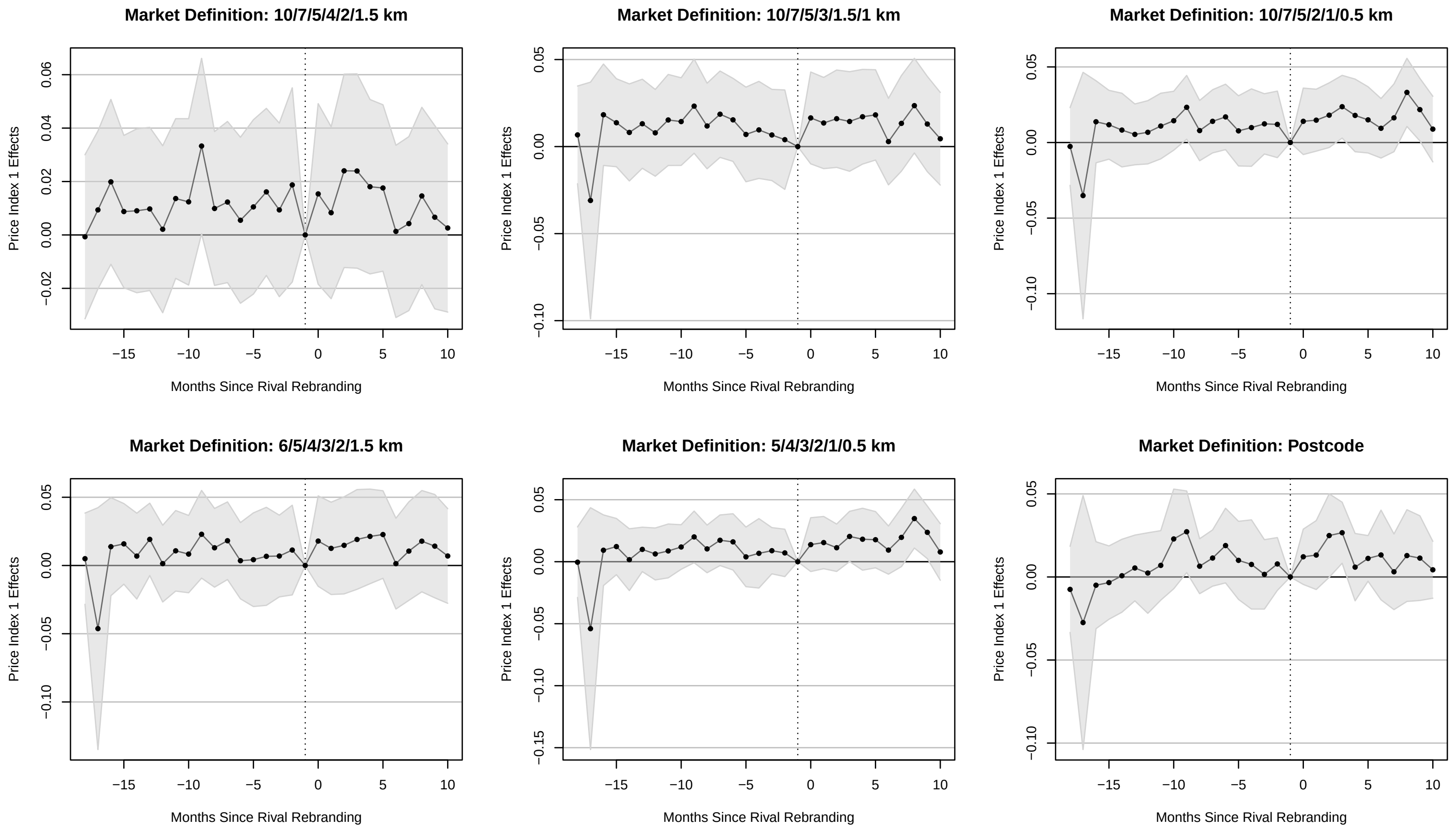


Figure C.7: The percentage price effects of a rival rebranding to Bunnpris as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.8: Effect of Store Closings on Local Prices

	$\hat{P}^1_{it}$ (1)	$\hat{P}^2_{it}$ (2)	$\hat{P}^3_{it}$ (3)	$\hat{P}^1_{it}$ (4)	$\hat{P}^2_{it}$ (5)	$\hat{P}^3_{it}$ (6)
T_{Closed}	0.015	0.001	0.007^{**}	0.005	-0.000	-0.002
	(0.010)	(0.001)	(0.003)	(0.008)	(0.001)	(0.002)
ln(Population)	-0.045	0.046^{***}	-0.073^{*}	-0.048^{***}	0.008	-0.014
	(0.067)	(0.013)	(0.037)	(0.019)	(0.007)	(0.010)
ln(Median Income)	0.028	0.010	0.038	-0.036	0.009	0.008
	(0.066)	(0.011)	(0.032)	(0.065)	(0.017)	(0.032)
Market Definition	10-1 km	10-1 km	10-1 km	Postcode	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	355	355	355	504	504	504
Observations	11,363	11,363	11,363	16,626	16,626	16,626
R^2	0.79	0.16	0.92	0.83	0.17	0.93

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with the different Price indices and local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Rival Closing - Price Index 1

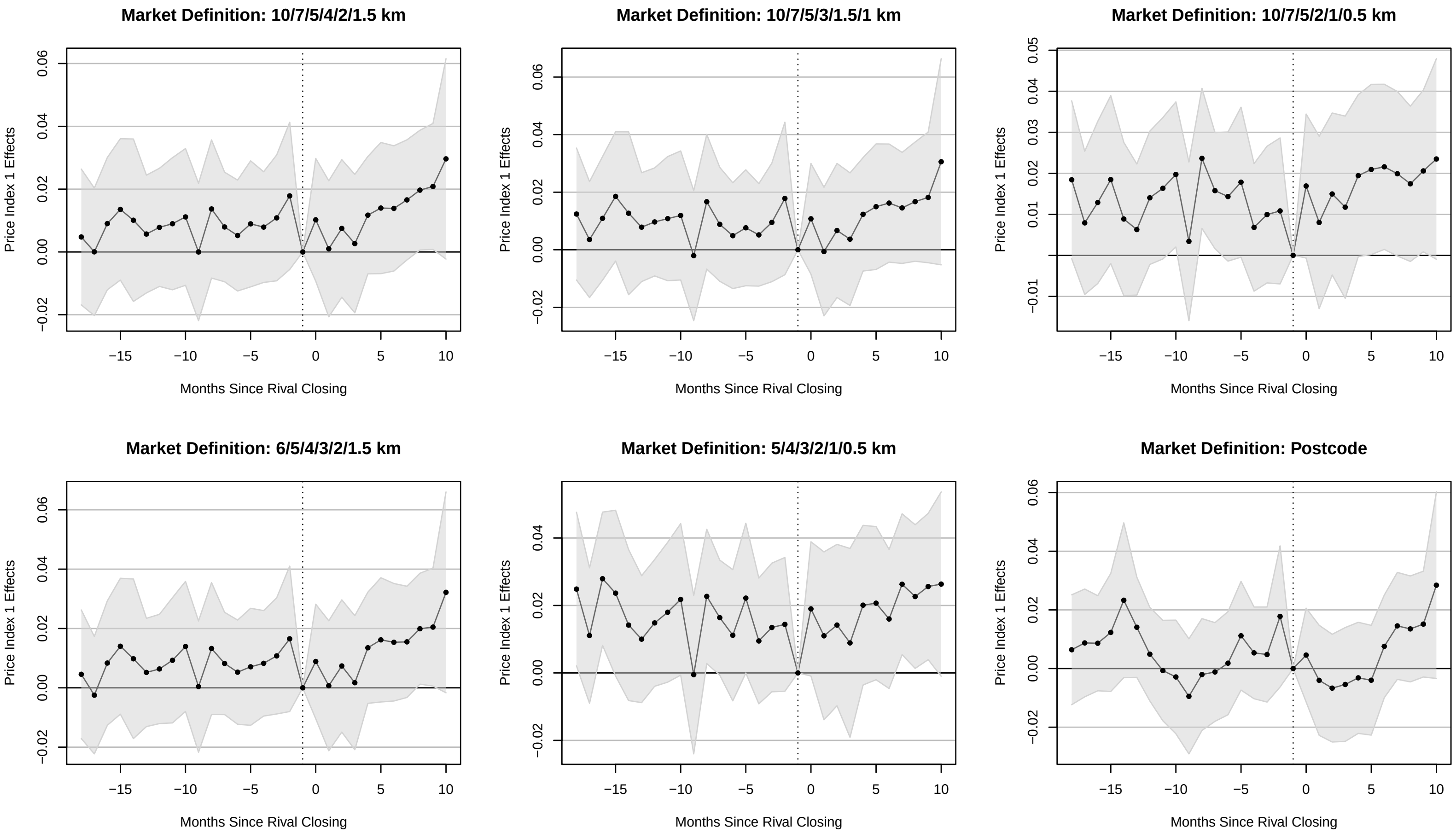


Figure C.8: The percentage price effects of a rival closing as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.9: Effect of Extra on Variety

