ESSAYS ON RETAIL ENTRY AND EXIT

Zhiling Bei

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ABSTRACT

Zhiling Bei: Essays on Retail Entry and Exit
(Under the direction of Katrijn Gielens)

The landscape of the retail industry has witnessed dramatic changes over the past decades. Both manufacturers and retailers are increasingly challenged to find innovative ways to reach and delight not only their existing customers, but also potential new customers. In this dissertation, I aim to pin down the entry effects of an innovative channel -- online marketplaces in Essay 1 and Essay 2, and the exit effects of a traditional channel – Walmart supercenter in Essay 3.

In Essay 1 “The Value of Online Marketplaces to Brand Manufacturers in Emerging Markets”, I apply an event-study methodology to examine whether manufacturers’ decisions are justified by studying the net impact of adopting marketplaces on a firm’s stock market return. To further gain insight into to whom gains may arise, I use a contingency framework and relate manufacturers’ short-term abnormal returns to manufacturers’ market knowledge and marketing strengths. The findings provide comprehensive guidance for manufacturers, global or local, to assess whether and to what extent they can take advantage of online marketplaces to thrive in emerging economies.

In Essay 2 “For Better or for Worse: The Halo Effects of Online Marketplaces on Entrenched Brick-and-Mortar Stores”, I evaluate the impact of online marketplaces on entrenched brick-and-mortar stores -- whether and to what extent retailers and all brands within the category stand to lose or win. To address this question, I use a seemingly unrelated regression

(SUR) model to quantify the impact of online marketplaces. The study not only contributes theoretically to the scant literature on the interaction between online marketplaces and offline channels but also offers manufacturers insightful instructions on multichannel decisions.

In Essay 3 “When Stores Leave: The Impact of Walmart Supercenter Closure on Retail Price”, I seek to understand how retail prices change following the exit of a local retailer by using Walmart supercenter closures in local U.S. markets as a working example. By using a difference-in-difference estimator with correction for selection bias, I find that, on average, consumers have to pay a higher price (+1.6%) after a Walmart supercenter’ exit. The study provides valuable insights into the potential impact of retail exit on price and consumer welfare.

To my parents.
Thank you for your *unconditional* love.

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CHAPTER 1: INTRODUCTION

The landscape of the retail industry has witnessed dramatic changes over the past decades. Both manufacturers and retailers are increasingly challenged to find innovative ways to reach and delight not only their existing customers, but also potential new customers. On the one hand, we see that some firms are thriving, adding new stores, online or offline, to complement their entrenched channels. On the other hand, a rash of bankruptcies and store closings reminds us that other firms are struggling to keep pace with their competitors, and even have to shut down their business. Although it is still unclear whether the net effect of these recent entries and exits reflects a permanent restructuring in the retail industry, they are unlikely to be purely random events. From a manager's perspective, it is worthwhile to see whether there is a lesson to be learned from these past events. Equipped with both econometric techniques and marketing theory, in this dissertation, I aim to pin down the entry effects of an innovative channel -- online marketplaces in Essay 1 and Essay 2, and the exit effects of a traditional channel -- brick-and-mortar stores in Essay 3.

The growth of online marketplaces represents perhaps the largest seismic shift in the retail world for decades, with hundreds of thousands of brand manufacturers across various consumer goods categories, from consumer electronics to automotive, from cosmetics to pharmaceuticals, and from packaged food to alcoholic drinks, adopting the marketplace platform. Under this format, manufacturers sell *directly* to their consumers through marketplaces' sites for a fee and make decisions regarding key factors such as consumer prices without having to invest in retail space or an e-commerce website. Why do brand manufacturers increasingly opt for online marketplaces? Why especially so in emerging markets? Firms have been reluctant to disclose specific information on performance, but anecdotal evidence suggests a mixed success rate as examples of both unexplained success and failure are abound. In Essay 1 “The Value of Online Marketplaces to Brand Manufacturers in Emerging Markets”, I apply an event-study methodology to examine whether manufacturers’ decisions are justified by studying the net impact of adopting marketplaces on a firm’s stock market return. To further gain insight into to whom gains may arise, I use a contingency framework and relate manufacturers’ short-term abnormal returns to manufacturers’ market knowledge and marketing strengths. The findings provide comprehensive guidance for manufacturers, global or local, to assess whether and to what extent they can take advantage of online marketplaces to thrive in emerging economies. Capturing supply-side implications of online marketplaces is seeing only half the picture. In Essay 2 “For Better or for Worse: The Halo Effects of Online Marketplaces on Entrenched Brick-and-Mortar Stores”, I evaluate the impact of online marketplaces on entrenched brick-and-mortar stores -- whether and to what extent retailers and all brands within the category stand to lose or win. To address this question, I use a seemingly unrelated regression (SUR) model to quantify the impact of online marketplaces. The study not only contributes theoretically to the scant literature on the interaction between online marketplaces and offline channels but also offers manufacturers insightful instructions on multichannel decisions.

Whereas much of extant research has studied the entry effects of retailers (e.g., Walmart) on competitor sales, pricing, assortment, stakeouts, and propensity to exits (e.g., Ellickson and Grieco 2013; Jia 2008; Martens 2008; Nishida 2014; Stone 1995), little research has shed light on the exit effects of retail stores. Whether the exit effects will take the exact mirror image of the entry effects is still unknown. Obviously, it is not a simple yes-or-no question. In Essay 3 “When

Stores Leave: The Impact of Walmart Supercenter Closure on Retail Price", I seek to understand how retail prices change following the exit of a local retailer by using Walmart supercenter closures in local U.S. markets as a working example. By using a difference-in-difference estimator with correction for selection bias, I find that, on average, consumers have to pay a higher price (+1.6%) after a Walmart supercenter' exit. The study provides valuable insights into the potential impact of retail exit on price and consumer welfare.

In summary, I have done research in depicting the latest trends of entry and exit in the retail industry and deriving the managerially relevant implications. I hope these studies enrich the understanding of retail channel management in academic community and provide practical guidance to marketing managers.

CHAPTER 2:THE VALUE OF ONLINE MARKETPLACES TO BRAND MANUFACTURERS IN EMERGING MARKETS

Abstract

Due to the unorganized retail structure in emerging markets, manufacturers often find it impossible to work with retailers to reach potential consumers. The advent of online marketplaces provides brand manufacturers a new model to tackle these structural challenges. The question remains, however, whether and to what extent manufacturers stand to gain from joining online marketplaces in emerging markets. To answer this question, the authors examine the net impact of opening a store on Tmall, China's largest online marketplace, on a firm's stock market return. Although the abnormal returns are, on average, significant and positive, stock markets recognize that not all manufacturers can reap benefits to the same extent. To delve deeper into this variation, the authors relate the abnormal returns to various sources of manufacturers' market knowledge and marketing strengths. They find that less diversified manufacturers with high brand equity and marketplace experience are expected to achieve greater gains, irrespective of their origin. However, the effects of marketing strengths diverge for foreign and local firms. Whereas foreign firms with a stronger market position that rely less on advertising benefit more from marketplaces, local firms stand to gain more when their market position is weaker, they advertise more and innovate less.

Keywords: retailing, online marketplaces, emerging markets, financial event study

Introduction

The growth of online marketplaces represents perhaps the largest seismic shift in the retail world, with many brand manufacturers across various consumer goods categories adopting the marketplace platform. Under this format, manufacturers sell directly to consumers through the marketplace website for a fee, and make decisions independently regarding key factors such as retail prices without having to make investments in retail space or e-commerce websites (Abhishek et al. 2016). At first glance, marketplaces seem a winning proposition because they not only provide manufacturers an additional channel to sell products but also reduce their dependencies on retailers. However, given some manufacturers' relatively short history of (directly) interacting with consumers and (independently) setting up retail space (e.g., retail prices), online marketplaces may put manufacturers in a vulnerable position while increasing the risk of channel conflict and confusion.

So far, brand manufacturers have been reluctant to disclose information on marketplace performance, thereby not allowing researchers to study the potential of this platform. As a result, despite more than two decades of history, it is still unclear whether and when manufacturers should opt for online marketplaces. Anecdotal evidence suggests a mixed success rate as examples of both unexplained success and failure abound. Procter & Gamble, for example, opened eight more stores for its brands on Alibaba's Tmall in China after its debut in 2009. In contrast, Hewlett-Packard, once entered eBay to sell refurbished products in 2002 and quietly closed the store several years later (Peters 2002).

Although extant studies on online marketplaces (e.g., Abhishek et al. 2016; Hagiu and Wright 2016; Hagiu and Wright 2015a; Hagiu and Wright 2015b) have made important contributions, they do not allow us to gain insight in whether and to what extent brand manufacturers may benefit from online marketplaces. So far, the extant work typically took the perspective of intermediaries (or middleman) and assessed whether these intermediaries should become online marketplaces or remain as resellers, mainly using analytical models that may not allow us to factor in the role of firm and brand characteristics. Typically, these studies often focused on one particular industry, and did not allow us to generalize across many consumer goods.

More importantly, the body of extant work is primarily based on case studies (e.g., eBay, Amazon Marketplace) in developed economies. However, the marketplace phenomenon has taken off more strongly in emerging markets. More so, emerging markets are the birth region of some of the most important online platform players in the world. China's largest marketplace - Tmall.com - accounts for 58 percent of China's online B2C sales, and India's marketplace leader Flipkart.com has a market share of 44 percent (Carew et al. 2016; Tang 2015). In addition, China's Alibaba is not only believed to become the largest online marketplace in the world, but also to overtake Walmart as the world's largest retail business by 2022, a position Walmart has held for over 15 years (Planet Retail 2017b). Marketplaces thus appear an extremely important gateway in conquering emerging markets. Against this setting, the question can be raised how the existing insights can be readily used by various brand manufacturers assessing marketplaces as a suitable digital channel option in different industries in emerging markets. To formulate answers to this question, we assess the net impact of adopting marketplaces on a firm's stock market return using the announcements of store openings on Alibaba's Tmall.com in China by 408 firms in 39 industries originating from 20 countries between 2008 and 2015.

The study contributes to the literature in several ways. At a broader level, our empirical findings, particularly on whether and how marketplaces benefit manufacturers from various industries, complement the rich stream of theoretical literature on marketplaces (e.g., see Abhishek et al. 2016). Specifically, our study is useful to manufacturers because it provides clear guidance for them to assess under what circumstance marketplaces may create substantive synergy. More importantly, as our study focuses on the largest online marketplace in emerging markets, Alibaba's Tmall, the insights from this research may not only be useful for brands operating in emerging markets but may also allow for reverse marketing learnings in developed markets. Indeed, as online markets are further penetrating developed markets and the emerging market platform giants are eyeing footholds in these markets, knowing how to benefit from these emerging market players' platform operations may help brand manufacturers to successfully deal with these operators outside of emerging markets. Using experience gained on the Tmall platform may thus help manufacturers establish stronger positions on online marketplaces globally.

Conceptual framework

Typically, each brand, big or small, can sell to consumers through three models -- through retailers such as Amazon.com and Walmart ("reselling" model), through own brand stores or sites such as Apple store and Nike.com ("direct model"), or through online marketplace platforms such as Alibaba's Tmall and eBay ("marketplace" model)[1]. In a reselling model, retailers take ownership and control over products from branded manufacturers and decide how to sell them in their stores (i.e. they have full control over the marketing mix, de/listing, and layout decisions). In contrast, in both marketplace and direct models, the full ownership and control rights shift back to manufacturers. Although marketplace and direct models look similar in terms of ownership, the two models differ drastically operationally. In direct models, manufacturers have to do everything by themselves, from building a retail space to acquiring new consumers, from maintaining the retail space to handling logistics. In contrast, manufacturers, in marketplaces, share a small

[1] Apart from these three models, hybrid models exist. For example, retailers like Amazon and Walmart also offer marketplace formats, i.e. Amazon marketplace and Walmart marketplace, respectively.

portion of their revenues with marketplace owners and these marketplaces will help them achieve the same tasks at a much lower cost by exploiting the economies of scale (Hagiu and Wright 2015b; Wells 2016). Table 2.1 presents a comparison of the three models.

In general, joining an online marketplace impacts a brand's short- and long-term revenue streams and costs through different routes. Essentially an online marketplace facilitates shopping from many different brand manufacturers. Digital marketplaces thus build expansive ecosystems that aggregate users and become the place to transact, changing the shopper journey and the opportunities to engage with consumers.

In addition, unlike working through these e-retailers, brand managers keep full control over the marketing mix on the online platform (Tsay and Agrawal 2000). The marketplace operator, unlike retailers, does not own any inventory, merely presents brands' inventory to potential consumers, facilitates a transaction and typically charges a percentage of the final price as a fee to the manufacturer (for example Amazon marketplace takes a 15% fee, Tmall 5% at most), thereby providing brand manufacturers the freedom to choose prices (Dukes and Liu 2016). So like branded websites, the marketplace offers a direct sales channel to the brands, eliminates the middleman and preserves high margins. Moreover, typically e-retailers leave little room for unique brand presentation, facilitate side-by-side comparison of functional attributes of brands and have a strong focus on price. Working through marketplaces, however, may reduce the risk of brand erosion and commoditization in the longer run. In essence, online markets may allow the future to belong to brands, not to Amazon or Zalando, as stated by Xavier Court CEO of Vente-privee.com.

Unlike a direct brand website, however, the brand outsources order fulfillment to the marketplace operator thus heightening manufacturers service capabilities while keeping transaction costs low (Laudon and Traver 2016). For example, Unilever is building momentum by tapping into Tmall's expertise in such areas as fast delivery and secure payment systems, while focusing on what Unilever does best: innovative advertising and merchandising (Hoffmann et al. 2012).

