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How Consumers Respond to New Store Entry by Franchise Brand

– An Empirical Investigation of Geographical Encroachment Using Individual-level Transaction Data –

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How Consumers Respond to New Store Entry by Franchise Brand:

An Empirical Investigation of Geographical Encroachment Using Individual-level Transaction Data

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Abstract

Understanding the effects of retail encroachment, in which franchisors add new stores in proximate locations to their existing stores, has been an important topic from both managers' and policy makers' perspectives. However, empirical studies on this topic have been limited due to the dearth, or limited nature of data. Using individual-level transaction data from a cluster of franchise stores in a metropolitan area, we study the effects of new store entry on the performance of existing stores. Our results show that the incumbent stores experience cannibalization, but the effect size is diminished by the distance between the incumbent and new stores. We also find that the effect size is moderated by store and customer characteristics. Lastly, we report that the customer segment that patronizes both the incumbent and new stores at the time of new store entry spends more at the brand level, thus contributing to the sales expansion from the franchisor's perspective. Concurrently, they lower their spending at the incumbent stores, contributing to cannibalization from the franchisee's perspective. We discuss the managerial implications of our findings in the context of segmenting and targeting in the conclusion.

Keyword : Franchise, franchise retail, cannibalization, market expansion, difference–in–differences

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Chapter 1. Introduction

One of the most explosive issues in intra−brand competition is encroachment in the franchise industry. Especially, geographical encroachment by offline franchise retailers who add new stores in proximity to their existing stores. With the rapid growth of the franchise industry, various issues occur, such as territorial encroachment caused by misaligned incentives between franchisors and franchisees (Lafontaine & Kaufmann, 1994). In most cases, the goal of franchisors is to maximize the brand's total revenue, whereas franchisees are interested in maximizing the profits of their own stores (Mallapragada & Srinivasan, 2017). Therefore, franchise brands are not likely to provide exclusive territories to franchisees to protect their profits (Azoulay & Shane, 2001). However, the economic status of the franchise industry is too significant to leave without solving encroachment conflict. According to the International Franchise Association, franchise businesses contributed $670 billions of economic output to the U.S. economy in 2020, representing 3% of the total nominal Gross Domestic Product (GDP). Franchisors opened more than 26,000 retail stores, creating almost 800,000 additional jobs, and increasing by approximately 7% in 2021, recovering to pre−COVID economic levels by the end of the year. Therefore, it is necessary to investigate and quantify the economic magnitude of territory encroachment in the franchise industry.

The franchise industry has proliferated in Korea since the late 1990s. Since 1997, the Korean government has encouraged the franchise market to increase its employment rate and promote investment. According to the franchise survey by Statistics Korea, gross sales in the franchise market accounted for 3.5% of GDP, accounting for 19% of the employees in the manufacturing sector in 2018. However, many side effects of this growth have occurred due to the lack of legal and institutional systems. One of the most frequent legal disputes between franchisors and franchisees is geographical encroachment. Among all legal dispute types, encroachment disputes ranked 4th, accounting for 5% of the total. To resolve this issue, the Korea Fair Trade Commission (KFTC) established several acts, such as the exclusive territory restraint on entry of franchise retail in 2012, called the Franchising Best Practice Code. For example, in the case of a coffee shop or bakery, the same franchise brand cannot open a new store within 500 meters. Although the Best Practice Code has been applied for less than two years, there is controversy. One opinion is that business area restriction is illegal as an anti−competitive practice, and another is that the business area restriction is necessary to protect commercial rights. Therefore, the economic magnitude of territorial encroachment within a brand has to be systematically quantified. The objective of this study is to provide a better understanding of intra-brand competition caused by geographical encroachment. First, we evaluate whether there is a negative impact of new store entry on the incumbent stores' financial performance and quantify the extent of the impact. We also investigate the store and customer characteristics that influence the magnitude of the new store entry effects. From a consumer behavior perspective, we identify the mechanism through which customers affect the sales of incumbent stores by differentiating their purchase behavior. Unlike previous research, we focus on customer-level analysis since the customer shopping tendency is a crucial attribute for both franchisor and franchisee to secure the market and make more profits.

Chapter 2. Related Literature & Hypothesis

In this section, we review the related literature on encroachment in various channels. Encroachment can affect the incumbent stores both positively and negatively (Kim & Jap, 2021). On the one hand, new store entry proximately to the incumbents can negatively affect the performance of incumbent stores, primarily because adding additional stores can reinforce competition between the stores. We regard this as a substitution effect. On the other hand, a positive agglomeration effect occurs in the group of same-brand stores, because of brand awareness (Avery et al., 2012), or brand quality signaling (Ackerberg, 2001). We regard this as a complementary effect. The substitution and complementary effects occur in various channels, such as online and offline, online and other online platforms, or offline. Choi and Bell (2011) found that the substitution relationship between offline and online stores applies to preference minorities. Xu et al. (2017) studied the substitution effect of tablets to PCs and the complementary effect of tablets to smartphones. They also show that cross-device browsing can affect sales revenue. Work by Xu et al. (2014) focuses on the complementarity in demand between mobile applications and mobile websites. They report that new app adoption considerably increases the visiting rate of a mobile website. There are various studies on multi-channel relationships. However, in this paper, we would like to take a more in-depth look at relationships between offline franchise retailers. For example, Kalnins (2004) studied the impact of territorial encroachment in the Texas hotel industry data on incumbents across same-brand and company-owned units. In the case of same-brand units, adding a new same-brand unit proximately to incumbent units causes cannibalization of the incumbents. In contrast, adding a company-owned unit near the same-brand units positively affected the incumbents' revenue. Ingram and Baum (1997) use the data from hotels in Manhattan to find evidence for the cannibalization effect. Pancras, Sriram, and Kumar (2012) studied the territorial cannibalization effect in fast−food franchises in a large U.S city. They found that incumbents' profits are negatively associated with a new store opening, but the distance mitigates the cannibalization effect by reducing the sales lost. Davis (2006) develops an econometric model of spatial competition between movie theaters. He demonstrated that products are location specific, which affects the customer preferences toward the stores and products. This result is similar to Pancras et al. (2012), whose results support evidence for the diminishing spatial competition with distance. Other research suggests that adding new units can be helpful for customers and beneficial for incumbents by creating the agglomeration effect. For example, Chung and Kalnins (2001) show that large franchise hotels benefit from the agglomeration effect in rural areas.