	Variety (1)	ln(Variety) (2)	Variety (3)	ln(Variety) (4)	Variety (5)	ln(Variety) (6)
T_{Extra}	-17.400**	-0.009**	-6.484	-0.007*	-10.105	-0.007**
	(8.143)	(0.003)	(8.707)	(0.004)	(6.732)	(0.003)
ln(Population)	-14.376	-0.031	90.146	0.015	-17.672	0.000
	(336.145)	(0.128)	(318.227)	(0.123)	(102.042)	(0.038)
ln(Median Income)	-52.048	0.038	17.788	0.080	-6.288	0.052
	(227.395)	(0.096)	(221.067)	(0.096)	(299.261)	(0.113)
Market Definition	10-1	10-1 km	6-1.5 km	6-1.5 km	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	396	396	372	372	529	529
Observations	12,371	12,371	11,662	11,662	17,351	17,351
R^2	0.98	0.97	0.98	0.97	0.98	0.97

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions in levels and logarithms. Products with less than 100 units sold nationally in all periods are excluded. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Extra Rebranding - ln(Variety)

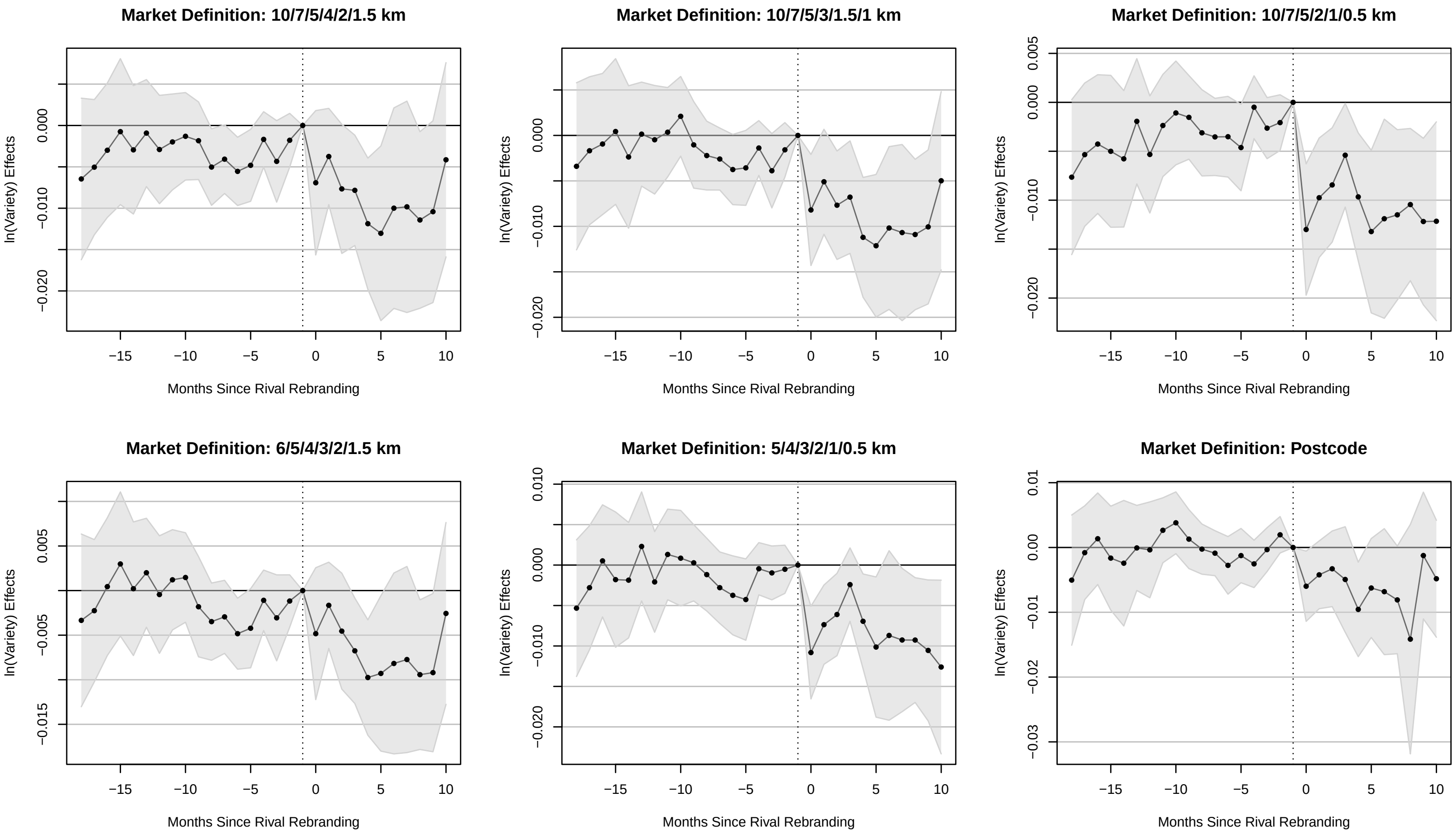


Figure C.9: The percentage Variety effects of a rival rebranding to Extra as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.10: Effect of Prix on Variety

	Variety (1)	ln(Variety) (2)	Variety (3)	ln(Variety) (4)	Variety (5)	ln(Variety) (6)
T_{Prix}	-16.013	-0.007	-1.786	-0.002	-4.105	-0.000
	(11.358)	(0.004)	(9.812)	(0.004)	(9.838)	(0.004)
ln(Population)	75.401	-0.001	147.409	0.038	-7.150	0.008
	(348.595)	(0.133)	(323.401)	(0.122)	(99.309)	(0.035)
ln(Median Income)	-29.684	0.047	13.163	0.077	8.497	0.065
	(235.911)	(0.099)	(225.247)	(0.097)	(297.888)	(0.109)
Market Definition	10-1	10-1 km	6-1.5 km	6-1.5 km	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	372	372	350	350	512	512
Observations	11,615	11,615	10,889	10,889	16,705	16,705
R^2	0.97	0.96	0.98	0.96	0.98	0.97

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions in levels and logarithms. Products with less than 100 units sold nationally in all periods are excluded. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Prix Rebranding - ln(Variety)

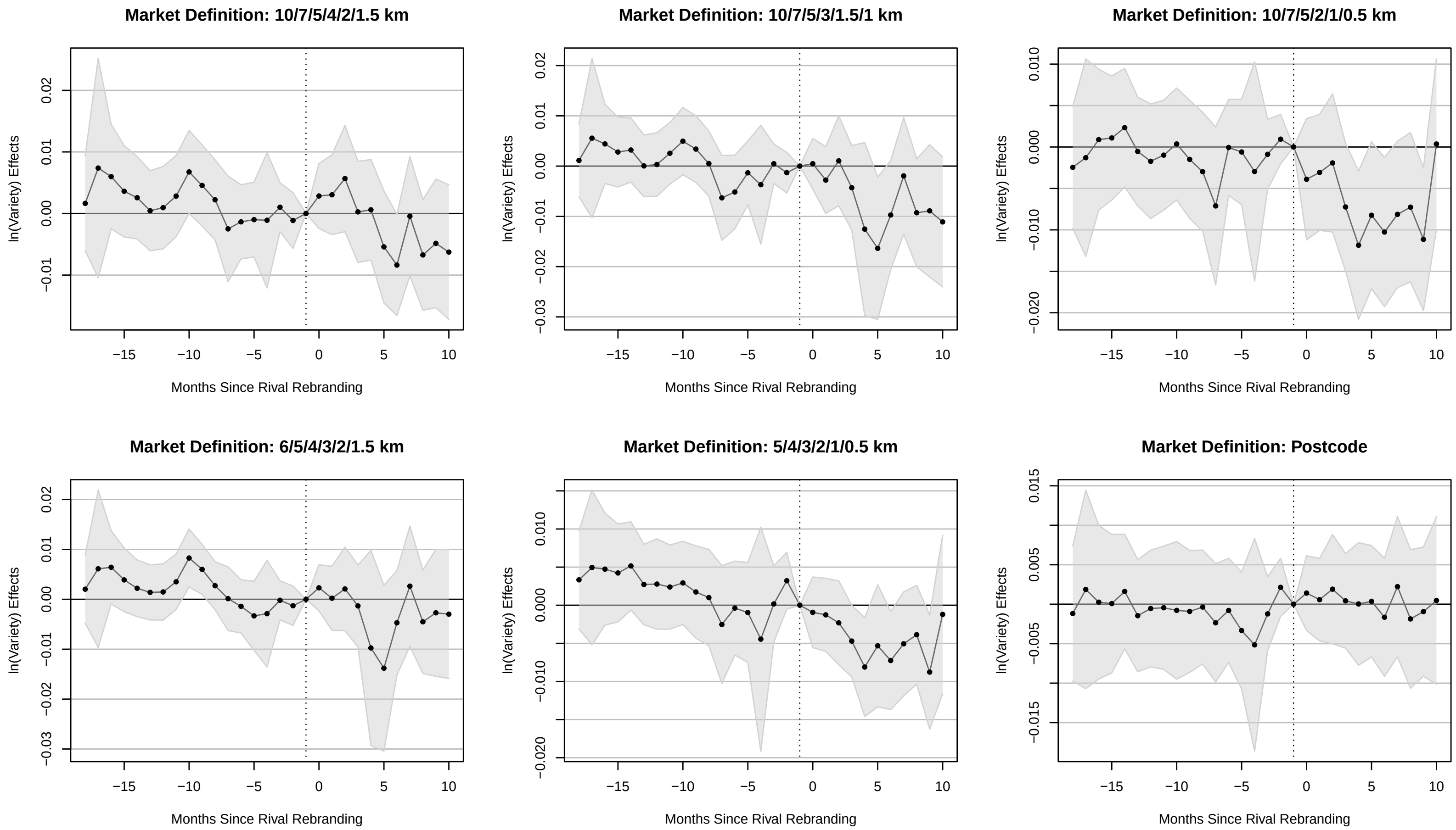


Figure C.10: The percentage Variety effects of a rival rebranding to Prix as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.11: Effect of Bunnpris on Variety