Still, skepsis exists about the net, long-term revenue and cost gains of online marketplaces above and beyond other (online) channel alternatives. As it is it imperative for online platforms to continuously bring on board fresh and diverse brands to offer the widest assortment possible, standing out on a marketplace may be very difficult. Unlike negotiating shelf space with traditional retailers, selling via marketplaces presents a far more level playing field (Planet Retail 2017c), turning big, global and small, local brands equal in the eye of the consumer. While online marketplaces offer convenient comparisons for consumers, brands will have an increasingly difficult time differentiating from other. The increased competition and ‘no rules’ environment on marketplace platforms may ultimately challenge brands to protect price and brand equity.

In emerging markets, this skepsis may be even more warranted. On the one hand, as online marketplaces allow brands in emerging markets to reach consumers in parts that have no easy access to modern distribution, these marketplaces may seem the most efficient gateway to unlock substantial parts of the market while leapfrogging brick and mortar distribution. So, while online marketplaces may offer opportunities, in emerging markets they are even more profound, offering even small brands to look big. Moreover, online marketplaces can be particularly effective in emerging markets because they do not require brand manufacturers to create their own infrastructure to sell online. As such, online marketplaces can be a low-cost way to gain exposure in new markets and better understand shopper behavior. Still, although many consumers in emerging markets seem profoundly enamored with (Western) brands (Sethuraman 2017), the possibility still exists that these may eventually lose their initial appeal to local consumers. Therefore, it becomes even more imperative for the online platform to continuously bring new brands to keep the consumer excited.

In sum, joining an online marketplace can lead to different short- and long-term costs and revenues for different brand manufacturers and thus produce different net outcomes. For some manufacturers, the negatives will predominate, while for others, the positives will outweigh the negatives. We therefore propose a contingency framework that pinpoints the type of brand most likely to reap the benefits or, at the very least, downplay the negative effects in an emerging market.

Contingency Framework

Brand manufacturers often find it difficult to maintain a sustained competitive advantage in emerging markets where institutional challenges or deficits abound (Khanna and Palepu 1997). Only those manufacturers who dynamically integrate, build, and reconfigure both internal and external competencies to address the rapidly changing environments can survive (Eisenhardt and Martin 2000; Teece et al. 1997). In general, marketplaces help manufacturers to overcome these institutional challenges. More specifically, they help to overcome (1) *the lack of market knowledge* with respect to the business climate, cultural patterns, structure of the market system, and, most importantly, characteristics of the individual customers (Johanson and Vahlne 1977), and (2) *institutional infrastructure weaknesses* which reflects the paucity of specialized intermediaries, transportation and distribution networks, regulatory systems, and contract-enforcing mechanisms (Khanna and Palepu 2006).

Closing the knowledge gap. In emerging economies, sufficient knowledge about local consumers has become an essential piece of the marketing strategy puzzle (Shane and Venkataraman 2000; Wiklund and Shepherd 2003). This may be a daunting task because the tastes of consumers in these markets are quickly changing (Hoffmann and Lannes 2013).

Marketplaces, however, aid manufacturers to close the knowledge gap by allowing them to directly observe consumers and attain valuable customer information by themselves, whereas, in a reselling format, all this information is secured by the retailers (Corsten and Kumar 2005). Undoubtedly, customer information does not necessarily equal consumer knowledge. Marketplaces like Alibaba's Tmall further provide manufacturers with services to correctly 'decode' consumer behavior (Swanson 2015). Moreover, brand manufacturers can also hone their knowledge about products in online marketplaces. Consumers on a marketplace can rate the products and leave feedback to each product. The product information collected through word-of-mouth networks can deepen manufacturers' understanding for all products and facilitate product innovation in the future (Dellarocas 2003; Kozinets et al. 2010).

Curing infrastructure weaknesses. Infrastructure weaknesses in emerging markets are materialized in two key ways: logistics and channel regulatory systems. Manufacturers can alleviate paucity of distribution and logistics in emerging markets by taking advantage of the marketplace's distribution networks. In addition, ever-shortening delivery timelines, both consistently and predictably, are the key differentiators in emerging market competition. Although fulfilling this demand is costly for manufacturers, marketplaces cut the costs by exploiting economies of scales (Xia and Zhang 2010). Finally, marketplaces also help to close down gray channels. For example, Alibaba announced its intentions to crack down gray-market vendors on Tmall (Chu and Chiu 2014). Poor channel regulatory systems in emerging markets make gray-market activity a severe issue (Antia et al. 2006). Unlike counterfeit products, gray-market goods are branded products initially sold in a market designated by the manufacturer, but then resold, usually at a sharp discount, through channels not authorized by that manufacturer into a different market (Autrey et al. 2015). Gray-market activities are problematic for manufacturers as they result in discounted prices, erosion of brand image, and ultimately increased competition leading to lower manufacturer profit margins globally (Ahmadi and Yang 2000; Autrey et al. 2015).

Consistent with prior research on emerging markets (e.g., Johnson and Tellis 2008; London and Hart 2004; Luo 2003; Peng et al. 2005), we posit that the extent to which a marketplace can benefit manufacturers in emerging markets will largely hinge on its ability to address these institutional challenges. Asymmetric benefits across firms are contingent on firms' knowledge and experience and marketing strengths and capabilities. Moreover, foreign firms in emerging markets face more severe institutional challenges than indigenous firms due to the "liability of foreignness" (Hymer 1969; Zaheer 1995). This liability may moderate the main effects of the firms' knowledge and experience base and marketing strengths and capabilities. Figure 2.1 depicts the conceptual framework.

Market Knowledge and Experience

We distinguish three sources of knowledge and experience in this setting: (1) market position, (2) marketplace experience, and (3) product portfolio experience.

Market position. A superior market position is an important source of market power (Liu and Yang 2009). More powerful firms can extract more favorable concessions from channel members (Jacobson and Aaker 1985), are in a superior position to secure shelf space, and are less likely to be exploited by retailers (Gielens and Steenkamp 2007). On marketplaces, however, a brand regardless of whether it is small or big, can acquire an unabridged control of the marketing mix elements and safeguard itself without intervention from assertive retailers. Moreover, brands with a weaker local market position are more likely to have less rich market experience (Catry and Chevalier 1974) allowing them to benefit more from improved methods and procedures (Jacobson and Aaker 1985). Hence, they can gain more from the external resources provided by marketplaces to tackle institutional challenges (Pfeffer and Salancik 2003).

Channel experience. One of the great benefits of marketplace channels is that manufacturers obtain direct access to observe and interact with consumers, which otherwise is impossible in the reselling channel (Corsten and Kumar 2005). Once a manufacturer debuts on a marketplace, it starts to accumulate knowledge about local consumers and markets as well as experience with respect to market operations, distribution systems, and regulatory practices. Over time, these experiences accumulate into tacit knowledge and expertise (Cohen and Levinthal 1989) which can be translated to operations in other non-direct and non-digital channels (Malerba 1992). However, the added value of joining more than one marketplace may therefore be less substantial as the benefits of working through marketplaces may already have been accumulated. Therefore, when establishing a store on a new marketplace platform, a firm with prior marketplace experience will find it less beneficial.

Product portfolio. More diversified firms are more likely to maintain a rich mix of different knowledge stocks, which enriches its ability to recombine knowledge in related fields in a more complex and creative manner (Kogut and Zander 1992; Prabhu et al. 2005). A firm holding a wider product portfolio may thus gain and maintain a competitive advantage because of this knowledge spillover effect (Rothaermel et al. 2006). Hence, firms with rich product portfolios can identify and target finer segments more effectively, and satisfy the varying needs and wants more precisely (Quelch and Kenny 1995). In addition to knowledge spillovers, a large portfolio of products also helps firms to achieve economies of scale and scope in marketing and distribution, thus reducing unit costs (Varadarajan 1986). Therefore, less diversified firms need to rely much more on external infrastructures as offered by marketplaces than highly diversified firms to close the market knowledge gap.

Marketing Strengths and Capabilities

We consider three marketing strengths and capabilities: (1) brand equity, (2) advertising, and (3) innovativeness.

Brand equity. Brand equity assets such as name awareness, perceived quality association, and brand loyalty all have the potential to provide a brand with a price premium vis-à-vis competing brands (Aaker 1991). Marketplaces can help protect brand equity because marketplaces render the control rights over the marketing mix to manufacturers and these control rights are of utmost importance to build and maintain strong brands (Yoo et al. 2000). Not only do manufacturers readily control the price and price promotions, at the same time, they can achieve high levels of distribution services by partnering with the marketplace operator at a low cost. Brand manufacturers may thus more easily avoid intrachannel conflict while maintaining its initial and intended brand positioning. Hence, manufacturers with more brand equity may gain more from joining a marketplace.

Advertising. Advertising plays an important role in increasing brand awareness (Yoo et al. 2000) and creating a pull effect in the market. The insufficient infrastructure in emerging markets, however, makes the availability of advertised brands extremely low in the rural areas of emerging markets, thereby countering and even nullifying the pull effect. Marketplaces allow consumers in emerging markets, regardless of their geographic locations, more easy access to the products they learn about through ads. Advertised brands may thus benefit more from joining marketplaces.

Innovativeness. Understanding consumer heterogeneity is of critical importance to develop new products (Adner and Levinthal 2001). Access to consumers in the marketplace allows manufacturers to obtain these data, which in distribution channels are typically seized by retailers. More innovative manufacturers are better equipped to use this information to develop new products and services (Griffin and Hauser 1996). Therefore, innovative manufacturers can notably benefit more from joining a marketplace.

The Liability of Foreignness

Lack of market knowledge is obviously much less of an issue for local firms (Kogut and Zander 1992; Zeng and Williamson 2003), as they are generally familiar with local markets and consumers (Barkema and Vermeulen 1998; Makino and Delios 1996). Foreign firms, in contrast, rarely find it painless to understand the local consumers (Ganesh et al. 1997). Moreover, the usefulness of foreign firms' operational knowledge and experiences that are accumulated from earlier operations is highly contingent on the similarity of the new setting to those settings already experienced by the foreign firms (Cohen and Levinthal 1990). Infrastructure weaknesses can also be more pronounced for foreign firms than local firms. Foreign firms often need help from local partners with local knowledge to conduct business in the local environment (Inkpen and Beamish 1997). For example, foreign suppliers may need local distributors to help them deliver products to consumers. Cultural differences between foreign firms and local partners may entail considerable risk and ambiguities, which may lead to conflict (Barkema and Vermeulen 1997). In addition, manufacturers usually deter gray-market activities by ensuring distributors' compliances with resale restrictions, including fines, litigation, social ostracism, and termination (Antia et al. 2006). However, cultural distance limits the usage and effectiveness of these traditional tools that govern the relationship between a foreign firm and its distributor (Zhang et al. 2003). Compared to local firms, foreign firms may thus find it harder to enforce a distributor to work in their favor.

Foreignness galvanizes the marketplace's benefits even when knowledgeable. As we argue above, the more knowledge and experience a firm has accumulated about local market practices, the less it can benefit from a marketplace. Given that market knowledge is more of an issue for foreign firms than local firms, we expect the extent to which these three contingency factors regarding market knowledge and experience affect local firms and foreign firms to differ. The liability of foreignness exerts an extra layer of knowledge scarcity preventing firms from decoding and translating information, making the adoption of marketplaces more beneficial to foreign suppliers than local ones, even when they have already accumulated previous knowledge (Makino and Delios 1996). Therefore, we expect the negative main effects of knowledge and experience to be attenuated for foreign firms and the three interaction terms with foreignness to be positive.

Foreignness devaluates the marketplace's protective benefits of marketing strengths and capabilities. As we argue above, marketplaces endow manufacturers with the direct control over marketing-mix instruments. Foreignness reduces local market knowledge and makes it harder for manufacturers to make the right decisions. Whereas intermediaries help manufacturers curate assortments, set the right prices, provide the right store environment that appeals to local consumers and hence reach the right consumers for the brand, marketplaces leave foreign suppliers at their own devices. As such, the positive benefits of direct control can be diminished by not knowing the market sufficiently and firms may even run the risk of devaluating their core strengths in the foreign market. Therefore, we expect the positive main effects of marketing capabilities and strengths to be attenuated for foreign brand manufacturers.

Methodology

We use a quasi-natural experiment as offered by brand manufacturers' joining Alibaba's Tmall.com in China. We believe this setting to offer potential to derive interesting insights for two reasons. First, China is the leading e-commerce market in many ways -- it is the world's second economy but is characterized still by fairly basic brick-and-mortar distribution in large parts of the country (Clover 2015; eMarketer 2016), in which respect it is more similar to other major emerging markets like India and Brazil, than to the U.S. Moreover, as the largest marketplace in China, Alibaba's Tmall controls about 58% of China's B2C sales in 2015 (Statista 2016a). Second, the richness of the Tmall platform allows for generalizable insights. Since its introduction in 2008, numerous manufacturers from various categories have been attracted by the opportunities provided by Tmall and have opened stores on Tmall. So far, Tmall hosts more than 70,000 sellers from more than 30 industries (at the 2-digit SIC level) and serves 439 million active buyers (Osawa and Chu 2014; Statista 2016b).