Inspired by empirical research on the cannibalization effect and its diminishing trend with distance, we first develop a hypothesis on the impact of new store entrants on the sales of incumbent stores. We focus on geographical encroachment of same−brand franchisees, consistent with Kalnins (2004), that same−brand encroachment is negatively associated with the incumbents' sales, and hypothesize the following:

Hypothesis 1. New store entrants cause a decrease in sales of treated incumbent stores. That is, there exists a cannibalization effect after the new store entry.

Additionally, following Pancras et al. (2012) and Davis (2016), we want to assess whether the waning effects with distance still occur with walking−distance outlets in urban areas. The hypothesis is as follows:

Hypothesis 2. The cannibalization effect diminishes as the distance between the incumbent and new stores becomes longer.

In addition, we further presumed the moderating role of store characteristics. That is, certain store characteristics will moderate the magnitude of the new store effect on incumbents. According to Pan and Zinkhan (2006), product assortment is one of the crucial market drivers of customers' patronage decisions. Dhar et al. (2001) also suggest that retailers with broad product assortments are more attractive to customers. Even though we cannot observe the product assortment status of each store in our data, we posit that the number of products sold can represent the product assortment in each store. Given the assumption that the stores with more products sold have a broader product range, we hypothesize that the cannibalization effect is less for stores that sell more products. In addition, we presume that the cannibalization effect is less for stores with more loyal customers. Wang et al. (2015) found that after the adoption of mobile shopping, low-spending customers increase their order rate and order size in the mobile environment. If we consider a mobile application as the entry of a new store and low spending customers as relatively non-loyal customers, then we can maintain that non-loyal customers are more likely to move to the new stores than loyal customers. Based on this, we can hypothesize that more loyal customers can alleviate the cannibalization effect by not switching from incumbent to new stores. In other words, the cannibalization effect is less for stores with more loyal customers. The following hypothesis includes these two arguments:

Hypothesis 3. The cannibalization effect will be alleviated for stores with (a) more products sold and/or (b) relatively more frequent visit customers.

Chapter 3. Data Description

The data for our empirical research is from one of the famous bakery franchises in South Korea. Their product assortment varies across more than 40 categories, including bread, beverages, and dairy products. We have two different data sets. One is individual-level panel data, and the other is store information. The panel data come from 49 stores located in one of the most densely populated areas in Seoul, covering 15 months from April 2017 to June 2018. The total number of customers is around five hundred thousand, and there were over 5 million transactions during the analysis period. The data contains customers' daily transaction information such as timestamps, products, quantities, stores, and sales. Since we can observe when, where, what, and how much customers purchase, we can classify the customers based on their shopping behavior and the inflow and outflow of the market. We will utilize the customer classification process to examine the mechanism of new store impact. The detail will be discussed in Section 4. The other one is store information data. The data provide us with the store opening date, geographic location, and district type. Since the dates of store entry vary, it is burdensome to divide the stores into incumbent and new stores. However, the store opening date enables us to distinguish between incumbent and new stores. As I will mention below in the analysis period section, we define new stores as those that opened during the “treatment” period. With the exact store location data, we can pinpoint the store location on the map and identify the control group and treatment group and we will compare these two groups’ change in sales by using the difference−in−differences method. Table 1 presents the simple statistics of stores by type.

Table 1 Simple Statistics by Store Type

	Stores	Average Weekly Sales	Max Sales	Min. Sales	Average # of Customers
Incumbent	41	803.3 (109.3)	2,228.9	287.0	16,331 (9,872)
New	8	826.6 (72.3)	1,322.6	496.5	3,631 (1,152)

* The number in parentheses is SD

Chapter 4. Estimation Strategy

4.1. Empirical Challenges

One of the key challenges when estimating the unbiased marginal effects in our analysis is the endogeneity that store location decisions are made strategically by the franchisors. Without controlling for this location endogeneity, the estimates we infer are likely to be underestimated, since the stores located in an attractive area will be less affected by the new stores (Pancras et al., 2012). To circumvent this issue, we include the store fixed effects in the model. These store fixed effects can capture the observed and unobserved store−specific components, which could affect the attractiveness of the corresponding stores (Evans et al., 1993). Along with the store fixed effects, we adopt time−specific fixed effects for unobserved factors to rule out the possible bias across time. By including these fixed effects, we can address the potential endogeneities and avoid potential confounding issues (Kalnins, 2004).

Store entry decisions can be made strategically. However, the exact entry timing is difficult to predict because of various external forces, such as the timing of commercial sales in lots (Kim, 2021). This exogenous entry timing assumption is also in line with Ching's (2010), which presumes the FDA's unpredictable approval timing of generic drugs. Even if we completely rule out the endogeneities of location and entry decisions, including the store fixed effects in the model and the assumption induced by the industry knowledge can mitigate this concern.

Lastly, since we cannot access the competitors' store-level sales transaction data, we are restricted in estimating the competitive effects (Kalnins, 2003). However, with the data on the number of competitors belonging to each incumbent store across time, we can accommodate the competitive effects in the model with the store fixed effects. In our context, the analysis period is relatively short, leading to little temporal variation in the number of competitive stores. Because the store fixed effects could accompany the competitive effects, estimation models with and without competition yield similar results. That is, relatively invariant competition is likely to add limited explanatory power to the model with store fixed effects (Pancras et al., 2012).

4.2. Analysis Period

Inferring the impact of new store entry is complex in a dynamic context, especially because of various store entry dates (Pancras et al. 2012). To make the inference simple, we use the temporal aggregation method to identify the analysis period and define the group of new stores. The temporal aggregation method is useful when it is difficult to pinpoint a specific intervention date and to decrease the degree of complexity due to the varying entry dates across stores. A similar approach was used in various studies, such as Xu et al. (2014) or Son et al. (2020). We use nine months, from August 2017 to April 2018, as the "treatment" period. The stores that opened during the treatment period are identified as new stores. To compare the changes in sales before and after the treatment period, we use two months from June 2017 to July 2017 as the "pre-treatment" period and two months from May 2018 to June 2018 as the "post-treatment" period. We also specify the two-month calibration period prior to the pre-treatment, which will be used to construct the moderating variables to capture the store and customer characteristics. The classification of the time period for analysis is presented in Table 2.