	Variety	ln(Variety)	Variety	ln(Variety)	Variety	ln(Variety)
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Bunnpris}	-4.002	-0.003	-1.217	-0.002	3.035	0.001
	(6.406)	(0.003)	(13.583)	(0.005)	(9.566)	(0.005)
ln(Population)	30.736	-0.008	128.351	0.032	-2.497	0.010
	(344.919)	(0.129)	(334.665)	(0.127)	(101.170)	(0.036)
ln(Median Income)	40.252	0.079	105.050	0.110	67.684	0.083
	(222.969)	(0.093)	(226.557)	(0.097)	(294.507)	(0.108)
Market Definition	10-1	10-1 km	6-1.5 km	6-1.5 km	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	342	342	317	317	489	489
Observations	10,951	10,951	10,158	10,158	16,112	16,112
R^2	0.97	0.96	0.97	0.96	0.98	0.97

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions in levels and logarithms. Products with less than 100 units sold nationally in all periods are excluded. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Bunnpris Rebranding Rebranding - ln(Variety)

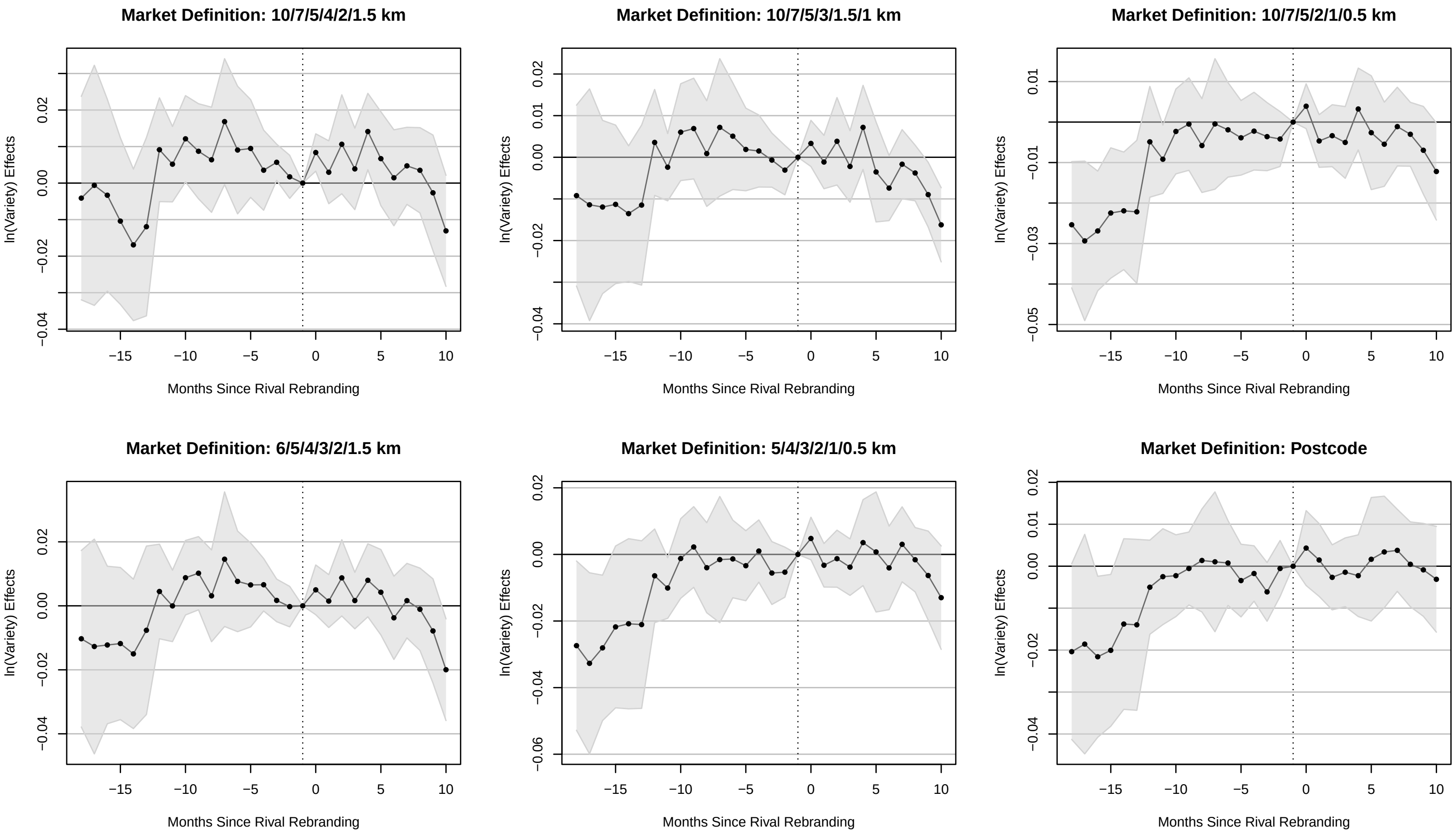


Figure C.11: The percentage Variety effects of a rival rebranding to Bunnpris as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.12: Effect of Store Closings on Variety

	Variety (1)	ln(Variety) (2)	Variety (3)	ln(Variety) (4)	Variety (5)	ln(Variety) (6)
T_{Closed}	7.373	0.006*	7.785	0.007**	10.278**	0.004**
	(7.608)	(0.004)	(6.927)	(0.003)	(4.687)	(0.002)
ln(Population)	-17.614	-0.036	25.880	-0.011	-14.209	0.004
	(340.041)	(0.129)	(333.975)	(0.128)	(101.815)	(0.037)
ln(Median Income)	-45.187	0.055	-17.052	0.072	4.767	0.059
	(241.533)	(0.100)	(242.500)	(0.103)	(298.647)	(0.111)
Market Definition	10-1	10-1 km	6-1.5 km	6-1.5 km	Postcode	Postcode
Months	36	36	36	36	36	36
Stores	355	355	337	337	504	504
Observations	11,363	11,363	10,815	10,815	16,626	16,626
R^2	0.97	0.96	0.97	0.96	0.98	0.97

$* \, p < 0.1$, $** \, p < 0.05$, $*** \, p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions in levels and logarithms. Products with less than 100 units sold nationally in all periods are excluded. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Rival Closing - ln(Variety)