Performance Evaluation: Event Study Approach

Two particular challenges in measuring the performance impact of joining online marketplaces are that (1) brand manufacturers do not disclose information on revenues or costs resulting from the marketplace entry, and (2) a temporal asymmetry exists between the investment and its potential payoff (see, e. g., Borah and Tellis 2014; Geyskens et al. 2002 for a similar reasoning). To overcome these issues, we rely on the well-established event study method and use abnormal returns around the announcement date to infer the financial implications of manufacturers' adopting a marketplace format. By using an event study methodology, we assume that the long-term impact of new public information on future firm cash flows is immediately captured by changes in the equity price of the focal manufacturer and hence use abnormal stock returns as the focal performance metric (Swaminathan and Moorman 2009). This performance metric is forward looking, integrates multiple dimensions of performance, and is less easily manipulated by managers than other measures (Geyskens et al. 2002). Given that manufacturers who announced joining Tmall originate from multiple countries, the typical market model in a single-country setting may no longer be appropriate (Beckers et al. 1996; Harvey 1991).

We follow Park (2004) and make use of the world market model to obtain the estimate of the expected returns by adding a world market factor into the model as shown in equation 1[2]:

(1) $$R_{ijt} = \alpha_{ij} + \beta_{ij} R_{mjt} + \gamma_i R_{wmt} + \mu_{ijt}$$

where R_{ijt} is firm *i*'s stock return in its home country *j* on day *t*, R_{mjt} is the market index return in country *j* on day *t*, R_{wt} is the world market index return on day *t*. The parameter estimates α, β, and γ are obtained by an ordinary least squares regressing R_{ijt} on R_{mjt} and R_{wmt} by using the daily stock return data for each firm over a period of 250 trading days, ranging from 260 to 10 calendar days prior to the event day (Fang et al. 2015; Swaminathan and Moorman 2009). We use the MSCI World Market Index as R_{wmt}, which covers 1,612 large and mid-cap stocks across 23 countries (Harvey 1991). We then use the estimates obtained from this model to predict the daily abnormal returns for each firm *i* originating from country *j* at time *t* as $AR_{ijt} = R_{ijt} - E(R_{ijt}) = R_{ijt} - (\alpha_{ij} + \beta_{ij} R_{mjt} + \gamma_i R_{wmt})$.

The effect of joining a marketplace may be spread over a couple of days, especially in a multiple-country setting. First, possible leakage of information prior to the event day and gradual dissipation of information after the event occurs at various speeds in different countries. Second, the asynchronism in stock market trading hours between the home and host countries prevents potential investors from simultaneously responding to major announcements (Chan et al. 1992). Third, the stock and local markets in different countries may have different schedules for such events because of national holidays or regional celebrations. To account for this possible gradual dissipation of information, the daily abnormal returns of a firm *i* from home country *j* are cumulated over a time window [t_1, t_2]:

$$CAR_{\mathrm{ij}}[\mathrm{-t}_1, \mathrm{t}_2] = \sum_{\mathrm{t=-t}_1}^{\mathrm{t}_2} AR_{ij} \ .$$

The selection of the appropriate event window is empirically determined on the basis

[2] Please note that we cannot use a Fama-French approach because Fama-French factors are only available for the American stock market.

of the significance of the CARs for various event windows surrounding the event day, beginning ten days before the announcement and ending ten days after the announcement. We choose the event windows with the most significant Patell t-statistics (Agrawal and Kamakura 1995; Swaminathan and Moorman 2009). Moreover, to correct for the firms' differences in variance in daily stock prices, we standardized the cumulated abnormal returns (SCAR_i) by using the standard deviation of abnormal returns over the estimation window (Aktas et al. 2007; Geyskens et al. 2002; Homburg et al. 2014).

Hypotheses Testing

To test our hypotheses, we regress the SCARs on our set of substantive predictors and control variables:

$$
\begin{aligned}
\text{SCAR}_{i,t} = {} & \gamma_0 + \gamma_1(MKTPOS_{i,t}) + \gamma_2(CHLEXP_{i,t}) + \gamma_3(PORWID_{i,t}) \\
& + \gamma_4(FOREIGN_i * MKTPOS_{i,t}) + \gamma_5(FOREIGN_i * CHLEXP_{i,t}) \\
& + \gamma_6(FOREIGN_i * PORWID_{i,t}) + \gamma_7(BRDEQY_{i,t}) + \gamma_8(ADV_{i,t}) + \gamma_9(INV_{i,t}) \\
& + \gamma_{10}(FOREIGN_i * BRDEQY_{i,t}) + \gamma_{11}(FOREIGN_i * ADV_{i,t}) + \gamma_{12}(FOREIGN_i * INV_{i,t}) \\
& + \gamma_{13}(FOREIGN_i) + \gamma_{14}(TOA_{i,t}) + \gamma_{15}(ROA_{i,t}) + \gamma_{16}(LVG_{i,t}) + \gamma_{17}(SEV_i) \\
& + \gamma_{18}(GDP_{i,t}) + \gamma_{19}(IMR_i) + \sum_{l=1}^{L} \gamma_{19+l}(YEAR_l) + \varepsilon_{i,t}
\end{aligned}
\tag{2}
$$

where *MKTPOS, CHLEXP, and PORWID* reflect the experience constructs market position in China, marketplace experience, and product portfolio, respectively. The firm's marketing strengths are captured by brand equity (*BRDEQY),* advertising in the local market (*ADV)*, and innovativeness (*INV)*. *FOREIGN* is a dummy variable that equals 1 if the firm does not originate from China. We further control for other variables that might affect abnormal stock returns. More specifically, we include total assets (*TOA*), return on assets (*ROA*), and financial leverage (*LVG*) (Dhaliwal 1986) because the adoption of the marketplace format may be more valuable for more profitable firms (Homburg et al. 2014). At the category level, we capture whether the firm operates in a service industry rather than in consumer product industries by including a service dummy variable (*SEV*). Finally, we augment the model with country- and year-specific influences by including the gross domestic product (*GDP*) in the year of opening the store, store opening year dummies (*YEAR*), and the inverse Mills ratio (*IMR*). All continuous independent variables are mean-centered to ease interpretation except for the inverse Mills ratio. To correct for a potential violation of the statistical independence assumption that exists because some firms have the same country of origin, we clustered standard errors at the country level (Auerbach and Hassett 2005). The error term $\varepsilon_{i,t}$ follows a normal distribution.

Correction for sample selection. In estimating this model, we may encounter a potential selection bias. Firms may have relevant private information that is not fully known to the market but that influences their decisions to join a marketplace in an emerging market. However, we can only observe firms that actually announced store establishment at Tmall in public media sources (i.e., Open_Store$_{i,t}$ = 1). To account for this potential selection effect, we use a two-stage Heckman selection model (Heckman 1977) and estimate the following binary probit regression to explain the probability of opening a store on Tmall:

$$\begin{aligned}\Pr(\text{Open\_Store}_{i,t}) = {} & \lambda_0 + \lambda_1(CHLEXP_{i,t}) + \lambda_2(BRDEQY_{i,t}) + \lambda_3(SGA_{i,t}) + \lambda_4(INV_{i,t}) \\ & + \lambda_5(ADPRAT_{i,t}) + \lambda_6(FOREIGN_i) + \lambda_7(TOA_{i,t}) + \lambda_8(ROA_{i,t}) \\ & + \lambda_9(LVG_{i,t}) + \lambda_{10}(SEV_i) + \sum_{l=1}^{L} \lambda_{10+l}(YEAR_l) + \zeta_{i,t}\end{aligned} \tag{3}$$

We include an exclusion variable that is expected to affect a brand manufacturer's decision to open a store on a marketplace but does not affect performance. Specically, we add the cummulative adoption rate (*ADPRAT*) - the percentage of firms originating from the same home country as the focal firm that have already opened a Tmall store. To meet the relevance criterion, we argue that firms may mimic the adoption decision of its own country's peers (Gielens and Dekimpe 2007). To meet the exclusion restriction, we argue that peer firms collectively either cannot observe or measure the focal firm's omitted variable(s) or cannot act on those variable(s) strategically (Germann et al. 2015).

In addition, we include the same variables in the selection model as in Eq. (3), unless the required information was not available for the suppliers that uniquely feature in the selection sample (see, e.g., Robinson et al. 2015; Swaminathan and Moorman 2009 for a similar practice). In addition, we use a manufacturer's selling, general, and administrative expenses (*SGA*) as a proxy measure for its advertising and its brand equity, as this construct is available for all firms in the selection sample (Gielens et al. 2017). Furthermore, we add year-fixed effects to control for time fluctuations. To ensure temporal separation between the independent variables and the decision adoption, we use one year lagged independent variables.

We estimate Eq. (3) on a sample of 1,571 firms. We include firms that are a reasonable proxy for our set of focal firms by selecting proxy firms whose size ranges within +/-50% of the focal firm's size and that operate in the same industry (based on the four-digit SIC code) (Swaminathan and Moorman (2009). All proxy firms are evaluated in the same year as the focal firm's decision to open a store on Tmall. We draw on the parameters to compute the inverse Mills ratio (*IMR*), which we add as a regressor to Eq. (3).

Data

Sample Composition

Following recent research on event studies (Fang et al. 2015; Homburg et al. 2014), we follow four steps to define the sample.

First, we identify all public firms that launched a store on Tmall from 2008 to 2015 by manually researching each store in 20 categories[3] on Tmall.com. In addition, in our sample we only keep public firms which, in their home country, are traded on a stock exchange

[3] Please see Tmall's category definition at http://about.tmall.com/tmall/fee_schedule.

which belongs to the World Federation of Exchange (WFE).[4] Membership of the WFE requires the stock exchange to be significant within its country of origin, to be regulated by a supervisory body, to be within a statutory framework, and to be a public good (World Exchanges 2017), which ensures that the stock exchanges demonstrate leadership in the public and regulated marketplace. The stock exchanges we maintained in our sample are listed in Web Appendix W1. In addition, we exclude all cross-listed equities and retain the stock price in the firm's home country. For example, China United Network Communications Group is listed on three pubic stock exchanges; that is, Shanghai Stock Exchange, Hong Kong Stock Exchange, and New York Stock Exchange. Because China is the home country, we retain China United's listing on the Shanghai Stock Exchange and exclude the listings on both the Hong Kong Stock Exchange and New York Stock Exchange.

Since accurate event dates are critical to ensure a valid event study (Brown and Warner 1985), we retrieve the event date of the announcements through two sources: (1) disclosures, press releases, and articles obtained from the Factiva and LexisNexis databases, which provide access to extensive documents from various news and business sources as well as company website searches, and (2) the Internet Archive Digital Library (https://archive.org/web), which provides access to past online websites and allows us to track when a website was created (Babić Rosario et al. 2016). After comparing the event date from the two sources, we retain whichever is earlier as the final event date. As a result, we compile a sample of 501 announcements.

Next, we cross-validate the events for which a possible confounding event occurred within 20 days of the announcement of the Tmall store opening by searching on Factiva and LexisNexis. Confounding events include such activities as stock splits and structural stock

[4] http://www.world-exchanges.org/home/

changes, damage suits, product recalls, dividends, joint venture announcements, and merger and acquisition activities. Moreover, if a firm launches more than one store on Tmall, we only retain the earliest observation for this firm to avoid confounding effects of earlier events on later events. Using this criterion, 440 announcements are retained. To ensure that equity data are available for the 250 trading days required in the market model, we cross-checked the firm in the DataStream database and found equity data to be available for 416 announcements.

Finally, research in marketing (Aksoy et al. 2008) and finance (Cowan 1992) suggests that abnormal returns can be sensitive to the presence of outliers. Consistent with this line of research, we trim the top and bottom 1% of the abnormal returns to ensure that extreme outliers do not influence our results. After applying this criterion, the final sample consists of 408 announcements from firms in 39 industries (at the two-digit SIC level) between 2008 and 2015 across 20 countries or regions.

The manufacturers in our sample are active in various categories, such as automobiles (e.g., Ford, Toyota, and Volkswagen), consumer electronics (e.g., Apple, Lenovo, and Philips), personal care (e.g., L'Oréal, Henkel, and Procter & Gamble), apparel (e.g., GAP, Hugo Boss, and VF Corporation), packaged food (e.g., China National Cereals, Oils and Foodstuffs Corporation, General Mills, and Kellogg's), alcoholic drinks (e.g., Budweiser, Diageo, and Kweichow Moutai), as well as pharmaceuticals (e.g., Harbin Pharmaceutical Group, Pfizer, and Johnson & Johnson). The sample spans well-known billion dollar companies, like Unilever and Royal Dutch Shell, but also covers a variety of smaller, unknown suppliers such as Joyoung and Septwolves. The countries in our sample represent approximately 75% of the world's economy, and are graphically depicted in Figure 2.2.

Measures

We measure market position as a firm's weighted market share of all brands it sells in China. Marketplace experience is a dummy variable that equals 1 when the firm previously entered JD.com, the second largest marketplace in China, before entering Tmall, and 0 otherwise. A firm's portfolio width is measured as the number of categories the brand manufacturer operates in China. To capture brand equity, we use a dummy variable that equals 1 when the firm is listed in Brand Finance's Global 500 Most Valuable Brands list, and 0 otherwise. Advertising is a firm's total annual advertising expenditure in China. We measure innovativeness as the logarithm of the firm's annual (global) research and development expenditures (Banerjee et al. 2015). All independent variables are measured in the year prior to Tmall entry.

Table 2.2 provides a more extensive overview of the operationalization of the various measures, and Table 2.3 summarizes the descriptive statistics and correlations of the variables.

Results

Does Marketplace Adoption Influence Abnormal Returns?