Table 2 Time Window for Each Phase in the Empirical Analysis

Classification	Time window	Description
Calibration period	April 2017 ~ May 2017	Pre-sample
Pre-treatment period	June 2017 ~ July 2017	Before new store entry
Treatment period	Aug 2017 ~ April 2018	New store entry
Post-treatment period	May 2018 ~ June 2018	After new store entry

4.3. Control and Treatment Group

It is necessary to classify control and treatment groups for a difference-in-differences (DID) estimation. To divide the incumbent stores into control and treatment groups, we need to define the incumbent's encroachment area where stores can be affected by the new store entry impact. This study adopts the distance of a specific new store from the incumbents to establish the encroachment area by referring to Kalnins (2004). This criterion is appropriate because there had been a guideline on distance restriction between the same type of franchise by the KFTC (FTC) in 2012. The distance is typically 15 miles (Patel & Corgel, 1995). However, in our context, we define the encroachment area as up to 500 meters from the new store. It is appropriate since the analysis area is within walking distance and the distance restriction guideline by the Korea FTC was 500 meters. We further apply 400 and 600 meters to investigate the diminishing effects. With the exact street address of stores, I obtained control and treatment groups of incumbents. The distribution of control and treatment groups by each criterion is presented in Table 3.

Table 3 Store Distribution of Each Group

Criteria	Treatment Stores	Control Stores	Total
Within 400M	5	36	41
Within 500M	9	32	41
Within 600M	16	15	41

Chapter 5. Model Specification & Main Results

We followed the DID approach in the analysis. The DID method is used to investigate the causal effect of a specific treatment (or intervention) by comparing the changes in outcome between control and treatment groups during the analysis period (Angrist & Pischke, 2008).

5.1. Store-Level Effects of New Store Entry on Sales

We investigate the relative changes in sales in the control and treatment stores before and after the new store entrants, using the following equation:

$$y_{jt} = \beta_0 + \alpha_j + v_t + \beta_1 \cdot Trt_j + \beta_2 \cdot Time_t + \beta_3 \cdot Trt_j \times Time_t + e_{jt} \quad (1)$$

Where j denotes the incumbent stores and t time (week). y_{jt} is the dependent variable, representing the total sales of store j at week t. Trt_j denotes a treatment dummy variable equal to one if the store j belongs to the treatment group and zero otherwise. $Time_t$ is a time dummy variable that equals one if t belongs to the post-treatment period and zero otherwise. Equation (1) includes store (α_j) and time (v_t) fixed effects to control for the store-specific heterogeneity and temporal effects applied across all stores (Kalnins, 2004).

The parameter of interest is β_3, which captures the effects of new store entrants on the dependent variable for the treated stores compared to controlled stores. If the value of β_3 is significant and negative, we can say that the new store entry leads to a decrease in sales in treatment stores, which supports Hypothesis 1. Table 4 provides the estimation results of Equation (1) with three criteria of the treatment group. Each column represents 400-, 500-, and 600-meters, respectively. The estimates of β_3 indicates that the sales in stores located within the encroachment area decrease after the new store entrants. The weekly decrease of each criterion is about 70, 65, and 50, respectively (unit: 10,000 KRW). Thus, the results support Hypothesis 1. It also seems that the cannibalization effect diminishes as the distance between incumbent and new stores gets longer. We further investigate this phenomenon in a later section.

Table 4 Effect of New Store Entry on Treatment Stores' Sales

Variable	Parameter estimate (Standard error)		
	DV: Sales amount (Unit:10,000 KRW)		
	400M	500M	600M
Trt_j	213.926 *** (45.360)	414.367 *** (43.583)	407.232 *** (43.238)
$Time_t$	282.823 ***	288.992 ***	294.720 ***

	(29.342)	(29.509)	(30.108)
$Trt_j \cdot Time_t$	−69.599 *	−65.528 **	−50.465 *
	(29.804)	(23.098)	(19.600)
Intercept	266.658 ***	263.896 ***	261.203 ***
	(36.043)	(36.015)	(36.160)
Store Fixed Effects		Yes	
Time Fixed Effects		Yes	
Adjusted R2	0.894	0.3346	0.3385

† p <0.1; *p < 0.05; **p < 0.01; ***p < 0.001

Note that the decrease in total sales may be due to a decrease in average sales, decrease in purchase frequency, or some combination of both since the sales can be decomposed into the product of average sales and purchase frequency. Thus, we re−estimate Equation (1) with average sales and purchase frequency as dependent variables to quantify how much each component contributes to decreasing the sales in the post−treatment period.

Table 5 represents the estimate results of each dependent variable. The first three columns show results for the dependent variable of weekly average sales and the next three columns the dependent variable of weekly purchase frequency. The coefficients of $Trt_j \times Time_t$ for average sales are significant and negative, while the same coefficients for purchase frequency are insignificant. Thus, the estimate results indicate that a decrease in sales can be attributed to a decrease in average sales, not to a decrease in purchase frequency. We can conclude that the customers' number of store visits remains almost the same, but the average purchase amount per visit by customers has decreased in the post−treatment period. Interestingly, this is quite different from the results of previous studies, such as Son et al. (2020), which insist the significant change in purchase frequency, not the average purchase amount. One possible reason for this is that customers are likely to distribute their purchase amount within in a walking−distance environment because they do not have to buy everything at once. Nevertheless, it is necessary to investigate in−depth why customers spend less based on their dynamics of shopping behavior.