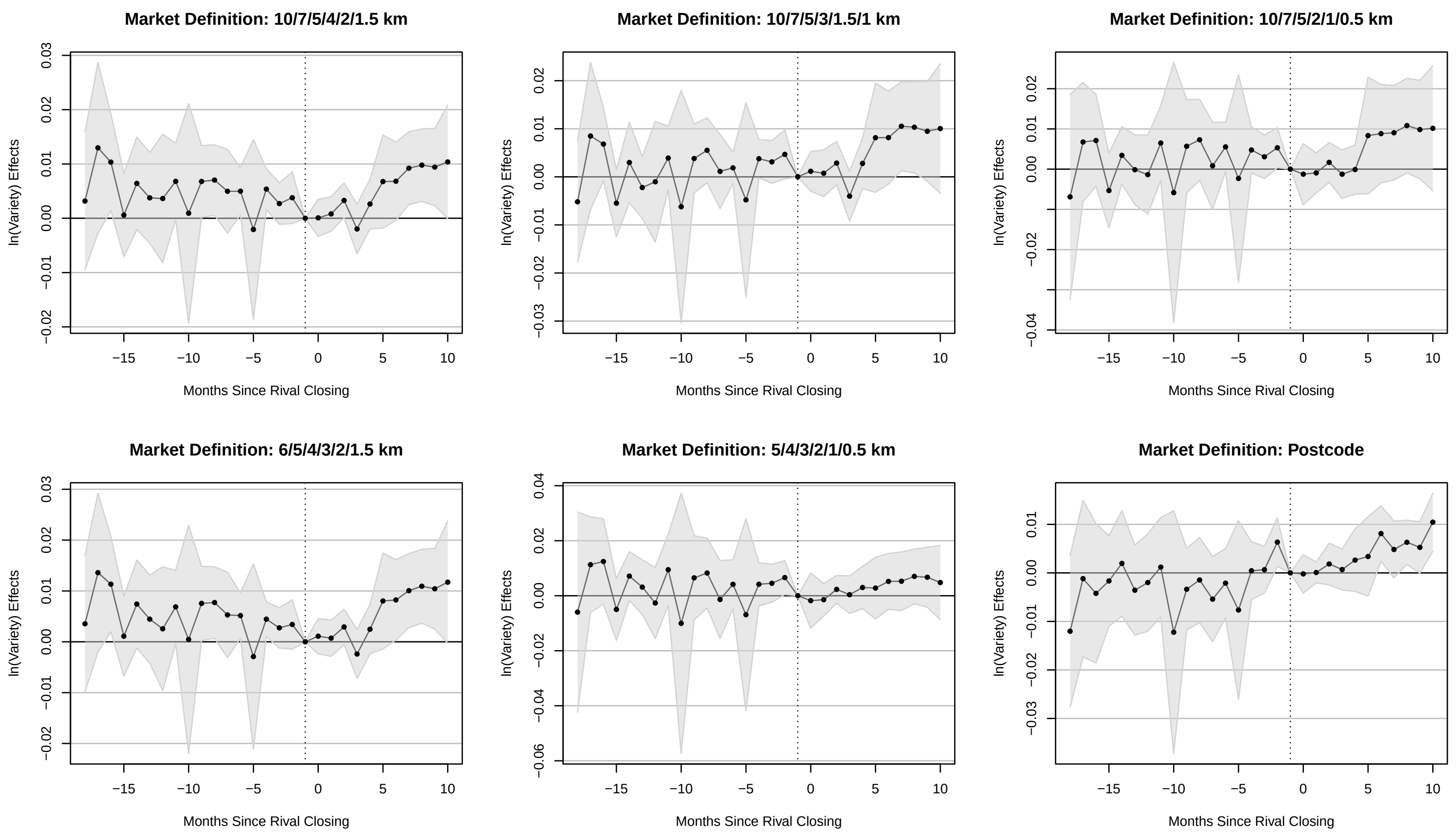


Figure C.12: The percentage Variety effects of a rival closing as a function of the time since shutdown. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.13: Effect of Extra on Variety Entropy

	Variety Entropy					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Extra}	-0.007	-0.006	-0.016***	-0.007	-0.020***	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
ln(Population)	0.180	0.140	0.108	0.165	0.106	0.097***
	(0.134)	(0.135)	(0.112)	(0.127)	(0.109)	(0.022)
ln(Median Income)	0.170*	0.131	0.155*	0.177*	0.163**	0.196**
	(0.099)	(0.100)	(0.079)	(0.096)	(0.077)	(0.078)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	348	396	468	372	492	529
Observations	10,808	12,371	14,955	11,662	15,893	17,351
R^2	0.88	0.89	0.90	0.89	0.90	0.90

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Extra Rebranding - Variety Entropy

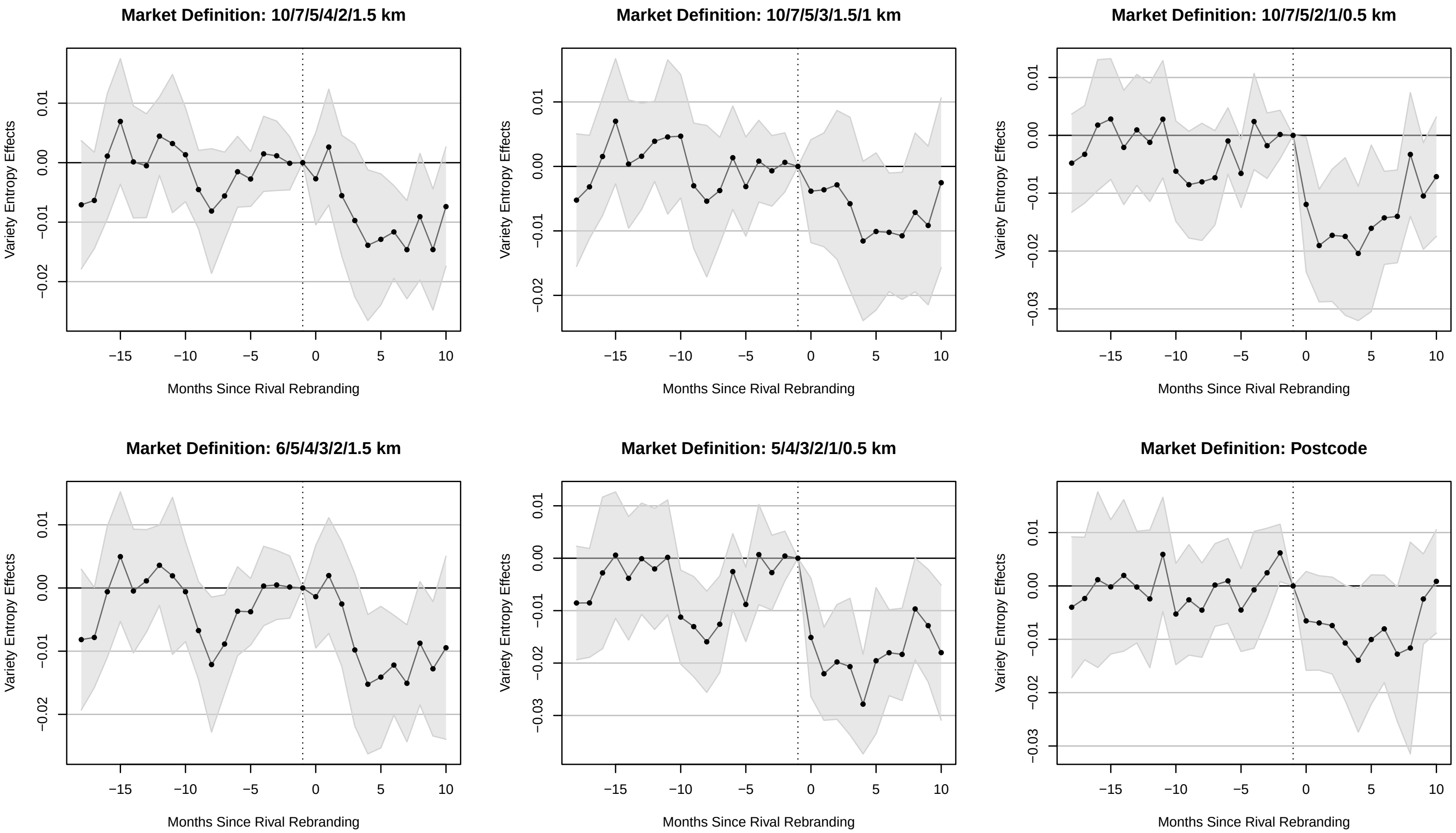


Figure C.13: The Variety Index effects of a rival rebranding to Extra as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.14: Effect of Prix on Variety Entropy

	Variety Entropy					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Prix}	0.003	0.004	0.005	0.003	0.008	0.005
	(0.007)	(0.006)	(0.004)	(0.007)	(0.005)	(0.007)
ln(Population)	0.193	0.160	0.132	0.176	0.110	0.102***
	(0.133)	(0.132)	(0.112)	(0.127)	(0.110)	(0.020)
ln(Median Income)	0.190*	0.164*	0.176**	0.194**	0.179**	0.214***
	(0.099)	(0.099)	(0.081)	(0.096)	(0.078)	(0.077)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	327	372	449	350	479	512
Observations	10,060	11,615	14,365	10,889	15,521	16,705
R^2	0.88	0.89	0.89	0.88	0.90	0.90

* p < 0.1, ** p < 0.05, * * * p < 0.01

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Prix Rebranding - Variety Entropy