Analysis of the daily abnormal returns for 10 days around the event, as described in Table 2.4, reveals that the day after the announcement exhibits a significant positive stock market reaction ($p < .05$). The effect at the day of the announcement itself is not significant. This is, however, encountered frequently in international settings where time differences have to be factored in (see e.g., Park 2004). The abnormal return on the day before the announcement is also not significant, indicating no evidence of information leakage before the announcement. With a positive abnormal stock returns of .13% ($p < .05$), on average, a manufacturer's performance is enhanced when a manufacturer joins a marketplace platform. This implies that with an average increase of .13% in the cumulative abnormal return, the shareholder value of a median-sized manufacturer (based on manufacturers' market capitalization on the day before the announcement) with a market capitalization of $2,141 million is augmented (adjusted for overall market movements) by $3 million in one day.

Stock markets thus acknowledge that marketplaces can effectively help manufacturers to address the potential challenges in emerging markets.

Although the abnormal returns are, on average, significant and positive for manufacturers, stock markets recognize that not all manufacturers can reap benefits from adopting marketplaces to the same extent, as is reflected by the substantial variation in CARs as shown in Figure 2.3. While 49% reported a positive effect, 51% experienced a negative outcome. Some manufacturers that gained the most are Nongshim and Gree Electric, with CARs of 3.0% and 2.2%, respectively. With a market capitalization of $264 million, Nongshim, for instance, gained $8 million in shareholder value. Still, some of the biggest losers were Mengniu Dairy and Li-Ning, with CARs amounting to -1.8% and -1.3%, who lost about $156 million and $52 million, respectively, in shareholder value. To understand the heterogeneity in manufacturers' CARs we relate them to the set of knowledge and marketing strength constructs as detailed in Eq. (2).

How Do Contingency Factors Influence the Value Creation of Marketplace Platforms?

Table 2.5 presents the results for the selection model. The likelihood ratio test shows good model fit ($\chi^2(15) = 1208.13$, $p < .001$). The hit rate of 96.3% is significantly better than chance ($61.5\% = \alpha^2 + (1- \alpha)^2$, with $\alpha = 26.0\%$; Morrison 1969). In terms of variance inflation factors (VIFs), none of the variables exceeds the commonly used threshold of 10 (maximum VIF = 1.47) (Hair et al. 2010). The exclusion restriction variable is significant and positive thereby indicating that firms mimic the adoption decision of its own country's peers ($p < .01$). Moreover, suppliers with higher brand equity ($p < .01$) that are more innovative ($p < .01$) have a higher chance of entering Tmall.

Table 2.6 reports the results of our contingency analysis. We also report the relative effect sizes for all estimates (Steenkamp et al. 1999). The correlations between all variables are below the recommended threshold of .8 (Judge et al. 1988), and none of the VIFs exceeds 10 (maximum VIF = 2.08) (Hair et al. 2010). Thus, multicollinearity is not likely to be a problem. The estimate of the inverse Mills ratio is significant (γ_{19} =.177, $p < .05$), implying that a selection correction is indeed warranted. The positive sign suggests that, on average, unobserved factors that make a firm more likely to open a store on Tmall tend to have a positive effect on the shareholder value implications.

With respect to market knowledge and experience, the results indicate, as expected, a negative and significant main effect (γ_1 = -.756, $p < .01$) for market position and for product portfolio width (γ_3 = -.036, $p < .01$), indicating that less diversified firms can benefit more from marketplaces. However, a positive effect (γ_2 = .363, $p < .01$) is reported for marketplace experience on firm returns and indicates that firms with prior experience of a marketplace channel can reap more benefits when joining a new marketplace. A potential explanation is that, when joining a new marketplace, a firm with prior marketplace experience has a learning-by-doing advantage (Argote and Ingram 2000). Previous learnings from one marketplace can provide manufacturers with a roadmap of pitfalls to avoid, which reduces the inherent risk of entering new marketplaces and making appropriate choices for sourcing, production, marketing, organizational, and other activities when later entering a new marketplace (Shaver et al. 1997).

Regarding the moderating effect of foreignness, the results lend support for its moderating effect on market position (γ_4 = 2.768, $p < .01$), but not on marketplace experience (γ_5 = -.096, $p > .10$) or portfolio width (γ_6 = .009, $p > .10$). Thus, for foreign firms with a strong market position in the host country, the value created by adopting marketplaces is stronger, thereby indicating that indeed a certain level of knowledge is required to allow foreign firms to be capable of decoding information and to harvest benefits from marketplaces.

With respect to marketing strengths and capabilities, we find that firms with high brand equity can benefit more from joining marketplaces ($\gamma_7 = .361$, $p < .01$). Moreover, we also find that firms that advertise substantively in the Chinese market can benefit more ($\gamma_8 = .017$, $p < .01$). Additionally, in contrast to our expectations, we find a negative effect of R&D ($\gamma_9 = -.031$, $p < .01$). This result may be explained as follows. When a manufacturer heavily relies on new products, more retailer support may be needed. New products represent a risk to consumers (Arndt 1967) which retailers may help to overcome. The retailer's decision to list and hence procure the new product may signal a certain level of trust in the success of the new product (Pavlou 2003). By operating on marketplaces the manufacturer foregoes this external seal of retailer commitment and thus potentially lowers the success of new products.

With respect to the moderating effects of foreignness, the results indicate that foreign firms that invest less in advertising, and therefore have lower brand awareness in the host country, can benefit more from joining a marketplace as indicated by the negative and significant effect ($\gamma_{11} = -.038$, $p < .01$). In contrast to our expectations, we find that an innovative, foreign firm may benefit more from the consumer knowledge offered by marketplaces when adopting marketplaces ($\gamma_{12} = .023$, $p < .10$).

The relative effect sizes indicate higher than average effects[5] for all main effects and two interaction terms, namely, advertising and market position. Specifically, for local firms, advertising, portfolio width, and marketplace experience matter the most, while, for foreign firms, advertising, market position, and innovativeness are more important.

[5] With 25 parameter estimates, the average relative effect size is .04.

To gain a better understanding of the moderating impact of country of origin, we plot the significant interactions in Figure 2.4 (Cohen et al. 2003). As can be seen from Figure 2.4 Panel A, the inverse association between a local firm's experience depth and market value ($\gamma = -.756$, $p < .01$) is reversed for foreign firms ($\gamma = 2.012$, $p < .05$). Local firms that hold a market position of more than .226, even stand to incur market value losses. This finding indicates that, *ceteris paribus*, a foreign firm that already has a deeper understanding of the local market can achieve a higher predicted market value, and thus financially benefit more than its local rivals when adopting a marketplace.

As for advertising, our results indicate that the effect diverges for foreign firms and local firms (see Figure 2.4 Panel B). Local firms that are heavily involved in advertising can reap more benefits when joining marketplaces ($\gamma = .017$, $p < .01$). In contrast, this effect reverses for foreign firms: foreign firms who spend less on advertising benefit more from adopting a marketplace format ($\gamma = -.021$, $p < .01$).

Again, the impact of R&D diverges for foreign and local firms. Figure 2.4 Panel C indicates that local firms which are more innovative benefit less from adopting marketplaces ($\gamma = -.031$, $p < .01$) and may even stand to lose if their R&D spending exceeds more than $54.355 million. In contrast, the negative effect of innovativeness on market value is nullified for foreign firms ($\gamma = -.008$, $p > .10$).

Robustness Checks

To further increase confidence in the results, we conducted various robustness checks. First, we conduct tests to verify whether the positive evaluation of marketplace adoption is a temporary reaction that is quickly corrected afterward. Specifically, we use a graphical test by plotting CARs over days before or after the announcements and a pooled regression of the abnormal returns on the number of trading days (up to 100 days) since the announcement.

Second, we verify the robustness of our results with regard to the calculation of abnormal returns and alternative event windows.

Table 2.7 summarizes all the concerns that may potentially affect our findings, along with details on how we assess their robustness. In addition, Web Appendix Tables 2.W2-2.W4 and Figure 2.W1 exhibit the results of each robustness check. Small numerical differences notwithstanding, all of our reported results are substantively robust.

Discussion

Due to the largely unorganized retail structure in emerging markets, global manufacturers often find it impossible to simply lean on retailers to reach all potential consumers, rural or urban, the way they are used to in developed economies (Kumar et al. 2015). The advent of online marketplaces, however, provides manufacturers a new model to tackle the infrastructural and knowledge challenges facing them in serving these emerging markets. Unsurprisingly many branded manufacturers are flocking to this model that offers them the promise of reaching their consumers directly without having to make upfront investments in logistics or infrastructure.

On paper, this model seems to be a winning proposition, especially given the increasing popularity among consumers in emerging markets like China and India. Still, online marketplaces still involve direct distribution, a function and skill very few brand manufacturers have mastered so far, especially not when targeting large-scale access in virtually untapped markets. To learn whether and to what extent brand manufacturers stand to gain from working through marketplaces in emerging markets, we collected data on over 400 Chinese and foreign brand manufacturers opening a storefront on China's largest online marketplace, Tmall, and assess to what extent these firms' market value changes following the announcement. To further gain insight into to whom gains may arise, we use a contingency framework and relate manufacturers' short-term abnormal returns to manufacturers' market knowledge and marketing strengths. The findings can provide comprehensive guidance for manufacturers, global or local, to assess whether and to what extent they can take advantage of online marketplaces to thrive in emerging economies.

1. *Do firms benefit from joining marketplaces?* Although we find an average positive CAR, indicating that brands can gain from online marketplaces, the substantial variation in CARs clearly indicates that online marketplaces are not a one-size-fit-all solution for all companies handling the daunting challenges in emerging markets. We find that the performance implications of adopting marketplaces are largely contingent on manufacturers' market knowledge and brand strengths.

2. *Is knowledge golden*? When scrutinizing the issue through the lens of the knowledge-based view (Grant 1996), we expect that more knowledgeable firms require less external infrastructure as offered by marketplaces to thrive. We find that local brands with a less established market position and all brands with less extensive product portfolios, irrespective of origin, reap more benefits when working with marketplaces, indicating that marketplaces may help these manufacturers overcome some of the knowledge hurdles in the Chinese market. Common belief may suggest that manufacturers with wider portfolios are more experienced and fare better than specialized manufacturers in dynamic environments. On the contrary, our findings show that marketplaces allow specialized manufacturers to closely observe consumers and understand the market dynamism to compensate their inadequacy of broad knowledge. Manufacturers with more marketplace experience, however, can substantively benefit more from joining a new marketplace. The learnings from one marketplace channel can significantly increase the efficiencies and reduce the uncertainties associated with new marketplace operations. Indeed, the extent to which manufacturers can achieve greater gains in financial performance depends on how fast they can learn to create synergy with online marketplaces and the previous learnings from one marketplace increase

the tendency for learning curves to “plateau” or level off (Epple et al. 1991). We, therefore, recommend firms, not to rush into a giant marketplace like Tmall but to first accumulate some operational experience in other marketplace channels.

3. *Can marketplaces prevent marketing strengths turning into weaknesses*? Unlike the common fear that marketplaces may bring substantive risk to valuable brands, our results indicate that marketplaces may safeguard their brand equity. In a marketplace, manufacturers can control the marketing mix instruments, which is a necessity when protecting brand equity. In a similar vein, we find that heavy advertisers may benefit from joining a marketplace, but only when the firm is a local player. Foreign firms who spend less on advertising benefit more from adopting a marketplace format than foreign firms who spend heavily. Thus, a foreign firm with a lower advertising budget will generate less brand awareness but can use a marketplace as a powerful tool to compensate for this weakness. On the contrary, a local firm that heavily invests in advertising is more likely to cultivate higher brand equity and can utilize a marketplace to preserve its brand equity.

4. *Can marketplaces galvanize R&D?* Marketplaces endow manufacturers with the access to consumers to collect consumer information, a necessity for product innovation and thus may enable more innovative firms to galvanize their R&D inputs. However, we find that this does not hold for local and Chinese firms alike. Foreign firms’ performance outcomes from joining a marketplace do not appear to be influenced by their innovativeness. On the other hand, local firms that rely heavily on new products, may benefit more from retailer rather than marketplace support, as retailers may help to build trust (Pavlou 2003). In addition, being a local player, the firm may have stronger relationships in place with the local retailers, thereby allowing them to leverage the retailer support more to their advantage. Forsaking this support in favor of marketplaces may thus harm local, innovative firms.

5. *So, is foreignness a liability when working on marketplaces*? The answer is not unqualifiedly positive. Unlike previous international business studies (e.g., Johanson and Vahlne 2009; Ojala and Tyrväinen 2007) that conclude that foreign firms are in an inferior position when competing with local firms, we find that foreign firms do not necessarily in all cases gain less from working with online marketplaces compared with their local counterparts. One possible reason for this is that online marketplaces are a brand-new model for each and every firm, regardless of country of origin. Since foreign and local firms actually stand on the same starting line, both face potentially steep learning curves (Yelle 1979). Therefore, the extent to which manufacturers can achieve greater gains in financial performance depends on how fast they can learn to create synergy with online marketplaces, through channel and product experience, or brand equity, regardless of country of origin. Still, when relying heavily on advertising to communicate with local consumers, foreignness can indeed be a liability when opening a store on a marketplace.

Limitations and Further Research

This study and the interpretation of the results must be considered in light of various general and special limitations, some of which suggest possible avenues for future study. First, we use shareholder value as the focal performance metric. Although shareholder value is generally used in marketing-finance interface studies (Swaminathan and Moorman 2009), it is not without limitations (Homburg et al. 2014). Therefore, future work may consider other metrics, such as sales and profit, to evaluate the impact of joining a marketplace.