Table 5 Decomposition of Sales

Variable	Parameter estimate (Standard error)					
	DV: Average sales amount (Unit: KRW)			DV: Purchase Frequency		
	400M	500M	600M	400M	500M	600M
Trt_j	46.726 (99.333)	−237.646 * (98.708)	−270.082 ** (98.243)	483.94 *** (96.23)	1080.52 *** (92.58)	1071.77 *** (91.78)
$Time_t$	40.493 (64.254)	37.623 (66.833)	61.445 (68.409)	598.08 *** (62.25)	610.42 *** (62.68)	611.46 *** (63.91)
$Trt_j \cdot Time_t$	−572.293 *** (65.266)	−285.319 *** (52.314)	−216.842 *** (44.534)	22.91 (63.23)	−46.42 (49.07)	−27.96 (41.61)
Intercept	4419.765 *** (78.929)	4423.428 *** (81.568)	4412.249 *** (82.160)	626.27 *** (76.46)	620.10 *** (76.50)	619.66 *** (76.76)
Store Fixed Effects	Yes					
Time Fixed Effects	Yes					
Adjusted R^2	0.806	0.793	0.791	0.90	0.90	0.90

† $p < 0.1$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

5.2. Diminishing Effects of New Store Entrants

In this section, we scrutinize the diminishing cannibalization effects in terms of distance between stores. Since the set of stores located within 500 and 600 meters from the new stores include the stores within 400 meters, the effects induced by the incumbents within 400 meters may dilute the effects from the stores outside 400 meters. To break down the effects into each group of stores, we include the additional indicator variables to divide the stores based on their location as follows:

$$y_{jt} = \beta_0 + \alpha_j + v_t + \beta_1 \cdot Trt_j + \beta_2 \cdot Time_t + \beta_3 \cdot Trt_j \times Time_t + \beta_4 \cdot Trt_j \times Time_t \times I(j \leq 400M) + \beta_5 \cdot Trt_j \times Time_t \times I(400M < j \leq 500M) + \beta_6 \cdot Trt_j \times Time_t \times I(500M < j \leq 600M) + e_{jt} \quad (2)$$

The store location indicator variable $I(j \leq 400M)$ is equal to one if the store j is located within 400 meters from the new store and zero otherwise. $I(400M < j \leq 500M)$ is equal to one if the store j is located within 500 meters and outside 400 meters from the new stores and zero otherwise. The same applies to the indicator variable $I(500M < j \leq 600M)$. We interact the interaction of Trt_j and $Time_t$ variables with each store location indicator variable. The three-way interaction terms enable us to estimate how much and how fast the cannibalization effects shrink. The key coefficients of interest are β_4, β_5, and β_6. If the absolute value of coefficients gets smaller from β_4 to β_6, then Hypothesis (2) is supported.

Table 6 Diminishing Effects of New Store Entry

Variable	Parameter estimate (Standard error)	
	DV: Sales Amount (Unit: 10,000 KRW)	DV: Average Sales Amount (Unit: KRW)
Trt_j	411.351 *** (44.901)	−380.022 *** (98.349)
$Time_t$	294.396 *** (30.096)	58.864 (65.921)
$Trt_j \cdot Time_t \cdot I(j \leq 400M)$	−81.210 ** (30.541)	−590.367 *** (66.896)

$Trt_j \cdot Time_t \cdot I(400M < j \le 500M)$	−59.162 † (32.312)	15.254 (70.774)
$Trt_j \cdot Time_t \cdot I(500M < j \le 600M)$	−24.436 (26.099)	−101.434 (57.166)
Intercept	261.210 *** (36.145)	4410.847 *** (79.170)
Store Fixed Effects	Yes	
Time Fixed Effects	Yes	
Adjusted R^2	0.89	0.807

† p <0.1; *p < 0.05; **p < 0.01; ***p < 0.001

We estimate Equation (2) for two dependent variables. The first column in Table 6 denotes the results for the dependent variable of weekly sales, and the second column is the dependent variable of weekly average sales. As presented in Table 6, the results support Hypothesis 2. In the dependent variable of weekly sales, the cannibalization effect is clear for the stores within 400 meters, barely evident for the stores between 400 and 500 meters ($p < 0.1$), and not present for the stores outside 500 meters. For the dependent variable of weekly average sales, the estimate of β_4 is only significant with the correct sign (−590.367, $p < 0.001$). Looking at the remaining two coefficients β_5 and β_6, we cannot find any diminishing trend, but they are insignificant. Therefore, taking the two results together, we verify that the cannibalization effect diminishes with distance, and the impact of new stores covers the area within 400 meters.

5.3. ModeratingEffects of Store Characteristics

The innate characteristics of stores may fortify or weaken the cannibalization effects. To test the moderating effects of store characteristics, we extend Equation (1) by adding three-way interaction terms and develop the following specification:

$$\begin{aligned} y_{jt} = {} & \beta_0 + \alpha_j + v_t + \beta_1 \cdot Trt_j + \beta_2 \cdot Time_t + \beta_3 \cdot Trt_j \times Time_t + \\ & \beta_4 \cdot Trt_j \times Time_t \times HiQty_j + \beta_5 \cdot Trt_j \times Time_t \times HiPerVisit_j + \Theta \cdot X_j + e_{jt} \end{aligned} \quad (3)$$

We create binary variables using the median split strategy (e.g., Xu et al., 2014). $HiQty_j$ is a binary variable that denotes the number of products sold at store j that equals one if the product quantities sold at store j are equal to or greater than the median and zero otherwise. $HiPerVisit_j$ is defined as the number of visits to store j divided by the number of unique customers at store j, which measures how many frequent visit customers store j retains. Thus, we regard this as an index to measure customers' store loyalty. We set $HiPerVisit_j$ to one if the value is equal to or greater than the median and zero otherwise. These two time−invariant variables represent the store size and the degree of transaction frequency, respectively. We use the data from the calibration period to construct these variables to avoid the possibility of selection bias. We estimate Equation (3) only with incumbent stores within 400 meters from the new stores, as shown in Table 6.