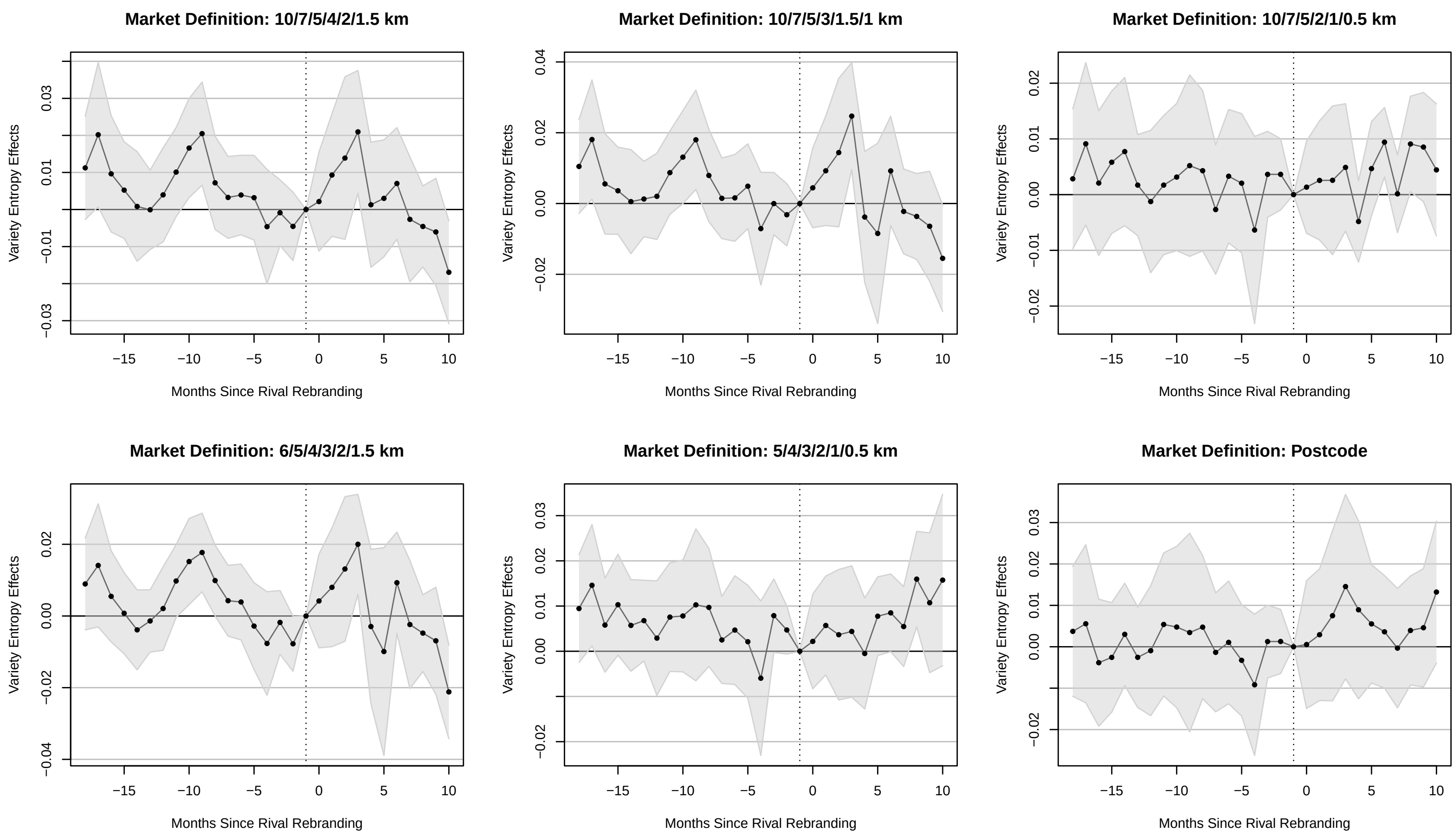


Figure C.14: The Variety Index effects of a rival rebranding to Prix as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.15: Effect of Bunnpris on Variety Entropy

	Variety Entropy					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Bunnpris}	0.020***	-0.002	-0.007	-0.002	-0.009	-0.005
	(0.006)	(0.009)	(0.009)	(0.011)	(0.010)	(0.008)
ln(Population)	0.180	0.150	0.112	0.172	0.101	0.104***
	(0.138)	(0.134)	(0.114)	(0.131)	(0.112)	(0.021)
ln(Median Income)	0.186*	0.164*	0.168**	0.217**	0.180**	0.226***
	(0.099)	(0.094)	(0.077)	(0.095)	(0.076)	(0.077)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	291	342	424	317	456	489
Observations	9,277	10,951	13,781	10,158	14,903	16,112
R^2	0.87	0.88	0.89	0.88	0.89	0.90

* $p < 0.1$, ** $p < 0.05$, * * * $p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Bunnpris Rebranding Rebranding - Variety Entropy

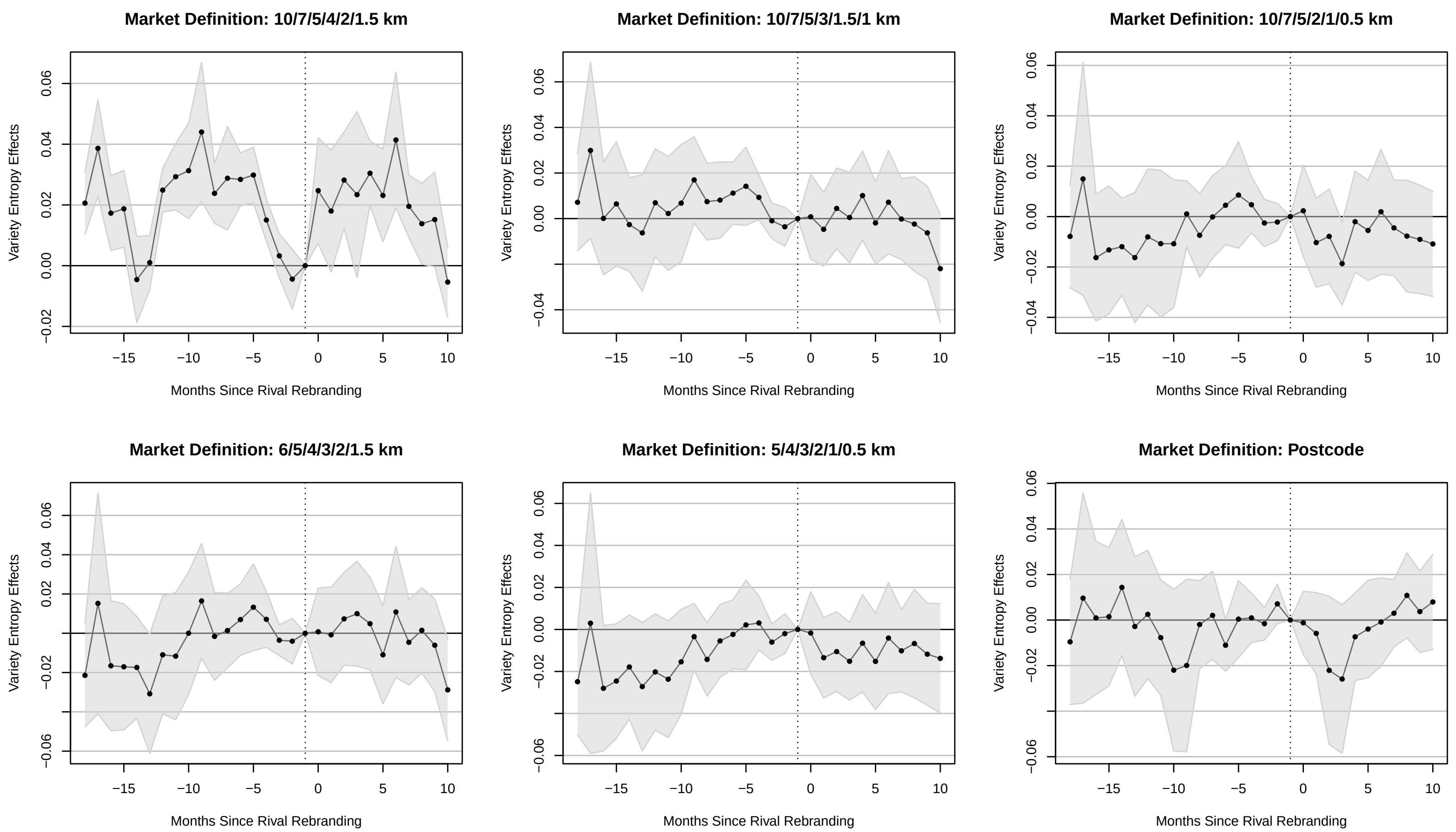


Figure C.15: The Variety Index effects of a rival rebranding to Bunnpris as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.16: Effect of Store Closings on Variety Entropy

	Variety Entropy					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Closed}	0.002	0.003	0.001	0.002	-0.002	-0.007
	(0.006)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)
ln(Population)	0.134	0.133	0.102	0.128	0.127	0.098***
	(0.146)	(0.138)	(0.123)	(0.138)	(0.114)	(0.021)
ln(Median Income)	0.175	0.174*	0.142	0.191*	0.140	0.201**
	(0.107)	(0.103)	(0.089)	(0.105)	(0.085)	(0.079)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	314	355	434	337	463	504
Observations	10,040	11,363	14,127	10,815	15,141	16,626
R^2	0.87	0.88	0.89	0.88	0.89	0.90

$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 and the demographics are measured at the municipality level. The standard errors shown in parentheses are clustered by Municipality.