Second, this study mainly focuses on the Chinese marketplace performance. Future research might investigate marketplaces in other emerging markets, such as Flipkart.com in India. The change in the country characteristics may lead to different performance implications. For example, Johnson and Tellis (2008) report significant differences between entry in the Chinese and Indian markets. This future line of of research will help manufacturers and academic researchers to better understand the mechanisms behind the scene.

In addition, although this study accounts for market knowledge and brand strength contingencies, further important moderators may be of central interest for managerial decisions. For example, a firm's operational experience (global vs. regional), brand positioning (global vs. local) may affect the performance of expansion in different markets (Meyer 2001; Townsend et al. 2009). Furthermore, previous studies (Roth 1995) have found culture and socioeconomics to influence consumers' perceptions of brands in foreign markets. Therefore, an investigation of the impact of underlying cultural, economic, and administrative differences between the home country and host country may be another fruitful area for future studies.

Finally, further research could also examine the potential for channel conflict due to the adoption of the marketplace. How will the existing channel members react to the new channels? What kind of remedy can the manufacturers take to mitigate the channel conflicts? This line of exploration may further contribute to the successful development of marketplace operations in the long run.

Table 2.1: Three models of selling to consumers

	Reselling	Marketplace	Direct
Control rights			
Manufacturers fully control the direct access to consumers	×	✓	✓
Manufacturers fully control marketing mix	×	✓	✓
Manufacturers fully control product de/listing	×	✓	✓
Manufacturers fully control store layout	×	✓	✓
Operational responsibilities			
Manufacturers have to build retail space (by themselves)	×	×	✓
Manufacturers have to acquire new consumers (by themselves)	×	×	✓
Manufacturers have to maintain retail space (by themselves)	×	×	✓
Manufacturers have to handle logistics (by themselves)	×	×	✓

✓ means that manufacturers have full control or take full responsibility

× means that manufacturers do not have full control or do not take full responsibility

Table 2.2: Summary of measures and data sources

Variable (label)	*Data Source*	*Measure*[a]
Market Position *(MKTPOS)*	Euromonitor, Mintel Oxygen	A firm's weighted market share in China (range is [0, 1]), whereby the weight is the percentage of a firm's total sales in the category.
Marketplace Experience *(CHLEXP)*	Factiva, Firm websites, Internet Archive Digital Library	Dummy variable that equals 1 when a firm launches a marketplace store on JD.COM, and 0 otherwise.
Portfolio Width *(PORWID)*	Euromonitor, Mintel Oxygen	Number of categories that a firm operates in China.
Brand Equity *(BRDEQY)*	BrandFinance.com	Dummy variable that equals 1 when a firm is listed in Brand Finance's Global 500 Most Valuable Brands list, and 0 otherwise.
Advertising *(ADV)*	Kantar Media	Annual advertising expenditure in China (Unit: Million Chinese Yuan).
Innovativeness *(INV)*	Compustat	Logarithm of annual R&D expenditure (Unit: Million US Dollar); Item: XRD.
Foreign Firm *(FOREIGN)*	Compustat	Dummy variable that equals 1 when a firm does not originate from China, and 0 otherwise; Item: LOC.
Total Assets (*TOA*)	Compustat	Annual total assets; Item: AT.
Return on Assets *(ROA)*	Compustat	A firm's net income divided by total assets; Items: NI/AT.
Financial Leverage *(LVG)*	Compustat	A firm's total liabilities divided by shareholder equity; Items: LT/SEQ.
Service *(SEV)*		Dummy variable that equals 1 when a firm's two digit SIC code is between 70 and 89, and 0 otherwise.
GDP of Home Country *(GDP)*	Compustat	GDP of a firm's home country j.
SGA*(SGA)*	Compustat	A firm's sales and general administrative expenses (SGA); Item: SGA.
Adoption Rate *(ADPRAT)* [b]	Compustat	Percentage of firms from the focal firm's home country *j* that adopted Tmall.

[a] All variables are measured in the year prior to event year.

[b] Variable featuring exclusively in the selection equation.

Table 2.3: Descriptive statistics

	1	2	3	4	5	6	7	8	9	10	11	12
1 Market Position	1.000											
Marketplace Experience	-.017	1.000										
3 Portfolio Width	.425	-.051	1.000									
4 Brand Equity	.313	-.217	.292	1.000								
5 Advertising	.325	-.027	-.042	.280	1.000							
6 Innovativeness	.103	.010	.239	.178	-.007	1.000						
7 Foreign Firm	.009	-.209	.187	.330	-.019	.461	1.000					
8 Total Assets	.159	-.213	.058	.540	.271	.059	.236	1.000				
8 Return on Assets	.062	.151	.089	.000	.074	-.053	-.009	-.071	1.000			
9 Financial Leverage	-.029	-.064	.097	.045	-.045	.239	.220	-.020	.008	1.000		
10 Service	.177	-.233	-.129	.137	.085	-.145	-.130	.367	-.087	-.071	1.000	
11 GDP of Home Country	-.019	-.165	.009	.157	-.021	.025	.463	.133	.090	-.109	-.030	0

[a] For dummy variables, we report the proportion of observations having a value of one.

Table 2.4: Abnormal stock returns

Table 2.4A: AAR_t

Event Day	Mean AR	Percentage Positive AR	Patell *t*
-10	-.09%	40.69%	-.83
-9	.03%	48.28%	.63
-8	-.16%	45.83%	-1.31
-7	.13%	50.00%	1.52
-6	-.02%	47.55%	-.48
-5	-.02%	49.76%	-.16
-4	.01%	51.23%	.53
-3	-.14%	43.63%	-1.15
-2	.17%	51.96%	1.46
-1	-.14%	42.16%	-1.49
0	-.09%	43.63%	-.80
1	.13%	49.27%	2.03**
2	.00%	45.10%	.52
3	-.24%	42.40%	-1.20
4	-.04%	45.83%	-.23
5	.06%	48.28%	.85
6	-.09%	45.59%	-1.12
7	-.14%	43.63%	-1.73
8	-.02%	48.04%	.34
9	-.02%	48.28%	.40
10	.01%	45.83%	.59

Table 2.4B:CAAR$_{[-t1,t2]}$

Event Day	Mean CAR	Mean SCAR	Percentage Positive CAR	Patell t
-10 to +10 days	-.07%	-1.78%	48.04%	-.36
-3 to +3 days	-.29%	-0.98%	45.48%	-.2
-3 to +2 days	-.06%	1.04%	47.19%	.21
-3 to +1 days	-.09%	-0.47%	46.70%	-.1
-2 to +2 days	.08%	3.99%	50.00%	.81
-2 to +1 days	.07%	2.65%	48.17%	.55
-1 to +1 days	-.10%	-1.03%	45.48%	-.21
0 to +1 days	.03%	3.64%	49.39%	.74
0 to +2 days	.05%	5.06%	50.12%	1.02
0 to +3 days	-.18%	1.80%	46.94%	.36
+1 to +2 days	.15%	9.46%	46.46%	1.91*
+1 to +3 days	-.08%	4.75%	46.46%	.96
+2 to +3 days	-.21%	-1.10%	45.48%	-.22

***$p < .01$, **$p < .05$, * $p < .10$

Table 2.5: Selection mode results

Selection Model Component	Coefficient	Standard Errors
Intercept	-3.992	.58***
Main Effects		
Marketplace Experience *(CHLEXP)*	7.446	154.00
Brand Equity *(BRDQEY)*	.780	.25***
Advertising *(SGA)*	2.320	2.19
Innovativeness *(INV)*	.102	.02***
Adoption Rate *(ADPRAT)*	2.721	.30***
Controls		
Foreign Firm *(FOREIGN)*	-.640	.15***
Total Assets (*TOA*)	.125	.04***
Return on Assets *(ROA)*	.004	.01
Financial Leverage *(LVG)*	.040	.26
Service *(SEV)*	-.506	.22**
Home Country's GDP *(GDP)*	.090	.02***
Year Fixed Effects (*YEAR*)	Included	
Hit Rate	96.3%	
LR-χ^2	1208.13***	

***$p < .01$, **$p < .05$, * $p < .10$

Table 2.6: Regression results

Dependent Variables: SCAR[+1,+1]	Estimate	*t*-value	Relative Effect Size
Intercept	-.146	-.88	
Market Knowledge and Experience			
Market Position *(MKTPOS)*	-.756	-5.27***	.067
Marketplace Experience *(CHLEXP)*	.363	4.27***	.061
Portfolio Width (PORWID)	-.036	-7.04***	.074
Market Position * Foreign Firm	2.768	2.91***	.048
Marketplace Experience * Foreign Firm	-.096	-.69	.014
Portfolio Width * Foreign Firm	.009	.39	.008
Marketing Strengths and Capabilities			
Brand Equity *(BRDQEY)*	.361	3.13***	.051
Advertising *(ADV)*	.017	11.31***	.081
Innovativeness *(INV)*	-.031	-7.35***	.075
Brand Equity * Foreign Firm	.151	1.31	.025
Advertising * Foreign Firm	-.038	-5.89***	.070
Innovativeness * Foreign Firm	.023	1.75*	.033
Control Variables			
Foreign Firm *(FOREIGN)*	-.103	-.97	.019
Total Assets (*TOA*)	-.001	-1.81*	.033
Return on Assets *(ROA)*	-.010	-2.54**	.044
Financial Leverage *(LVG)*	.353	2.32**	.041
Service *(SEV)*	.126	1.09	.021
Home Country's GDP *(GDP)*	-.009	-1.11	.022
Year Fixed Effects (*YEAR*)	Included		
Selectivity Parameter			
Inverse Mills Ratio (*IMR*)	.177	2.56**	
R^2	.10		

***$p < .01$, **$p < .05$, * $p < .10$

Table 2.7: Robustness checks

Concern	Proposed Robustness Check	Findings
Whether the positive evaluation of marketplace adoption is not just a temporary reaction that is quickly corrected afterward	We plot CAARs over days before or after the announcements.	CAARs stayed at a higher level after the event, indicating that the positive evaluation is not just a short-term lift that evaporates in the days following the announcement. See Figure 2.W1.
	We estimate a pooled regression of the abnormal returns on the number of trading days (up to 100 days) since the announcement.	This estimation shows no significant drift (i.e., b_{time}=0.00, p = 0.87), indicating that the initial positive evaluation is not merely a short-term reaction that is corrected in the subsequent weeks (Geyskens et al. 2002; Homburg et al. 2014).
Whether the results remain stable for alternative calculations of the abnormal stock returns	We reestimate the models with abnormal returns calculated by the market model, which has been widely used in prior studies (Geyskens et al. 2002).	The results remain stable in terms of directions and significance. See W2.
	We reestimate the models with unstandardized abnormal stock returns as the dependent variable (Swaminathan and Moorman 2009).	The results remain stable in terms of directions and significance. See W3.
Whether the results remain stable for alternative event windows	We reestimate the models with alternative windows – (1) day 1 to day 2, (2) day 1 to day 3, and (3) day 0 to day 2.	The results remain stable in terms of directions and significance. See W4.

Figure 2.1: Conceptual framework

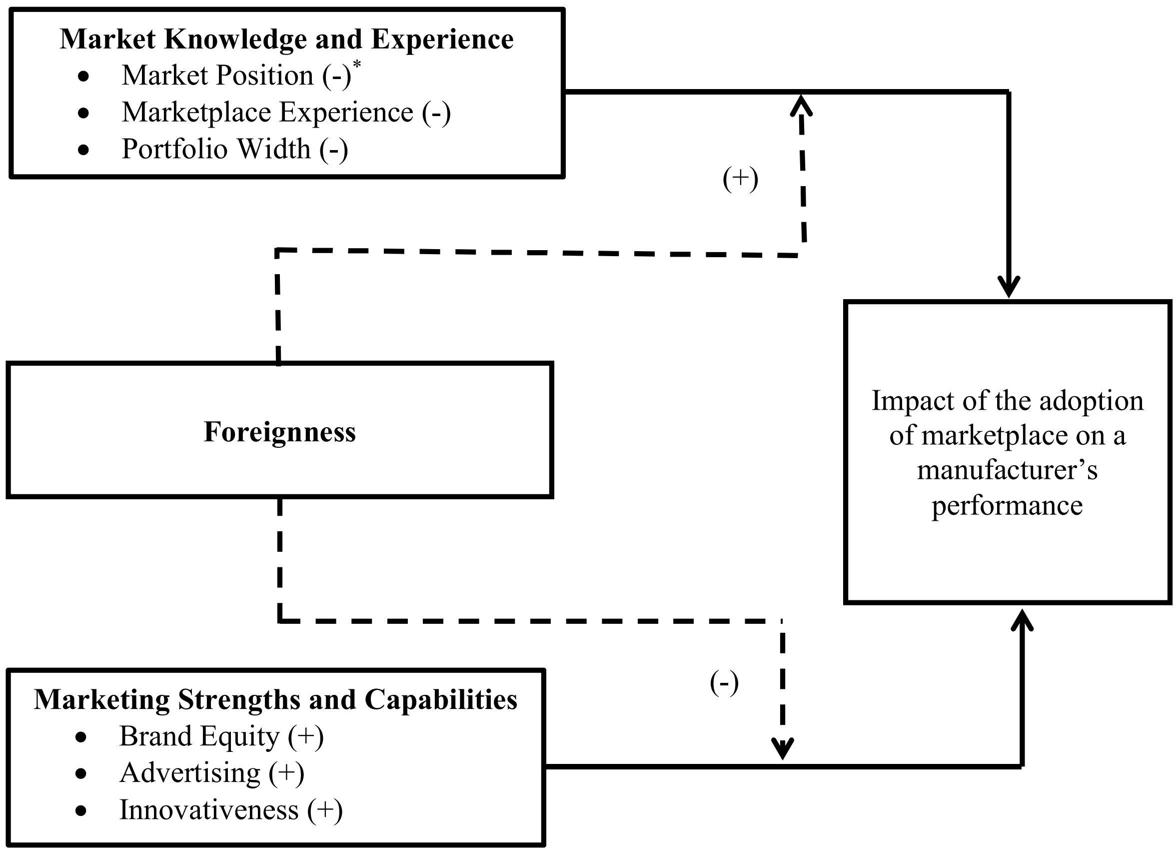


Figure 2.2: Countries represented in the sample and number of firms in each country