Table 7 Moderating Effects of Store Characteristics

Variable	Parameter estimate (Standard error)	
	DV: Sales Amount (Unit: 10,000 KRW)	DV: Average Sales Amount (Unit: KRW)
Trt_j	193.594 *** (52.488)	−273.707 * (112.633)
$Time_t$	280.965 *** (29.071)	35.002 (62.384)
$Trt_j \cdot Time_t$	−200.218 *** (45.489)	−991.583 *** (97.614)
$Trt_j \cdot Time_t \cdot HiQty_j$	237.306 *** (62.380)	497.318 *** (133.860)
$Trt_j \cdot Time_t \cdot HiPerVisit_j$	−66.237 (75.007)	561.700 *** (160.957)
$HiQty_j$	428.409 *** (446.523)	1104.068 *** (95.818)
$HiPerVisit_j$	−811.736 *** (446.523)	−731.272 *** (95.818)
Intercept	650.534 *** (35.707)	4048.244 *** (76.623)
Store Fixed Effects	Yes	
Time Fixed Effects	Yes	
Adjusted R^2	0.898	0.817

† p <0.1; *p < 0.05; **p < 0.01; ***p < 0.00

As shown in Table 7, the binary variable $HiQty_j$ has a significant positive impact on all dependent variables. Thus, we find evidence that the stores with more products sold are likely to alleviate the decrease in sales caused by new store entry. In the case of binary variables $HiPerVisit_j$, it only appears to be significant and positive on a dependent variable of average weekly sales and insignificant on a dependent variable of weekly sales. The lack of significance may be because the variable $HiPerVisit_j$ includes the component of customer characteristics, which affect the customers' average purchase amount per visit, but is diluted when it comes to the impact on total sales. Overall, we can see that store size and loyalty are negatively associated with the cannibalization effect, supporting Hypothesis 3.

Chapter 6. Customer Perspective Further Investigation

This section focuses on the mechanism of customer shopping behavior that affects the store performance after the entrance of the new store.

6.1. Customer Classification

We first classify customers based on their timeline of purchase history and the type of stores they visit. Customer classification provides information regarding their purchase behavior, which allow us to understand how customers behave and contribute to the new store impact. First, we divide customers based on whether they have purchase transactions during each analysis period: the pre- and post-treatment periods. We define customers who have purchase transactions during the pre-treatment period as A and customers who enter the market in the post-treatment period as B. We further divide group A into A1 and A2. The A1 group is defined as customers who still have purchase transactions in the post-treatment period. The A2 group have no purchase transactions in the post-treatment period. We consider these two groups of customers as active and inactive customers, respectively. Again, we divide the A1 groups of customers into two groups based on the type of stores. After the new store entrance, some customers still use the incumbent stores, and others visit both incumbent and new stores. Thus, we define A11 as customers who only use the incumbent stores in the post-treatment period and A12 as customers who have switching behavior between incumbent and new stores. Similarly, we classify B group customers into B11 and B12. Table 8 shows the framework of customer classification, and Figure 1 illustrates the classification process.

Figure 1 Illustration of Customer Type

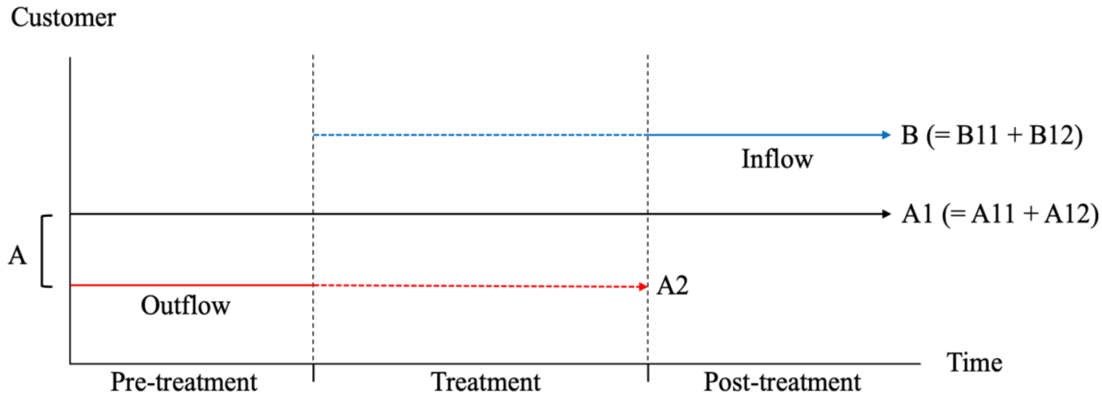

Table 8 Customer Classification Based on Purchase Behavior

<table>
<tr><th>Customer Types</th><th>Index</th><th>Definition</th><th>Index</th><th>Definition</th><th>Index</th><th>Definition</th></tr>
<tr><td rowspan="3">Existing Customer</td><td rowspan="3">A</td><td rowspan="3">Customers who have transaction history in the pre−treatment period</td><td rowspan="2">A1</td><td rowspan="2">Customers who have transaction history in the post−treatment period</td><td>A11</td><td>Customers who only visit the incumbent stores in the post−treatment period</td></tr>
<tr><td>A12</td><td>Customers who visit both incumbent and new stores in the post−treatment period</td></tr>
<tr><td>A2</td><td>Customers who are inactive (no transaction history) in the post−treatment period</td><td colspan="2"></td></tr>
<tr><td rowspan="2">New Customer</td><td rowspan="2">B</td><td rowspan="2">Customers who enter the market after the pre−treatment period</td><td colspan="2" rowspan="2"></td><td>B11</td><td>Customers who only visit the incumbent stores in the post−treatment period</td></tr>
<tr><td>B12</td><td>Customers who visit both incumbent and new stores in the post−treatment period</td></tr>
</table>

We also present each customer group's population and sales distribution in Tables 9 and 10, respectively. A notable point in Table 10 is that the purchase amount of A12 customers dramatically increases by 68% in the post-treatment period.

Table 9 Customer Distribution by Customer Type

Index	Number	%	Index	Number	%	Index	Number	%
A	124,057	0.53	A1	43,052	0.347	A11	36,841	0.856
						A12	6,211	0.144
			A2	81,005	0.653			
B	109,883	0.47				B11	87,706	0.798
						B12	22,177	0.202

Table 10 Sales Distribution by Customer Type (Unit: 1,000,000 KRW)

Customer Classification			Period		
			Pre-treatment	Post-treatment	Increase (%)
Existing Customer (A)	A1	A11	1,061.0	1,138.4	7.3%
		A12	155.6	261.8	68%
	A2		1,341.9	-	-
	Total		2,558.5	1,400.2	-54%
New Customer (B)	B11		-	1,568.9	-
	B12		-	547.0	-
Total			2558.5	3,516.1	37%

It may be because of sales in the new stores added after the treatment period or an increase in sales in incumbent stores. However, comparing the sales trend of A11 customers, new store entry seems to lead to a considerable sales increase from A12 customers. To clarify this, we compare A12 customers' average weekly purchase amount between treatment and new stores before and after the treatment period in Table 11.