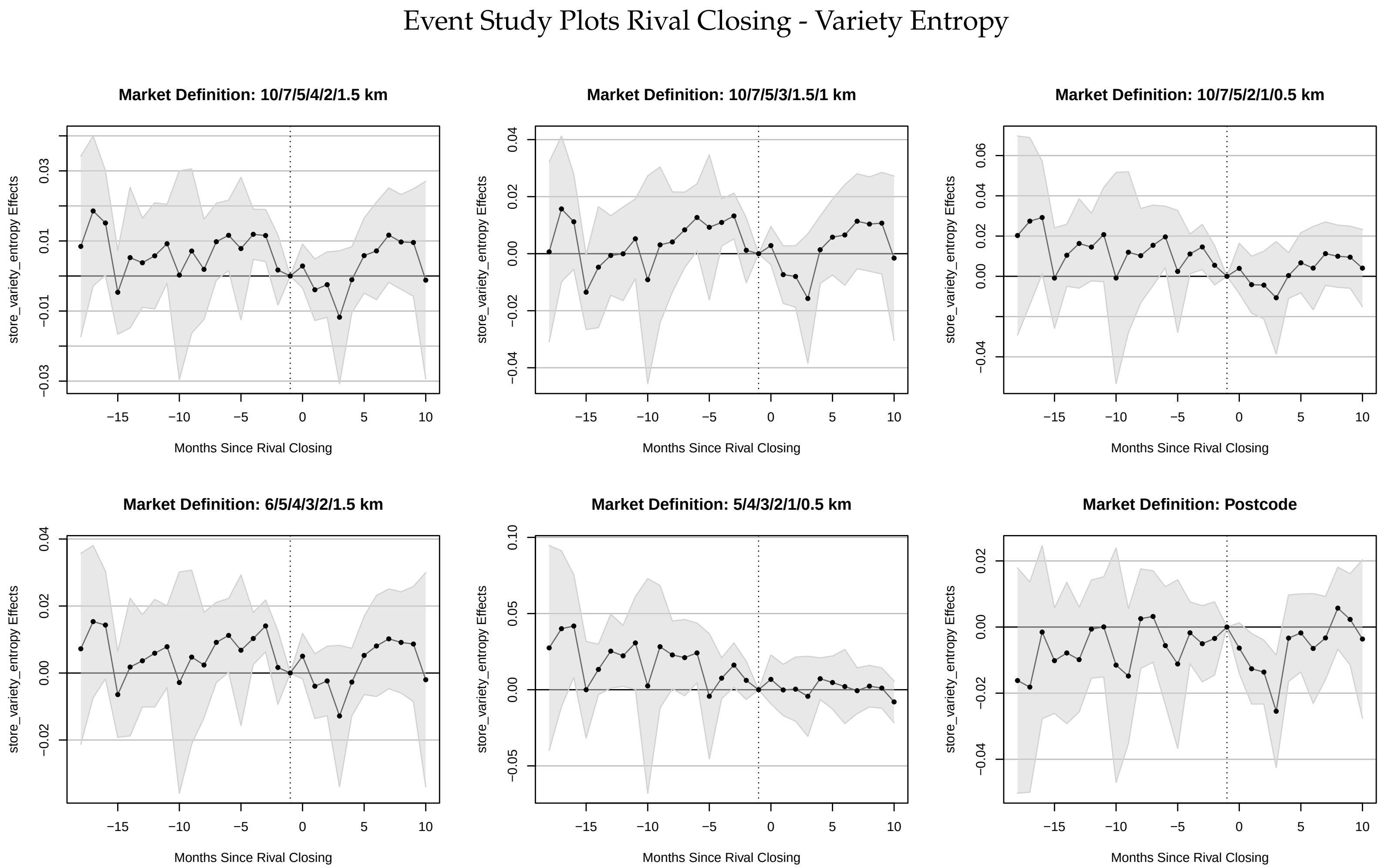


Figure C.16: The Variety Index effects of a rival closing as a function of the time since shutdown. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The vertical line indicates the month before the event occurs.

Table C.17: Effect of Extra on Sales - Last Period Before Event Excluded

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Extra}	-0.072***	-0.051***	-0.096***	-0.053***	-0.091***	-0.094***
	(0.017)	(0.018)	(0.015)	(0.018)	(0.013)	(0.022)
ln(Population)	-0.124	-0.017	-0.118	-0.023	-0.165	-0.043
	(0.390)	(0.403)	(0.397)	(0.402)	(0.463)	(0.069)
ln(Median Income)	0.573	0.461	0.158	0.563	0.117	0.356
	(0.350)	(0.335)	(0.309)	(0.342)	(0.321)	(0.271)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	348	396	468	372	492	529
Observations	10,744	12,306	14,902	11,600	15,850	17,301
R^2	0.83	0.84	0.84	0.83	0.84	0.85

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Each Column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The demographics are measured at the municipality level and the standard errors shown in parentheses are clustered by Municipality.

Table C.18: Effect of Extra on Sales - Group Specific Linear Trends

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
Affected × Trend	0.001	0.001	0.002	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
T_{Extra}	-0.069**	-0.055*	-0.108***	-0.044	-0.081***	-0.089***
	(0.029)	(0.030)	(0.022)	(0.032)	(0.023)	(0.030)
ln(Population)	-0.057	0.025	-0.084	0.048	-0.142	-0.043
	(0.376)	(0.394)	(0.389)	(0.390)	(0.452)	(0.067)
ln(Median Income)	0.570	0.447	0.156	0.566*	0.112	0.326
	(0.345)	(0.331)	(0.306)	(0.338)	(0.316)	(0.269)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	348	396	468	372	492	529
Observations	10,744	12,306	14,902	11,600	15,850	17,301
R^2	0.83	0.84	0.84	0.83	0.84	0.85

$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions and group specific linear trends. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Extra Rebranding - ln(Sales) - Last Period Before Event Excluded

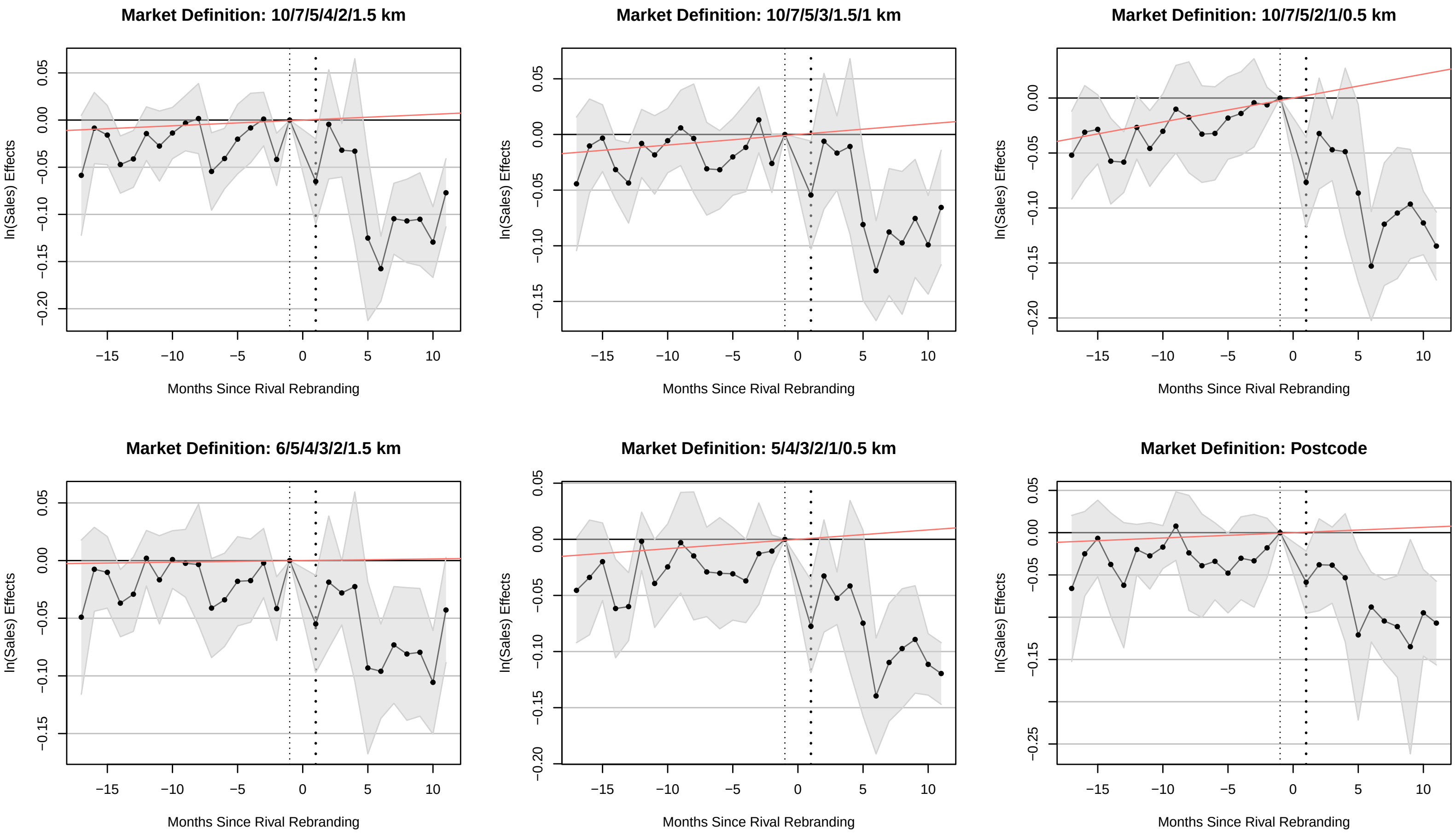


Figure C.17: The percentage sales effects of a rival rebranding to Extra as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The last period before the rival rebranding is excluded and the linear pretrend is extrapolated into the post rebranding period. The first vertical line indicates two periods before the event and the second line indicates the first period after the event.

Table C.19: Effect of Prix on Sales - Last Period Before Event Excluded

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Prix}	0.034	0.019	-0.030	0.007	-0.045	-0.065**
	(0.031)	(0.026)	(0.026)	(0.033)	(0.036)	(0.030)
ln(Population)	0.096	0.166	-0.011	0.181	-0.120	-0.003
	(0.379)	(0.385)	(0.407)	(0.391)	(0.471)	(0.057)
ln(Median Income)	0.538	0.430	0.064	0.549	0.061	0.442*
	(0.345)	(0.331)	(0.312)	(0.340)	(0.324)	(0.263)
Market Definition	10-1.5 km	10-1.5 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	327	372	449	350	479	512
Observations	10,017	11,574	14,331	10,849	15,491	16,672
R^2	0.83	0.84	0.84	0.83	0.84	0.85

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Each Column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The demographics are measured at the municipality level and the standard errors shown in parentheses are clustered by Municipality.