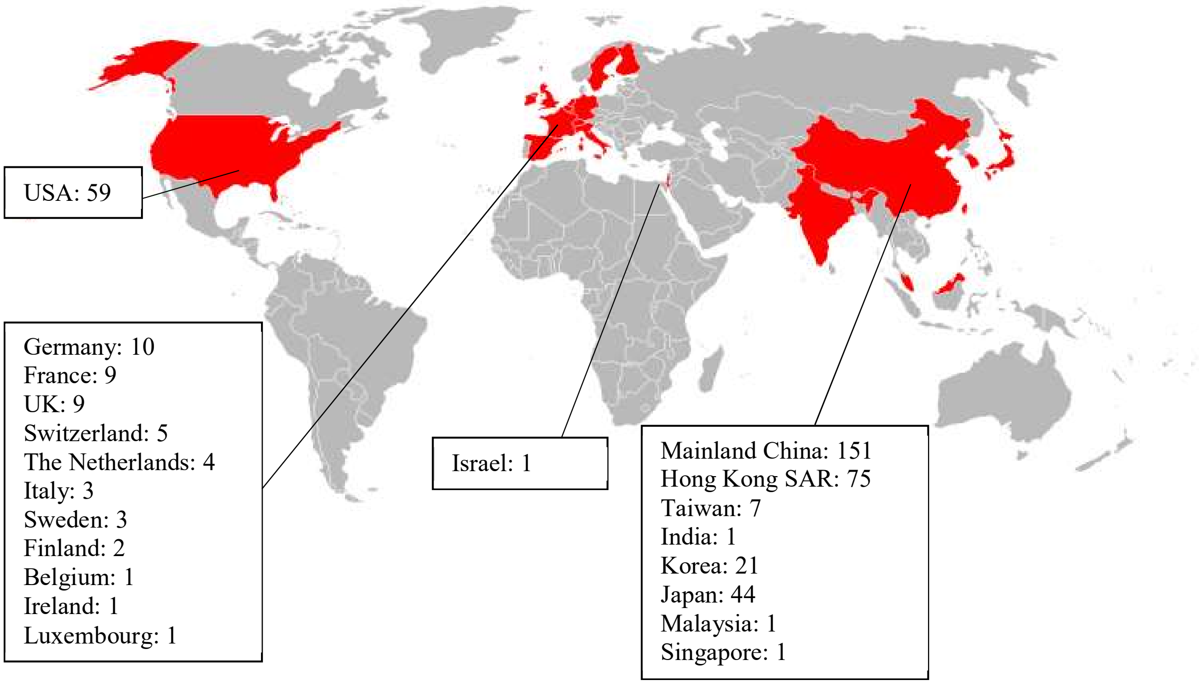


Figure 2.3: Distribution of cumulative abnormal returns

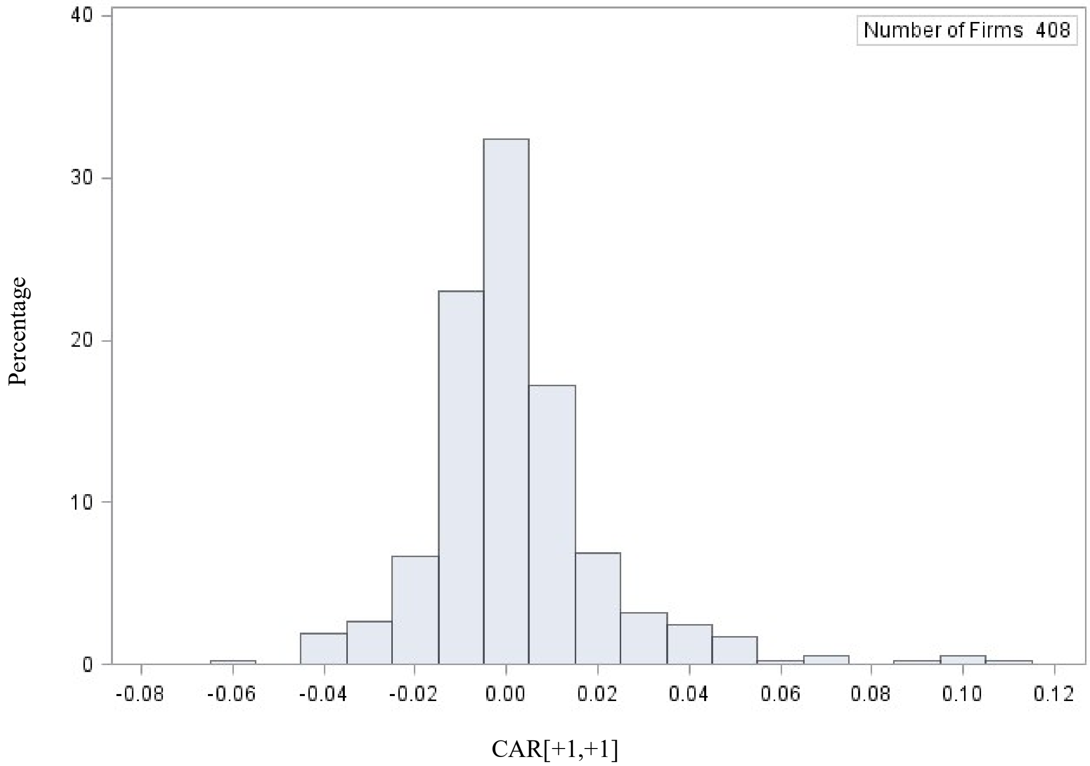


Figure 2.4: The moderating effects of liability of foreignness

Figure 2.4A: Market Position

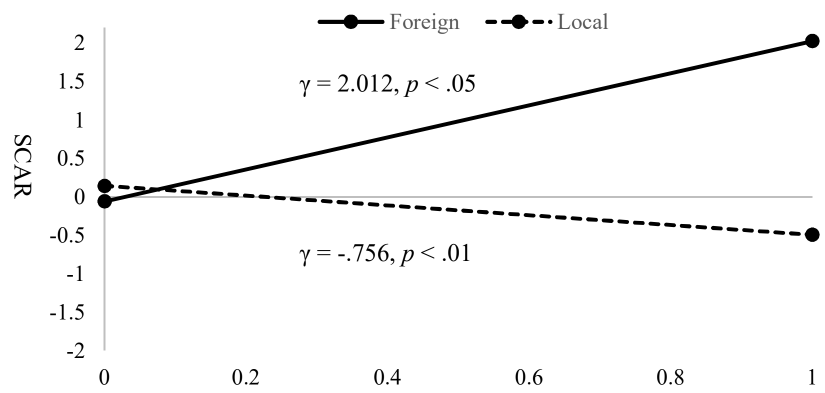


Figure 2.4B: Advertising

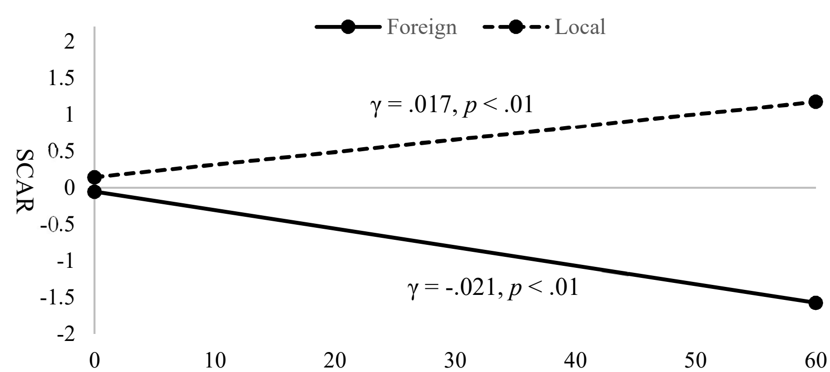


Figure 2.4C: Innovativeness

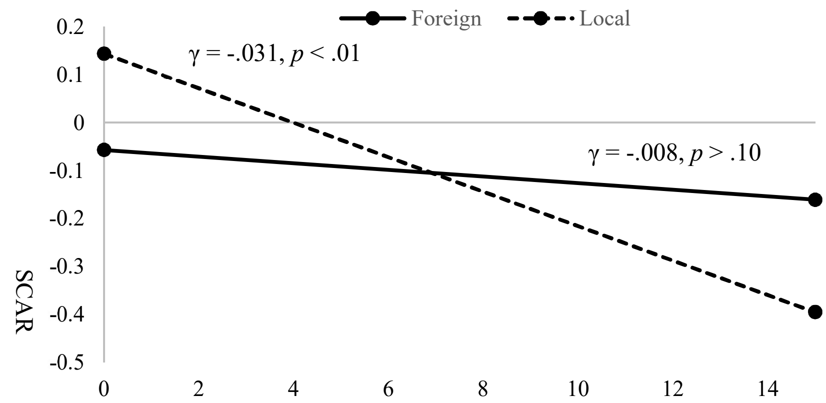


Table 2.W1: Exchange and index

Exchange Name	Country/Region	Region	Index
Euronext Amsterdam	The Netherlands	Europe	AMX
Euronext Brussels	Belgium	Europe	BEL20
Euronext Paris	France	Europe	CAC40
Singapore Exchange	Singapore	Asia Pacific	FSTAS
Borsa Italiana - MTA	Italy	Europe	FTSE_MIB
Boerse Frankfurt	Germany	Europe	HDAX
Nasdaq OMX - Helsinki	Finland	Europe	HEX
Hong Kong Stock Exchange	Hong Kong SAR, China	Asia Pacific	HSCI
Bolsa de Madrid	Spain	Europe	IBEX35
Bursa Malaysia	Malaysia	Asia Pacific	KLCI
Korea Stock Exchange	Korea	Asia Pacific	KOSPI
Tokyo Stock Exchange	Japan	Asia Pacific	NIKKEI225
London Stock Exchange	UK	Europe	NMX
Nasdaq OMX - Stockholm	Sweden	Europe	OMXS30
Bombay Stock Exchange	India	Asia Pacific	SENSEX
Shanghai Stock Exchange	China	Asia Pacific	SHCOMP
Swiss Exchange (SWX)	Swiss	Europe	SIX
New York Stock Exchange	US	Americas	NYSE
NASDAQ	US	Americas	NYSE
Shenzhen Stock Exchange	China	Asia Pacific	SZCOMP
Tel Aviv Stock Exchange	Israel	Middle East	TA100
Taiwan Stock Exchange	Taiwan	Asia Pacific	TWSE

Table 2.W2: Robustness to alternative calculations of abnormal stock returns by using the market model

Dependent Variables: SCAR[+1,+1]	**Estimate**	***t*-value**
Intercept	-.143	-.82
Market Knowledge and Experience		
Market Position *(MKTPOS)*	-.737	-5.04***
Marketplace Experience *(CHLEXP)*	.361	4.26***
Portfolio Width *(PORWID)*	-.036	-6.84***
Market Position * Foreign Firm	2.369	2.25**
Marketplace Experience * Foreign Firm	-.116	-.78
Portfolio Width * Foreign Firm	.011	.47
Marketing Strengths and Capabilities		
Brand Equity *(BRDQEY)*	.375	3.22***
Advertising *(ADV)*	.017	11.35***
Innovativeness *(INV)*	-.033	-7.44***
Brand Equity * Foreign Firm	.087	.76
Advertising * Foreign Firm	-.037	-5.54***
Innovativeness * Foreign Firm	.024	1.96*
Control Variables		
Foreign Firm *(FOREIGN)*	-.089	-.84
Total Assets (*TOA*)	-.001	-1.79*
Return on Assets *(ROA)*	-.010	-2.77**
Financial Leverage *(LVG)*	.368	2.44**
Service *(SEV)*	.115	.97
Home Country's GDP *(GDP)*	.009	-1.10
Year Fixed Effects (*YEAR*)	Included	
Selectivity Parameter		
Inverse Mills Ratio(*IMR*)	.173	2.32**
R^2	.09	

***$p < .01$, **$p < .05$, * $p < .10$

Table 2.W3: Robustness to unstandardized abnormal stock returns

Dependent Variables: CAR[+1,+1]	**Estimate**	***t*-value**
Intercept	-.006	-1.25
Market Knowledge and Experience		
Market Position *(MKTPOS)*	-.018	-7.84***
Marketplace Experience *(CHLEXP)*	.010	4.32***
Portfolio Width *(PORWID)*	-.0008	-16.68***
Market Position * Foreign Firm	.036	2.35**
Marketplace Experience * Foreign Firm	-.002	-1.10
Portfolio Width * Foreign Firm	.001	1.87*
Marketing Strengths and Capabilities		
Brand Equity *(BRDQEY)*	.006	2.86**
Advertising *(ADV)*	.0003	10.20***
Innovativeness *(INV)*	-.0004	-6.53***
Brand Equity * Foreign Firm	.003	2.02*
Advertising * Foreign Firm	-.001	-5.48***
Innovativeness * Foreign Firm	.0002	.97
Control Variables		
Foreign Firm *(FOREIGN)*	-.002	-1.12
Total Assets (*TOA*)	-.021	-1.92*
Return on Assets *(ROA)*	-.0004	-3.22**
Financial Leverage *(LVG)*	.007	2.11**
Service *(SEV)*	.003	2.72**
Home Country's GDP *(GDP)*	.0001	.33
Year Fixed Effects (*YEAR*)	Included	
Selectivity Parameter		
Inverse Mills Ratio(*IMR*)	.005	2.62**
$\mathbf{R^2}$	.09	