Table 11 Comparison of Avg. Weekly Purchase Amount by Store & Customer Type

(Unit: KRW)

	Pre−treatment (t=0)		Post−treatment (t=1)	
Customer	Treatment Store	New Store	Treatment Store	New Store
A11	2,639.2 (413.4)	−	2,653.5 (186.5)	−
A12	2,484.1 (503.1)	−	2,020.0 (132.7)	2,482.3 (122.1)

* The parenthesis indicates standard deviation
* Apply the within 400 meters criterion for treatment stores

6.2. Effects of Customer Switching Behavior on Change in Purchase Amount

Table 11 indicates that the A11 customers' average purchase amount slightly increased during the post−treatment period. In the case of the A12 customers, their additional expenditure increase during the post−treatment period is from the consumption in new stores. By contrast, A12 customers' average weekly purchase of treatment stores decreased by approximately 19% in the post−treatment period. Therefore, we presume that the cannibalization effect is attributed to the A12 customers' store switching behavior. To verify the effect of customers' switching behavior, we implement a customer−level analysis using the following model:

$$y_{it} = \beta_0 + \beta_1 \cdot I(i \in A12) + \beta_2 \cdot I(t = 1) + \beta_3 \cdot I(i \in A12) \times I(t = 1) + e_{it} \quad (4)$$

Where i includes the A1 group of customers since we focus on the dynamic behavior of existing customers during the analysis period. Time t indicates the analysis period where t equals zero in the pre−treatment period and one in the post−treatment period. y_{it} is the dependent variable, denoting the purchase amount of customer i in the treatment store at period t. Note that we focus on which customer types contributed to a decrease in sales of treatment stores, given that cannibalization effects exist. $I(i \in A12)$ denotes a customer group indicator variable that is equal to one if customer i belongs to A12 and zero otherwise. $I(t = 1)$ is a period indicator variable that equals one if t belongs to the post−treatment period and zero otherwise. The parameter of interest is β_3, which captures the A12 customers' change in purchase amount in treatment stores.

Table 12 Underlying Mechanism of New Store Entry Effects by Customer Level

Variable	Parameter estimate (Standard error)			
	DV: Purchase amount (Unit: KRW)		DV: Purchase Frequency	
	400M	500M	400M	500M
$I(i \in A12)$	−149.5 † (84.620)	−161.2 * (77.173)	−0.124 (0.155)	0.202 (0.143)
$I(t = 1)$	−111.3 † (58.405)	−100.0 * (50.085)	−0.038 (0.107)	−0.217 * (0.092)
$I(i \in A12) \cdot I(t = 1)$	−304.1 * (119.671)	−385.7 ** (109.14)	−0.732 *** (0.219)	−0.818 *** (0.202)
Intercept	1885.0 *** (41.299)	2180.9 *** (35.416)	3.721 *** (0.075)	4.464 *** (0.065)
N (Sample)	15920	25802	15920	25802
Adjusted R^2	0.003	0.003	0.002	0.002

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

As shown in Table 12, the results of β_3 indicate that the A12 customers reduce their spending and purchase frequency after the new store entrance. The results show that the A12 customers' purchase amount decreased in the post−treatment period by approximately 300 KRW and purchase frequency by approximately 0.73. Unlike the store−level results in Table 5, where the number of store visits is not affected by the treatment, customers' purchase frequency is negatively affected. It is probably due to the small portion of A12 customers (2.6%) among total customers. These results imply that customer types based on their shopping behavior can strengthen the cannibalization effect on sales in treatment stores. However, the causal relationship between new store entry and customer behavior change should be examined more in−depth. Since customers are preemptively classified by looking at the results of changes in customer shopping behavior, it cannot exclude problems such as selection bias, and cannot be interpreted as a causal relationship.

6.3. Diminishing Effects on Change in Purchase Amount

In addition to inferring the effect of customer switching behavior on change in their purchase amount, we scrutinize how far new store entry affects customer shopping behavior. Therefore, we implement a similar framework in Section 5.2 as follows:

$$y_{ijt} = \beta_0 + \beta_1 \cdot I(i \in A12) + \beta_2 \cdot I(t = 1) + \beta_3 \cdot I(i \in A12) \times I(t = 1) + \beta_4 \cdot I(i \in A12) \times I(t = 1) \times I(j \leq 400M) + \beta_5 \cdot I(i \in A12) \times I(t = 1) \times I(400M < j \leq 500M) + \beta_6 \cdot I(i \in A12) \times I(t = 1) \times I(500M < j \leq 600M) + e_{ijt} \quad (5)$$

Where i denotes the A1 group of customers, t as time and j as the treatment stores. Thus, store indicator variables $I(j \leq 400M)$, $I(400M < j \leq 500M)$, and $I(500M < j \leq 600M)$ are defined in the same way as in Equation (2). The three−way interaction terms estimate the extent to which the between−store distance affects the A12 customers' store switching behavior. Therefore, the key coefficients of our interest are β_4, β_5, and β_6.

Table 13 Customer Level Diminishing Effects of New Store Entry

Variable	Parameter estimate (Standard error)	
	DV: Purchase Amount (Unit: KRW)	DV: Purchase Frequency
$I(i \in A12)$	−194.0 *** (57.178)	−0.244 * (0.107)
$I(t = 1)$	37.048 (35.936)	−0.041 (0.067)
$I(i \in A12) \cdot I(t = 1) \cdot I(j \leq 400M)$	−674.1 *** (106.542)	−1.407 *** (0.199)
$I(i \in A12) \cdot I(t = 1) \cdot I(400M < j \leq 500M)$	−570.4 *** (126.396)	−1.320 *** (0.236)
$I(i \in A12) \cdot I(t = 1) \cdot I(500M < j \leq 600M)$	7.9 (100.106)	0.211 (0.187)
Intercept	2151.3 *** (25.410)	4.519 *** (0.047)
N (Sample)	54420	54420
Adjusted R^2	0.002	0.003

† p <0.1; *p < 0.05; **p < 0.01; ***p < 0.001

Diminishing effects are presented in Table 13. The new stores affect the A12 customers who visit the incumbent stores up to 500 meters from the new stores. This implies that the A12 customers are more sensitive to new stores than other customers, when comparing to the results in Table 6.