Table C.20: Effect of Prix on Sales - Group Specific Linear Trends

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
Affected × Trend	-0.002	-0.002	-0.001	-0.001	-0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
T_{Prix}	-0.003	-0.009	0.015	-0.012	0.028	-0.022
	(0.029)	(0.032)	(0.036)	(0.032)	(0.038)	(0.026)
ln(Population)	0.097	0.170	0.018	0.194	-0.094	-0.001
	(0.372)	(0.377)	(0.392)	(0.383)	(0.458)	(0.057)
ln(Median Income)	0.540	0.445	0.094	0.556^{*}	0.099	0.447^{*}
	(0.340)	(0.327)	(0.306)	(0.334)	(0.318)	(0.259)
Market Definition	10-1.5 km	10-1.5 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	327	372	449	350	479	512
Observations	10,017	11,574	14,331	10,849	15,491	16,672
R^2	0.83	0.84	0.84	0.82	0.84	0.85

$*$ $p < 0.1$, $**$ $p < 0.05$, $***$ $p < 0.01$

Notes: Each Column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The demographics are measured at the municipality level and the standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Prix Rebranding - ln(Sales) - Last Period Before Event Excluded

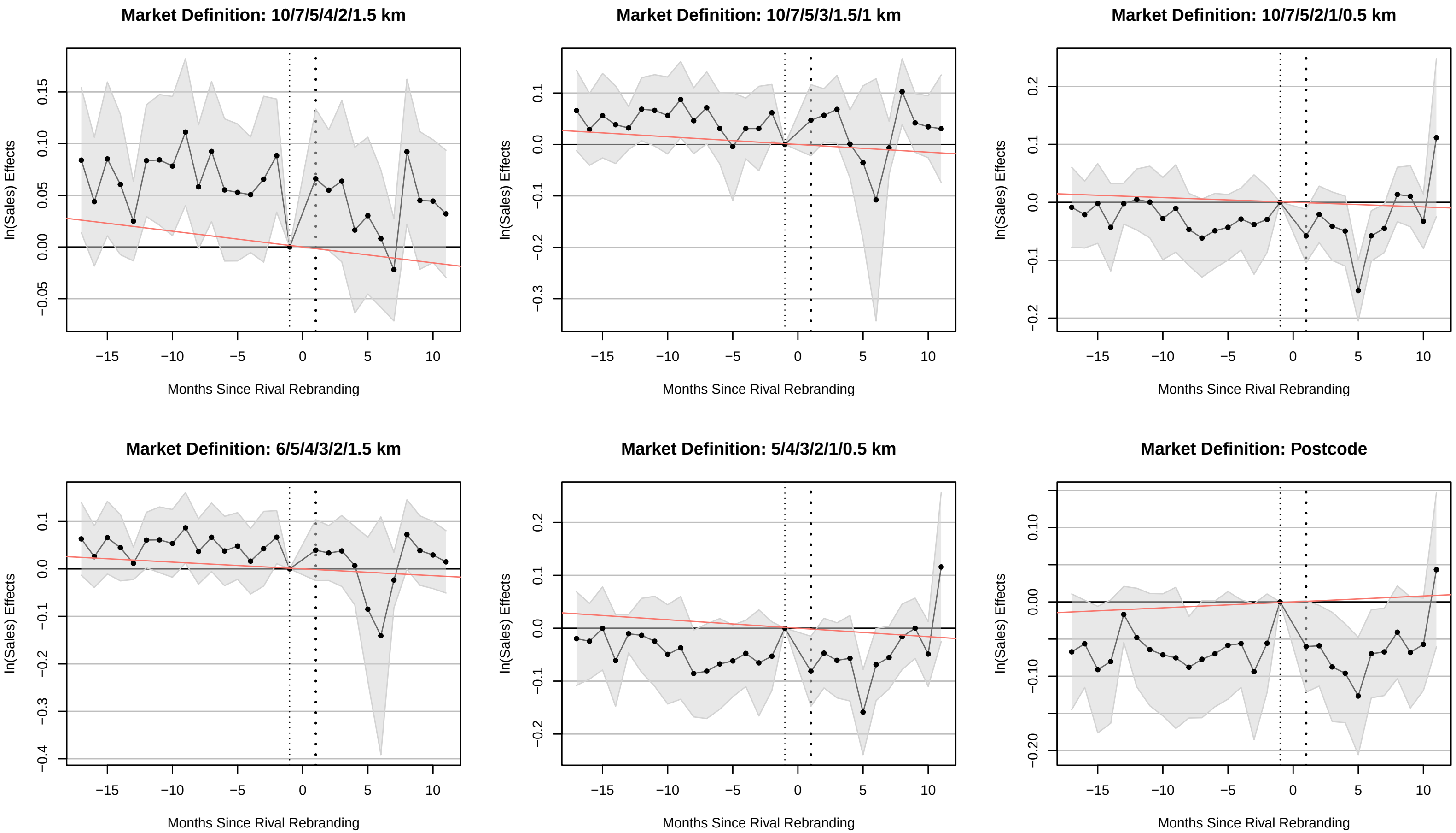


Figure C.18: The percentage sales effects of a rival rebranding to Prix as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The last period before the rival rebranding is excluded and the linear pretrend is extrapolated into the post rebranding period. The first vertical line indicates two periods before the event and the second line indicates the first period after the event.

Table C.21: Effect of Bunnpris on Sales - Last Period Before Event Excluded

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Bunnpris}	0.255***	0.176***	0.132***	0.223***	0.136***	0.019
	(0.061)	(0.040)	(0.032)	(0.063)	(0.041)	(0.056)
ln(Population)	0.012	0.113	-0.111	0.108	-0.197	-0.011
	(0.391)	(0.394)	(0.398)	(0.400)	(0.468)	(0.058)
ln(Median Income)	0.660*	0.454	0.058	0.558	0.059	0.419
	(0.351)	(0.328)	(0.295)	(0.348)	(0.312)	(0.268)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	291	342	424	317	456	489
Observations	9,270	10,940	13,772	10,151	14,896	16,102
R^2	0.82	0.83	0.83	0.82	0.84	0.85

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The demographics are measured at the municipality level and the standard errors shown in parentheses are clustered by Municipality.

Table C.22: Effect of Bunnpris on Sales - Group Specific Linear Trends

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
Affected × Trend	0.002	0.001	0.005	0.005	0.007	0.005
	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.004)
T_{Bunnpris}	0.058*	0.026	-0.015	-0.016	-0.049	-0.062
	(0.032)	(0.036)	(0.035)	(0.047)	(0.049)	(0.040)
ln(Population)	0.012	0.109	-0.113	0.108	-0.199	-0.011
	(0.390)	(0.394)	(0.398)	(0.400)	(0.468)	(0.058)
ln(Median Income)	0.661*	0.450	0.057	0.558	0.056	0.418
	(0.351)	(0.328)	(0.295)	(0.347)	(0.313)	(0.268)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	291	342	424	317	456	489
Observations	9,270	10,940	13,772	10,151	14,896	16,102
R^2	0.82	0.83	0.83	0.82	0.84	0.85

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Each column reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The demographics are measured at the municipality level and the standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Bunnpris Rebranding - ln(Sales) - Last Period Before Event Excluded