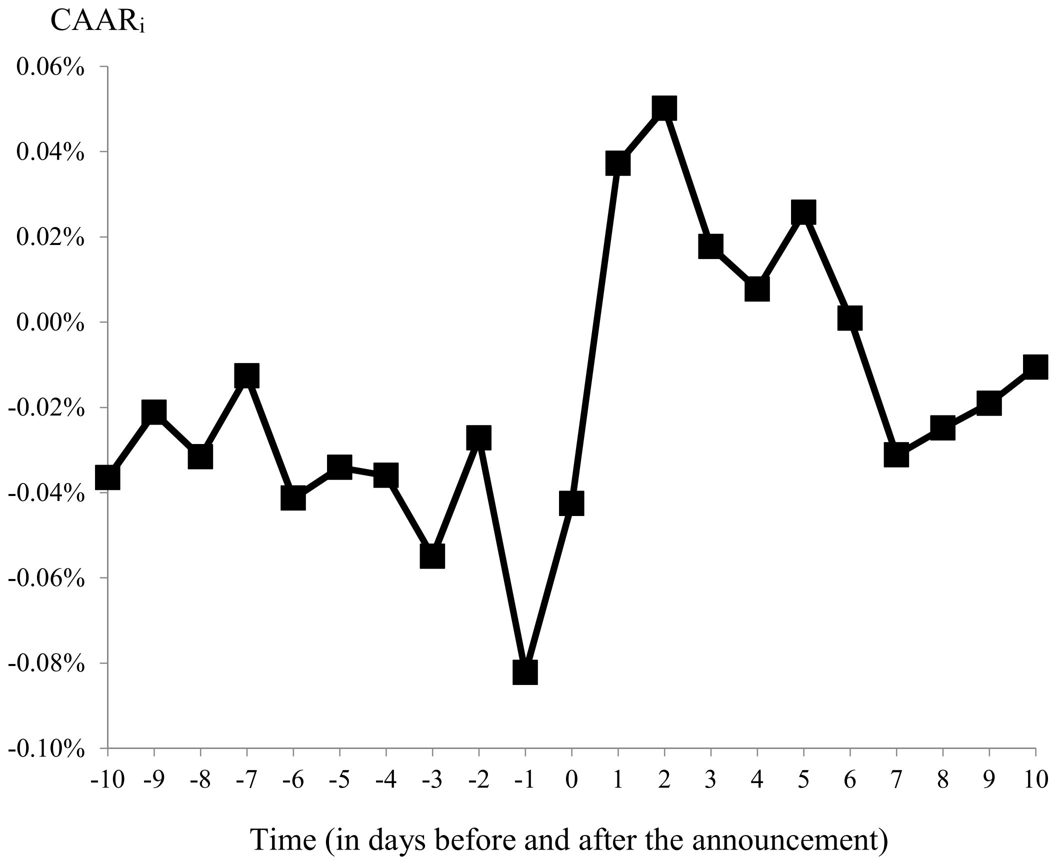
***$p < .01$, **$p < .05$, * $p < .10$

Table 2.W4: Robustness to alternative event windows

	β	*t*-value	β	*t*-value
Dependent Variables	**SCAR[+1,+2]**		**SCAR[+1,+3]**	
Intercept	.039	.18	-.285	-1.07
Market Knowledge and Experience				
Market Position *(MKTPOS)*	-1.326	-5.38***	-2.375	-10.23***
Marketplace Experience *(CHLEXP)*	.238	5.03***	.304	4.03***
Portfolio Width *(PORWID)*	-.043	-9.39***	-.029	-7.76***
Market Position * Foreign Firm	3.247	3.34***	4.626	6.17***
Marketplace Experience * Foreign Firm	-.028	-.16	-.139	-.76
Portfolio Width * Foreign Firm	.004	.17	-.032	-1.63
Marketing Strengths and Capabilities				
Brand Equity *(BRDQEY)*	.442	4.31***	.725	5.96***
Advertising *(ADV)*	.021	16.06***	.020	11.04***
Innovativeness *(INV)*	-.046	-2.76***	-.054	-17.96***
Brand Equity * Foreign Firm	-.132	-.95	-.309	-1.81*
Advertising * Foreign Firm	-.054	-12.53***	-.031	-6.41***
Innovativeness * Foreign Firm	.040	2.01**	.035	2.40**
Control Variables				
Foreign Firm *(FOREIGN)*	-.057	-.40	.035	.24
Total Assets (*TOA*)	.538	.90	-.056	-.09
Return on Assets *(ROA)*	-.005	-1.48	.0001	.08
Financial Leverage *(LVG)*	.230	1.06	.523	2.33**
Service *(SEV)*	-.218	-1.61	-.011	-.08
Home Country's GDP *(GDP)*	-.019	-1.82*	-.015	-1.77*
Year Fixed Effects (*YEAR*)	Included		Included	
Selectivity Parameter				
Inverse Mills Ratio(*IMR*)	.006	.10	.032	.48
R^2	0.11		.11	

****p* < .01, ***p* < .05, * *p* < .10

Figure 2.W1: Cumulative abnormal returns for the 10 days surrounding event date measure



CHAPTER 3: FOR BETTER OR FOR WORSE: THE HALO EFFECTS OF ONLINE MARKETPLACES ON ENTRENCHED BRICK-AND-MORTAR STORES

Abstract

Traditionally, consumer packaged goods (CPGs) manufacturers have no efficient and effective direct gateway to consumers but have to rely on retailers. With the advent of online marketplaces, direct access to consumers is becoming a truly realistic option for CPG manufacturers. However, given the fact that 93% of CPG retail sales are still happening in brick-and-mortar stores, where retailers typically have the exclusive control over retail price, promotion, and shelf space allocated to each brand, the brand's performance implications of complementing entrenched brick-and-mortar channels with online marketplaces are less straightforward. The question remains whether and to what extent retailers and all brands within the category stand to lose or win. To address this question, online marketplace store openings by 195 national brands (NBs) across 45 CPG categories between 2011 to and 2014 are analyzed using seemingly unrelated regression (SUR) that quantifies the impact of online marketplaces on category sales, focal NB share, rival NB share, rival private label (PL) share, focal NB price, rival NB price, and rival PL price. Drawing on empirical generalizations, the authors find that, on average, store openings by NBs boost categories sales as well as their own share in entrenched offline stores. With respect to the competitive impact, store openings by NBs tend to increase the share of rival NBs but hurt that of rival PLs. Turning to the retail price, when leading brands open stores, retailers cut off the price of PLs; when non-leading brands open stores, retailers tend to raise the price of focal brands. Moreover, the authors also find that online

marketplaces are more likely to create positive spillover effects on category sales for brands that either advertise very little or a lot. Specifically, more premium brands can break away from the 'stuck-in-the-middle' zone by investing more in advertising. More economy like brands, however, may want to be careful not to overshoot with advertising. Low equity brands, as long as they spend more on advertising, can enjoy positive spillover effects, whereas high equity brands are likely to be stuck in the middle.

Keywords: online marketplaces, supplier encroachment, multichannel retailing

Introduction

Traditionally, consumer packaged goods (CPGs) manufacturers have no efficient and effective direct gateway to consumers but have to rely on retailers. With the advent of online marketplaces, direct access to consumers is becoming a truly realistic option for CPG manufacturers (Abhishek et al. 2016). Using this platform, manufacturers can sell *directly* to their consumers through marketplaces' sites for a fee and make decisions regarding key factors such as retail prices without having to invest in retail space and logistic infrastructure; a combination that can rarely be achieved through any existing online or brick-and-mortar retailer (Hagiu and Wright 2015a).

Online marketplaces are increasingly gaining popularity across the globe, as their share of global retail sales is expected to rise to 15% by 2022, adding more than $860 billion in sales and accounting for 58% of global ecommerce sales (Planet Retail 2017a). Not only consumers are finding their way to these new purchase ecosystems, also millions of brands across thousands of categories, from luxury handbags to electric vehicles, from premium cosmetics to generic pharmaceuticals, and from high-end sneakers to sweet biscuits, are moving into marketplaces (eMarketer 2016; PwC 2017).

Among others, many CPG brands are also moving into this new, direct "playing field" (McKinsey 2017). Since its debut in 2009, Procter & Gamble, for example, opened eight more stores for its brands on Alibaba's Tmall -- China's largest online marketplaces. Prior to the birth of marketplaces, going direct to consumers in a profitable way seemed impossible for most CPG brands. Not only are the costs of order fulfillment, especially last-mile delivery, too high relative to unit value, alone brand websites mostly cannot generate sufficient traffic (Boston Consulting Group 2017).

Online marketplaces give CPG manufacturers access to consumers and allow manufacturers to present their brands exactly how they want without any retailer interface. In general, a CPG brand, big or small, can sell to consumers through three models -- through retailers such as Amazon.com and Walmart ("reselling" model), through own brand stores or sites such as the Apple store and Nike.com ("direct model"), or through online marketplace platforms such as Alibaba's Tmall and eBay ("marketplace" model)[6]. In a reselling model, retailers take ownership and control over products from branded manufacturers and decide how to sell them in their stores (i.e. they have full control over the marketing mix, de/listing, and layout decisions). In contrast, in both marketplace and direct models, the full ownership and control rights shift back to manufacturers. Although marketplace and direct models look similar in terms of ownership, the two models differ drastically operationally. In direct models, manufacturers have to do everything themselves, from building a retail space to acquiring new consumers, from maintaining the retail space to handling logistics. In contrast, on marketplaces manufacturers share a small portion of their revenues with marketplace owners and these marketplaces will help them achieve the same tasks at a much lower cost by exploiting the economies of scale (Hagiu and Wright 2015b; Wells 2016). Table 3.1 presents a comparison of the three models.

Despite the potential offered by this new digital channel to brands, consumers' intrinsic need for immediate gratification outside of planned stock-up trips implies that brick-and-mortar stores will always remain an important part for most CPG manufacturers (Wolfinbarger and Gilly 2001). Not too surprisingly, CPG products are still mainly bought in brick-and-mortar environments, accounting for 93% of total CPG retail sales (Nielsen 2017). Given the continued

[6] Apart from these three models, hybrid models exist. For example, retailers like Amazon and Walmart also offer marketplace formats, i.e. Amazon marketplace and Walmart marketplace, respectively.

importance of brick-and-mortar stores, CPG manufacturers have to monitor carefully whether and to what extent brick-and-mortar retailers could feel threatened by their brands' marketplace activities. If marketplaces manage to steal too many sales from retailers' entrenched channels, an upset retailer may aggressively reduce its level of support, if not eliminate all, for the focal brand and reallocate its support to its rival brands (Kumar and Ruan 2006). A retailer may also exploit its absolute control over retail prices to deteriorate the relative price positioning of the focal brand (Grewal et al. 1998). The retailer, for instance, may cut the price of rival brands but maintain that of the focal brand, making the latter less attractive to a more price-sensitive segment. In addition, retailers can further retaliate by using their strategic weapon -- private labels (PLs) and escalate the price differentiation to persuade consumers to switch (Geyskens et al. 2010).

Nevertheless, retailers may also benefit from online marketplaces. That is, online marketplaces may be complementary to entrenched brick-and-mortar stores and act as a communication platform. On online platforms brands can set up stores exactly as they want to and expose their brands to millions of marketplace consumers which they cannot reach by standalone operations. Online marketplaces may thus act as a living billboard for the brand, attracting consumer attention and creating brand awareness (McKinsey 2017). The awareness built up through online marketplaces may spill over to other channels and bring additional store traffic. Moreover, marketplaces are more than a place of transaction -- consumers can leave feedback and freely disseminate brand-related information for each product (PwC 2017). This user-generated content (UGC) serves as a new element in the marketing communication mix, turning shopping on online marketplaces a truly enjoyable experience. Such positive -- perhaps even memorable -- brand experience accumulated from marketplaces may once again transfer to other channels and benefits brick-and-mortar retailers and the brands sold in the store.

Although both positive and negative arguments are available, empirical evidence on how brands' online marketplace activities affect brick-and-mortar stores and alter the competitive performance of brands in the brick and mortar retail environment is still limited. Can brick-and-mortar retailer actually gain? Can category sales increase in the physical store? Do they change the competitive position of a brand on the retail shelf? How do they alter brand prices charged by the retailer? Moreover, can brands actively reinforce the potential positive billboard effects? This paper aims to address these questions and captures a holistic picture of competitive dynamics underlying the scene.

To achieve these goals, using Chinese household panel data we conduct a study to evaluate the impact of online marketplace store openings by 195 national brands (NBs) on category sales, focal NB, rival NB and private label (PL) shares, and focal NB, rival NB, and rival PL prices at three leading brick-and-mortar retailers in China's grocery market. In a first step, to capture the potential billboard effects, we treat marketplace store openings as separate events, allowing the cross-channel impact to differ between events, and explore whether the store openings result in significant cross-channel effects on category sales, brand shares and prices. In a next step, to test whether brands can potentially actively create win-win outcomes for both brands and retailers, we examine whether brands' advertising spending influences the impact of store openings on the retailers' category sales.