6.4. Moderating Effects on Change in Purchase Amount

Given that the new store affects the A12 customers' shopping behavior, we scrutinize what kind of customer attributes strengthen/weaken this effect by inferring the customer moderating variables. Specifically, we use customers' average purchase amount per product quantities, purchase frequency, and the number of purchased product categories to create the moderating variables. The equation including these moderating variables is as follows:

$$y_{it} = \beta_0 + \beta_1 \cdot I(i \in A12) + \beta_2 \cdot I(t=1) + \beta_3 \cdot I(i \in A12) \times I(t=1) + \beta_4 \cdot I(i \in A12) \times I(t=1) \times HiPrice_i + \beta_5 \cdot I(i \in A12) \times I(t=1) \times HiFreq_i + \beta_6 \cdot I(i \in A12) \times I(t=1) \times HiCat_i + e_{it} \quad (6)$$

The moderating variable $\boldsymbol{HiPrice_i}$ indicates the average purchase price of customer i, $\boldsymbol{HiFreq_i}$ as customer $\boldsymbol{i}$'s number of store visits, and $\boldsymbol{HiCat_i}$ as customer i's number of purchased product categories. We use the calibration period to apply the median split strategy. The other variables are defined in the same way as Equation (4).

Table 14 Moderating Effects of Customer Characteristics

Variable	Parameter estimate (Standard error)	
	DV: Purchase Amount (Unit: KRW)	DV: Purchase Frequency
$I(i \in A12)$	−161.72 † (84.37)	−0.137 (0.154)
$I(t=1)$	−111.30 † (58.16)	−0.038 (0.106)
$I(i \in A12) \cdot I(t=1) \cdot HiPrice_i$	−473.94 ** (161.97)	−0.995 *** (0.29653)
$I(i \in A12) \cdot I(t=1) \cdot HiFreq_i$	−418.73 ** (151.81)	−1.276 *** (0.277)

$I(i \in A12) \cdot I(t=1) \cdot HiNCat_i$	−831.12 *** (213.92)	−1.783 *** (0.39163)
Intercept	1583.77 *** (369.76)	2.685 *** (0.676)
Adjusted R^2	0.011	0.016

† p <0.1; *p < 0.05; **p < 0.01; ***p < 0.001

The results are shown in Table 14. It demonstrates that among the A12 customers, the effect is stronger for customers with higher unit purchase prices, for the more frequent visit customers. These findings suggest that customers who spent more and visited more frequently prior to new store entry will spend less in the incumbent stores during the post−treatment period. On the one hand, the effect is less for customers who buy various product categories, which implies that these customers are likely to maintain or increase their purchases in the incumbent stores during the post−treatment period.

6.5. Contribution to Market Expansion

Until now, we were concerned with the impact of the new store on treated incumbent stores. We investigated the change in the performance of treatment stores before and after the new store entrants and quantified how far the effect would cover and how much it would be. From the customer perspective, we disentangled the role of switching behavior that affects the customers' purchase amount in the treatment store. However, from the franchisor's perspective, it could be much more critical to predict how much sales the new stores will generate, which leads to brand growth in the market. We find evidence of A12 customers' contribution to sales of new stores in Table 11. Table 11 shows that the A12 customers spent as much as they consumed at the treated incumbent store during the pre−treatment period at the new store during the post−treatment period. The following equation shows the role of A12 customers in new store sales:

$$y_{ijt} = \beta_0 + \beta_1 \cdot I(i \in A12) + \beta_2 \cdot I(t=1) + \beta_3 \cdot I(i \in A12) \times I(t=1) + \beta_4 \cdot I(i \in A12) \times I(t=1) \times I(j \in New) + e_{ijt} \quad (7)$$

In Equation (7), i denotes the group of A1 customers, and t is time. Store j

includes both treatment and new stores. With the same notation and definition as in Equation (4), we set an additional dummy variable $I(j \in New)$ to one if store j is a new store and zero otherwise. Thus, if the coefficient β_4 has a significant and positive value, then we can infer **A12** customers' switching behavior is positively associated with new store sales. Furthermore, if the net value of adding β_3 and β_4 is positive, it suggests an additional increase in sales from **A12** customers.

Table 15 Market Expansion Effects by New Store Entry

Variable	Parameter estimate (Standard error)			
	DV: Purchase amount (Unit: KRW)		DV: Purchase Frequency	
	400M	500M	400M	500M
$I(i \in A12)$	−149.5 † (84.620)	−161.2 * (77.173)	−0.124 (0.155)	0.202 (0.143)
$I(t = 1)$	−111.3† (58.405)	−100.0 * (50.085)	−0.038 (0.107)	−0.217 * (0.092)
$I(i \in A12) \cdot I(t = 1)$	−304.1 * (119.671)	−385.7 *** (109.139)	−0.732 *** (0.219)	−0.818 *** (0.202)
$I(i \in A12) \cdot I(t = 1) \cdot I(j \in New)$	1112.8 *** (87.45)	899.0 *** (82.14)	2.071 *** (0.157)	1.672 *** (0.150)
Intercept	1885.0 *** (41.299)	2180.9 *** (35.416)	3.721 *** (0.075)	4.464 *** (0.065)
N (Sample)	22333	32215	22333	32215
Adjusted R^2	0.009	0.004	0.01	0.004

† p <0.1; *p < 0.05; **p < 0.01; ***p < 0.001

As expected, the 3rd and 4th row of Table 15 show that **A12** customers' contribution to sales of new stores is positively significant and leads to overall sales growth and market expansion in the area around new stores. For instance, a total of 6211 **A12** customers out of existing customers generated an additional 5 million (KRW) in sales in the area within 400 meters of the new stores and visited 8,300 times more in the post−treatment period.