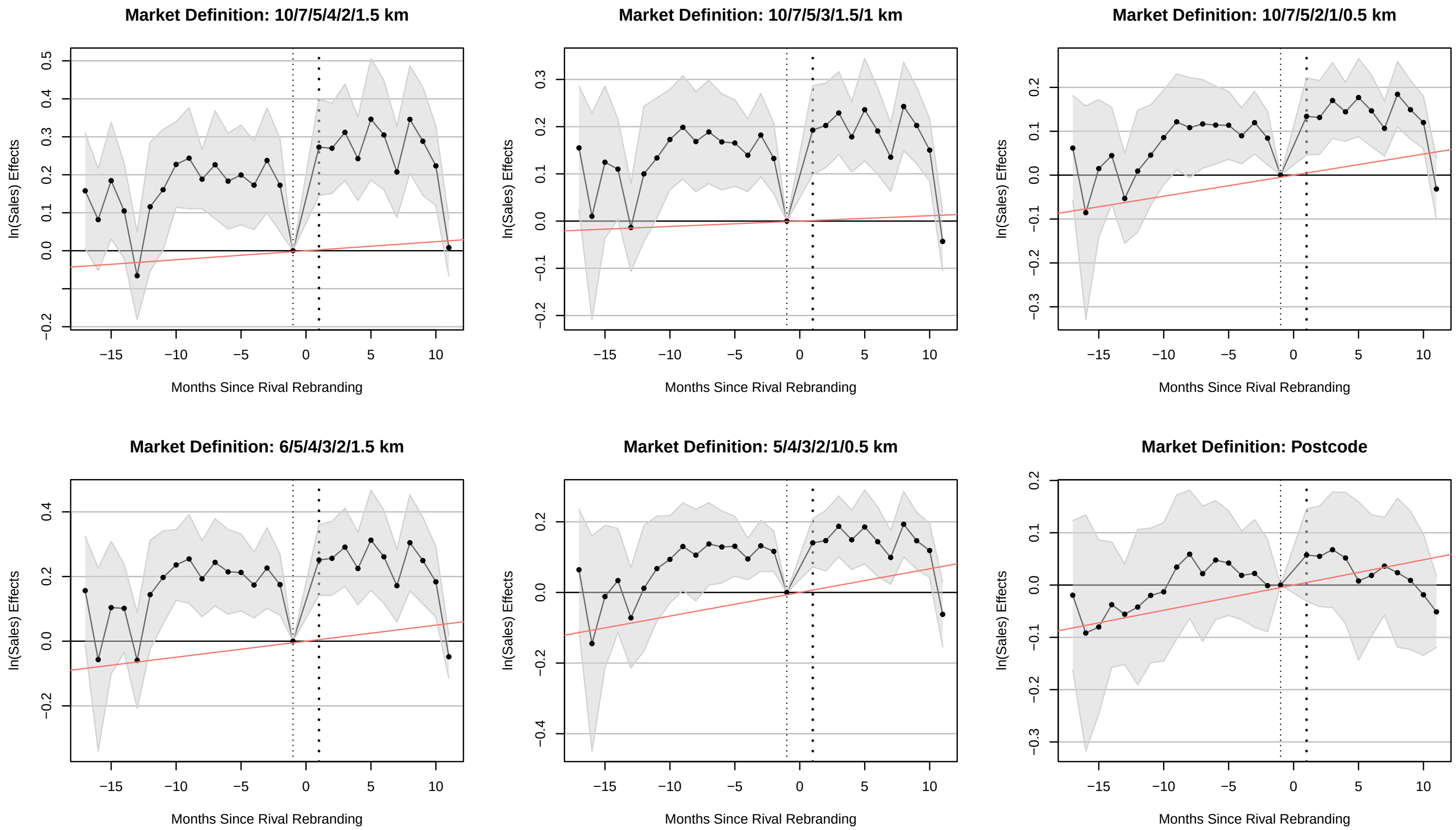


Figure C.19: The percentage sales effects a rival rebranding to Bunnpris as a function of the time since rebranding. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The last period before the rival rebranding is excluded and the linear pretrend is extrapolated into the post rebranding period. The first vertical line indicates two periods before the event and the second line indicates the first period after the event.

Table C.23: Effect of Store Closings on Sales - Last Period Before Event Excluded

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
T_{Closed}	0.044	0.046	0.056	0.044	0.051	-0.061
	(0.064)	(0.079)	(0.061)	(0.071)	(0.078)	(0.068)
ln(Population)	-0.065	0.062	-0.121	0.010	-0.170	-0.007
	(0.390)	(0.394)	(0.413)	(0.394)	(0.479)	(0.067)
ln(Median Income)	0.555	0.487	0.014	0.529	0.000	0.529*
	(0.355)	(0.341)	(0.319)	(0.346)	(0.329)	(0.274)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	314	355	434	337	463	504
Observations	10,010	11,339	14,108	10,788	15,127	16,601
R^2	0.81	0.83	0.83	0.82	0.84	0.85

$* \; p < 0.1$, $** \; p < 0.05$, $*** \; p < 0.01$

Notes: Each Column reports the reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The demographics are measured at the municipality level and the standard errors shown in parentheses are clustered by Municipality.

Table C.24: Effect of Store Closings on Sales - Group Specific Linear Trends

	ln(Sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
Affected × Trend	0.000	0.000	0.001	-0.001	-0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
T_{Closed}	0.073*	0.091**	0.083*	0.092**	0.111	0.037
	(0.037)	(0.041)	(0.047)	(0.038)	(0.075)	(0.043)
ln(Population)	-0.079	0.029	-0.137	-0.016	-0.172	-0.005
	(0.387)	(0.390)	(0.409)	(0.391)	(0.475)	(0.068)
ln(Median Income)	0.561	0.487	0.015	0.525	0.001	0.544**
	(0.355)	(0.340)	(0.318)	(0.345)	(0.329)	(0.273)
Market Definition	10-1.5 km	10-1 km	10-0.5 km	6-1.5 km	5-0.5 km	Postcode
Months	36	36	36	36	36	36
Stores	314	355	434	337	463	504
Observations	10,010	11,339	14,108	10,788	15,127	16,601
R^2	0.81	0.83	0.83	0.81	0.84	0.85

$* \ p < 0.1$, $** \ p < 0.05$, $*** \ p < 0.01$

Notes: Each Column reports the reports the estimated ATT using the estimator of Sun and Abraham (2020) with different local market definitions. The data span all months of 2014 - 2016 except the last period before the rival rebranding. The demographics are measured at the municipality level and the standard errors shown in parentheses are clustered by Municipality.

Event Study Plots Rival Closing - ln(Sales) - Last Period Before Event Excluded

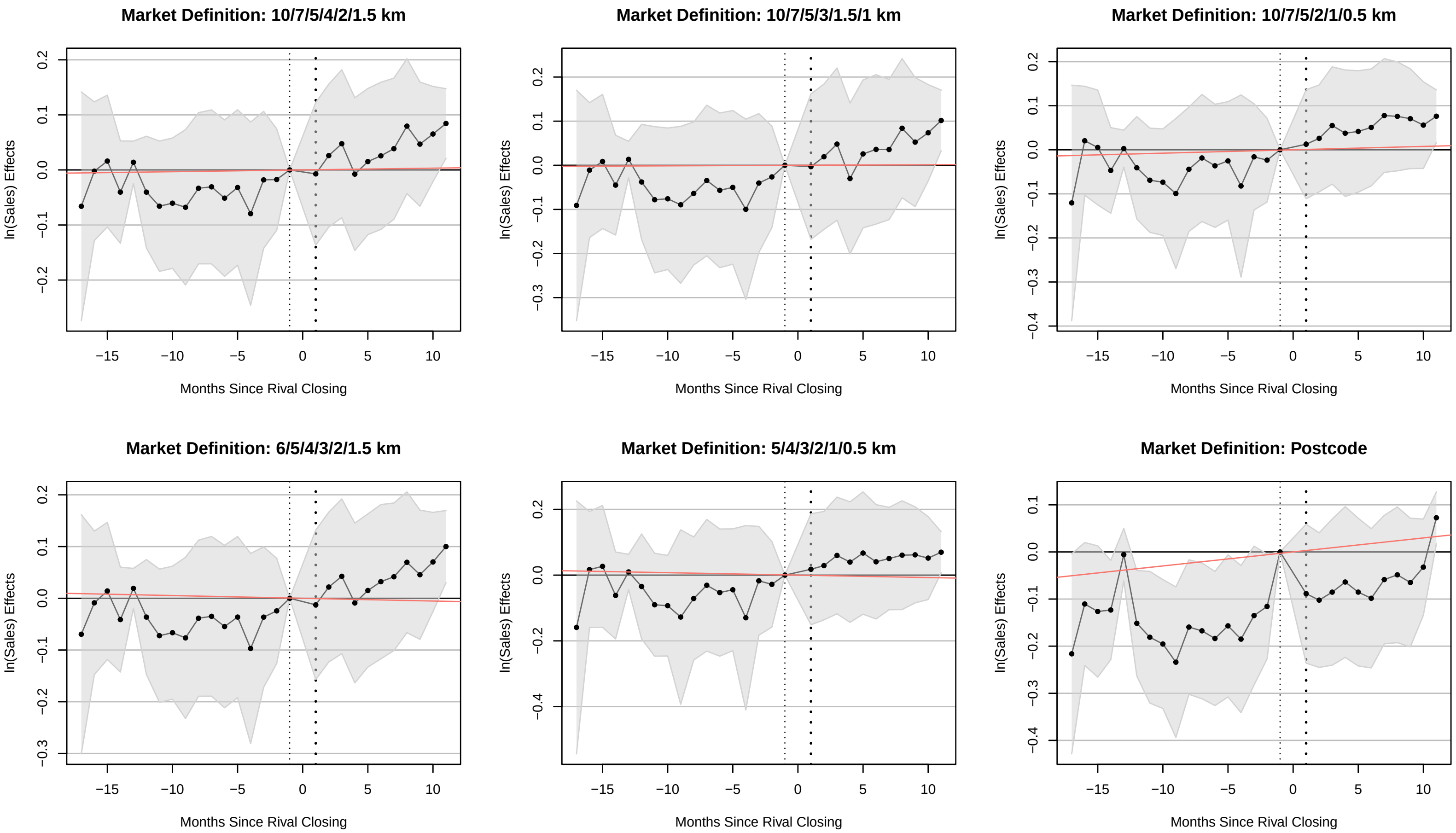


Figure C.20: The percentage sales effects of a rival closing as a function of the time since shutdown. The confidence intervals are calculated at the 95 % level using standard errors clustered at the municipality level. The last period before the rival rebranding is excluded and the linear pretrend is extrapolated into the post rebranding period. The first vertical line indicates two periods before the event and the second line indicates the first period after the event.