Chapter 7. Conclusions and Implications

7.1. Conclusions

We explore the impact of new store entry on the sales of incumbent stores in the franchise market. The existing research on the cannibalization effect of the franchise retailers has been conducted mainly at the store level. Therefore, the store−level studies only provide fragmentary results, not giving us insight into how the market worked at the customer level. However, by using the customer panel data from a bakery brand in South Korea, we investigate the cannibalization effect caused by new store entry at the store level and analyze the dynamics of customer purchase behavior to better understand the mechanism behind the phenomenon. From the franchisee perspective, our empirical findings indicate that (1) new store entry negatively affects the overall sales of the incumbent stores affected by the new stores, (2) the effect tends to diminish as the distance between new and incumbent stores gets longer, (3) the decrease in sales is due to the decrease in average purchase amount per visit rather than the decrease in purchase frequency by customers, and (4) the effect has been alleviated for relatively large stores and stores with more frequent visit customers. From the customer perspective, the results show that (1) there are switching behavior customers affected by the new store entrants, (2) the new stores negatively affect their basket size and purchase frequency during the post−treatment period, and (3) the effect is stronger for customers who pay a higher than average price, with higher purchase frequency, and less for customers who buy various product categories. Lastly, customers with switching behaviors enlarge their basket size by purchasing more at the new stores, leading to market expansion. We discuss the managerial implications in the next section.

7.2. Managerial Implications

This study examines the impact of new stores in the franchise retail industry from three pillars: franchisee, franchisor, and customers. We provide quantified results and new insights to brand managers deciding to open new stores and franchisees who need to prepare for the impact of new stores. First, in terms of regulations, we offer practical guidelines by providing precisely quantified effects of new store entrants and waning effects with distance. This result helps policymakers to enact market−driven legislation. Also, brand managers can use these findings as entry and location decision criteria. In a walking distance rural area, the new store entry affects the customers' basket size, but not their purchase frequency. Therefore, marketers need to understand the customers' purchase amount dispersion phenomenon to develop an appropriate marketing strategy. Also, based on an in−depth understanding of store and customer characteristics, franchisees can predict the impact of the new store entry and establish various plans to minimize the cannibalization effect. Lastly, this study aims to enhance our understanding of customer consumption behavior in the franchise industry. For instance, we demonstrate that customers with switching behavior tend to be more sensitive to new stores, which leads to a negative financial impact on incumbent stores. However, from the perspective of market sales, new store entrants are likely to enlarge switching behavior customers' basket size, resulting in overall brand expansion. Therefore, if marketers identify this group of customers preemptively, they can fortify the brand value by increasing the number of retailers and revenue.

7.2. Limitation & Future Research

Although this study broadens our understanding of the territorial encroachment effects in the franchise industry, we recognize a few limitations similar to other research. First, our panel data covers 15 months, including four months for analysis. Even if this duration is sufficient to capture the short−term effect of new store entry, it is limited in investigating the long−term effect. As in a study by Gu and Kannan (2021), who investigate the long−term effect of app adoption on customer purchases, or a study by Kim and Jap (2021) that uses 55 months to analyze the hotel encroachment effect, it can provide more comprehensive insights on understanding the mechanism of how encroachment affects the incumbent stores. The second limitation comes from the endogenous issue of store locations. As mentioned before, it is necessary to control for the location endogeneity, which causes estimation bias. Even though we manage the endogeneity with store fixed effects according to the study of Pancras et al. (2012), it is relatively limited for addressing endogeneity issues, compared to a randomized field experiment. Also, our customer−level analysis must be interpreted cautiously in terms of causal relationship. Since customer categorization is implemented ax−ante based on the results of customer shopping behavior in the post−treatment period, we cannot rule out possible barriers, such as a selection bias. Thus, it is appropriate to consider the bias when interpreting the result.

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초록

프랜차이즈 시장에 있어서 신규 매장의 진입으로 인해 발생하는 배타적 영업 지역 침해는 브랜드 매니저 그리고 정책 담당자 모두에게 중요한 문제로 인식되어 왔다. 국내 프랜차이즈 시장의 활성화를 위해 2007 년 산업통상자원부에서는 시장 경제 활성화를 위한 소자본 창업을 육성하고 이를 지원하기 위해 '가맹사업 진흥에 관한 법률' 을 제정하였다. 그 이후 국내 프랜차이즈 산업의 규모는 급속도로 증가하였다. 하지만 이러한 프랜차이즈 시장의 급속한 발전으로 야기될 수 있는 자기 잠식 현상에 관한 연구는 많지 않은 것이 현실이다. 특히, 점포 수준의 연구가 아닌 소비자 수준에서 신규 매장 진입 이후 그들의 구매 행동의 변화를 분석하고, 이러한 변화가 시장에 주는 영향력을 분석한 연구는 거의 전무하다 해도 과언이 아니다. 본 연구에서는 이러한 시장 상황과 연구 배경에 착안하여, 소비자 수준의 거래 내역 데이터를 활용한 프랜차이즈 시장에서의 배타적 영업 지역 침해에 관한 연구를 시행하였다. 신규 매장 입점 전과 후의 기존 매장들의 매출 변화를 분석하기 위해 이중차분법 (difference-in-differences) 분석을 이용하였고, 이를 통해 우리는 신규 매장 진입 이후 기존매장들의 매출이 감소하였음을 알 수 있었다. 또한 이 효과의 크기가 신규매장으로부터 멀어짐에 따라 감소함을 분석을 통해 입증하였다. 이와 더불어 신규 매장 진입의 효과는 매장의 특성과 고객의 특성에 따라 조절됨을 파악하였다. 또한 기존 매장과 신규 매장을 동시에 사용하는 고객들이 신규 매장 진입 이후 전체적인 소비를 증가시킴에 따라, 브랜드 매출 증가에 기여하는 점을 알 수 있었다. 이는 신규 매장의 진입이 특정 고객 군의 소비 패턴을 변화시키고, 이로 인해 시장 확장에 기여하는 측면이 있음을 시사한다.

핵심 주제어: 프랜차이즈 시장, 배타적 영업지역 침해, 시장 자기 잠식, 소비자 구매 패턴, 이중차분법(difference-in-differences)