In doing so, the study contributes to the literature in several ways. At a broader level, our empirical assessment of the impact of online marketplaces on brick-and-mortar stores complements the rich stream of literature on the interaction between online and offline channels (e.g., Brynjolfsson et al. 2009; Forman et al. 2009). Whereas extant research on this topic mainly studies *horizontal* supply chain relationships -- the effects of a channel addition *by a retailer,* on either its own (e.g., Avery et al. 2012) or its rivals' retail channels (e.g., Brynjolfsson et al. 2009), our research looks at *vertical* supply chain relationships -- the effects of a channel addition *by manufacturers* on the performance of *retailers* and the *entire set of brands* within the category in the established channel. Moreover, our study adds to the extant research on supplier encroachment (e.g., Arya et al. 2007; Li et al. 2015), in which analytical findings abound but empirical studies are scant. Specifically, we relax some of the assumptions (e.g., Arya et al. 2007 assume a homogeneous retail product by ruling out product complementarity) and demonstrate that contrary to the clear-cut predictions from prior literature, the consequences are much more nuanced as brand characteristics play a role.

The rest of the paper is organized as follows. We first conduct a literature review and discuss the conceptual framework of the study. Next, we give a full description of the empirical setting and model, before presenting the results and implications. Finally, we conclude with a discussion and suggestions for future work.

Literature review

Our study is closely related to two streams of literature: (1) interactions between online and offline channels, and (2) supplier encroachment.

A rich stream of literature looks at the interaction between online and offline channels. In Table 3.2 we summarize this literature based on three dimensions: ownership of the new channel (i.e., manufacturer or retailer), type of new channel (i.e., offline or online channel), and type of effect (i.e., intra-firm or inter-firm).

With respect to the owner of the new channel, either a retailer or a manufacturer can add a new channel. Regarding the type of new channel, we consider adding an offline channel as well as an online channel. Turning to the type of effect, we distinguish two scenarios: (1) an *intra-firm* scenario where the new channel affects entrenched channels, both controlled by the same firm and (2) an *inter-firm* scenario where the focal firm's new channel affects other firms' channels not owned by the focal firm. The distinction in ownership splits the body of literature into two different sets of conclusions regarding the potential for positive or negative spillover effects.

Most intra-firm research (e.g., Avery et al. 2012; Bell et al. 2018; Gallino and Moreno 2014; Wang and Goldfarb 2017) examined the coexistence of complementarity and substitution across channels from the perspective of the retailer. For example, Avery et al. (2012) find that the presence of retailer's new offline store decreases sales in the catalog but not the Internet channel in the short run but increases sales in both direct channels over time. The authors explain this effect by distinguishing the conspicuous capabilities from the experiential capabilities of the new channel, whereby the experiential capabilities are deemed more important in the longer run. Indeed, If the new channel provides (complementary) experiential capabilities that manage to attract new customers to the existing channels or cause existing customers to purchase more, incremental demand in the existing channels will be generated over time. Wang and Goldfarb (2017) find that the opening of an offline store is associated with a decrease in online sales and search in places where the retailer has a strong presence, whereas the effects reverse in places where the retailer does not have a strong presence. They explain the complementarity in the latter case by relating the phenomenon to the "living billboard effect" -- offline stores act as a billboard, inform potential consumers about the existence of the brand, and eventually drive online sales. So, in intra-firm studies, evidence for positive cross-channel spillovers is found. This may be easier to achieve in an intra-firm setting because a single firm is willing to coordinate its multi-channels while competing firms do not have such motivation at all (Tsai 2002).

Most of the inter-firm literature (e.g., Brynjolfsson et al. 2009; Forman et al. 2009; Goldmanis et al. 2010) also mainly takes the perspective of the retailer and documents the substitution between online channels and offline stores, with the degree of consumer substitution depending on local demographic characteristics, product type, and proximity to physical store locations. For example, Brynjolfsson et al. (2009) find that online retailers face significant competition from brick-and-mortar retailers when selling mainstream products, but are virtually immune from competition when selling niche products. Moreover, Forman et al. (2009) show that when a store opens locally, people substitute away from online purchasing, even controlling for product-specific preferences by location. Turning to the manufacturer's perspective almost no work has been done so far despite the fact that many brand manufacturers are actively adding direct channels (e.g., Hershey's opened Hershey's Chocolate World in New York City and Levi's are selling jeans directly to consumers online). To the best of our knowledge, the only exception is Van Crombrugge et al. (2018), in which they find that in the consumers electronics space brands' websites cause retailers to lose sales of the focal brand and to increase the price of the focal brand to discipline the manufacturer for encroaching on their terrain. So, for typical standalone brand online channels little evidence of positive spillover effects appears to exist. The question, however, remains whether CPG brand stores operated on online platforms manage to build on the platform's ecosystem to create additional awareness that positively spills over to existing channels.

Turning to the analytical literature on supplier encroachment, which refers to the rising competition between manufacturers and retailers when the former bypass intermediaries and sell directly to consumers (Arya et al. 2007) two distinct sets of conclusions are put forward. Some studies demonstrate that supplier encroachment can lead to "win-win" outcomes for both supplier and reseller. For example, Chiang et al. (2003) demonstrate that a supplier's threat of encroachment (i.e., sell through a direct channel) causes the reseller to lower his selling price, which can benefit both parties. Arya et al. (2007) establish, based on a quantity competition model, that the supplier's direct sale channel not only adds another source of revenue but also motivates the supplier to offer a lower wholesale price to the reseller. Consequently, encroachment has the potential to benefit the supplier as well as the reseller especially when the latter enjoys a significant cost advantage in the selling process. In contrast, some researchers find that supplier encroachment can lead to "lose-lose" or "lose-win" outcomes under certain conditions. For example, Li et al. (2014) find that supplier encroachment can sometimes amplify double-marginalization and hurt both the supplier and the reseller when the latter is privately informed about demand (i.e., information asymmetry). All in all, this stream of literature suggest that retailers can benefit from manufacturers' direct channels and that it is essential to include price effects. Our research differs from extant research by taking an empirical approach to gauge the effects for the full set of brands in the category at multiple retailers and evaluate to what extent both retailers and all brands stand to lose or win. The findings from our paper, hence, complement the rich stream of analytical research.

Conceptual framework

How Do Brands' Online Platform Stores Affect Brick-And-Mortar Performance?

Essentially, online marketplaces work as a complex digital ecosystem consisting of local and international brands, payment services, cloud services, social media, and logistics services -- all with the goal of making it easier for consumers to buy anytime and anywhere (Planet Retail 2017a). Unlike a standalone e-commerce site like Apple.com, which is dedicated to a specific brand, online marketplaces bring on board millions of brands from thousands of categories to offer the widest assortment possible. By exploiting the economies of scale, online marketplaces aggregate various sellers and buyers and cut the operation cost (e.g., stocking and logistics fee) to a much more affordable level than that of any other standalone ecommerce site (PwC 2017). Consumers, urban or rural, are gaining the equal chance to "touch" the brands that may not be available at all in their local stores due to high stocking and/or delivery costs. Not too surprisingly, consumers start to embrace online marketplaces and hunt for treasures on these platforms. For example, eBay -- one of the largest online marketplaces in the United States has more than 170 million active buyers shopping on its platform (eBay 2018). Its counterpart -- Alibaba's Tmall -- China's largest online marketplace has 454 million active consumers placing orders through its arena (Alibaba 2017).

Impact on category sales and brand shares. From the perspective of consumers, the shopping experience in this ecosystem exceeds the typical endless aisles offered by online retailers. As an ecosystem, online marketplaces are not only a platform of transaction. Marketplaces, such as India's largest marketplace, Flipkart, and Japan's largest, Rakuten, are expanding their businesses beyond retail to become integrated into more aspects of consumers' lives, including payment, social media, and entertainment (Planet Retail 2017a). Through marketplaces, brands are gaining multiple touchpoints, including but not limited to pre- and post-purchase occasions, to communicate their brand message to end users. Setting up a store on online marketplaces thus provides brands an unprecedented opportunity to expose themselves to a gigantic consumer base that they cannot reach otherwise. A recent survey demonstrated that 59 percent of consumers claimed that the place where they saw a product for the first time is online, making online platforms an almost common, but highly important, source of initial product awareness (KPMG 2017). The valuable brand associations built on and attributed to a marketplace may thus transfer to other channels (Jacoby and Mazursky 1984; Keller 1993), and positive associations formed through the knowledge and/or patronage of the marketplace store can transfer to the other channels and create a halo effect (Kwon and Lennon 2009).

In addition, consumers on online marketplaces are far more than mere passive message receivers. Indeed, they are becoming part of the ecosystem as content generators. Online marketplaces allow consumers to leave feedback and freely disseminate brand-related information for each product (Pavlou and Gefen 2004; PwC 2017). This user-generated content (UGC) serves as a new element in the marketing communication mix and works as free "sales assistants" to help consumers identify the products that best match their idiosyncratic usage conditions (Chen and Xie 2008). Shopping via online marketplaces, therefore, goes above and beyond business transactions and becomes a truly interactive consumer experience. Essentially, online marketplaces create a superior gateway for brands to develop interactive consumer experience as well as positive customer relationship (Godes and Mayzlin 2004; Liu 2006; Pauwels et al. 2016).

A natural question then to ask is whether the superior brand experience and awareness accumulated through online marketplaces transfer from the ecosystem to other channels outside of the ecosystem (cf. Dinner et al. 2014; Pauwels et al. 2011). If online marketplaces can truly act as a "living billboard" (cf. Anderson 2009 in the context of retailer channel additions; Avery et al. 2012; Wang and Goldfarb 2017), spillovers (i.e., synergies) across online and offline channels can indeed be created and the answer is likely to be positive. We therefore expect category sales and brand shares in brick-and-mortar stores to increase following a brand's marketplace store opening.

Impact on prices. Regarding brand prices, retailers, on one hand, may still treat online marketplaces as a potential threat and therefore react in a way that adversely hurts the brand manufacturer (Van Crombrugge et al. 2018). An upset retailer may exploit its absolute control over retail prices to deteriorate the relative price positioning of the focal brand (Grewal et al. 1998). The retailer, for instance, may cut the price of rival brands but increase (or maintain) that of the focal brand, making the latter less attractive to a more price-sensitive segment. On the other hand, when customers' acceptance of online marketplace channel exceeds the cannibalistic threshold, the retailer would prefer not to compete against the manufacturer's direct channel because it is a serious alternative to the retail market for consumers. The best that the retailer can do in this competitive situation is significantly cutting prices of all brands within the store (Chiang et al. 2003). In conclusion, given the conflicting arguments, we do not provide a directional expectation for brand prices.

Can Brands Actively Turn Online Platform Stores to Win-Win Outcomes for Brands and Retailers?

Ultimately, the best case scenario for both manufacturer and retailer emerges when the retailer notices category, thereby reducing the risk of channel conflict. A relevant question to ask is whether and to what extent a brand can actively leverage the awareness and experience effects outside the platform's ecosystem and signal its existence to new consumers and indirectly guide them to the category? This calls for the question whether brand advertising can further stimulate or hinder the potential "living billboard" effects of online platform stores. In general, brand advertising may further signal the brand's potential as well as impose a ceiling on its potential.

Signaling effects. The signaling effects of advertising on consumer perception have been well documented in the economics and marketing literature (e.g., Byzalov and Shachar 2004; Erdem et al. 2008; Gao et al. 2015; Wernerfelt 1988). Advertising signals product quality: brand manufacturers know more about the quality of their products than consumers do, and therefore, consumers may infer product quality based on observable firm actions (Kirmani and Rao 2000). In our setting, if a brand actively advertises before opening a store on an online marketplace, consumers may perceive this as a positive signal that the brand is confident about its operations. If online marketplaces indeed create a superior consumer experience and positive brand associations, advertising will further enhance the effects of platform stores on category sales.

Ceiling effects. Eventually, marketing spending aimed at awareness building will hit a proverbial ceiling as more consumes are already knowledgeable about the brand. The larger the remaining distance to the maximum awareness that can be generated for the brand, or ceiling, the higher the impact potential (Hanssens et al. 2014). In our context, online marketplace participation may inform consumers who were previously unfamiliar with the brands. When a brand was advertising less prior to its marketplace presence, it is likely to be less known to consumers. Therefore, online marketplaces have a higher potential to build further brand awareness and create stronger "living billboard" effects. As such, advertising may reduce the effects of platform stores on category sales.

To reconcile the opposing signaling and ceiling arguments we will capture the relationship between advertising and the platform store effects on category sales in a nonlinear way.

What Kind of Brands Can Reinforce Billboard Effects?

With these two opposite advertising effects in place, we propose that the extent to which brand can leverage advertising depends on specific brand characteristics. We identify two brand characteristics, i.e. (1) price positioning and (2) brand equity. Specifically, we propose that the former affects the signaling effect, whereas the latter reflects the degree of brand awareness and, thus, affects the strength of the ceiling effect.

The price positioning and the signaling effects. When premium-priced brands open marketplace stores, the potential for information asymmetry may be smaller because price also signals quality (Milgrom and Roberts 1986; Zeithaml 1988). With a lower degree of information asymmetry, we expect the signaling effect of advertising to be weaker for premium-priced brands because consumers use the price information to evaluate the product quality.

The brand equity and the ceiling effects. Brands with higher brand equity are typically well known and consumers are already quite knowledgeable about the brand. When brands with higher equity enters, the remaining distance to the maximum awareness that can be generated for the brand is more limited because brand equity reflects the extent to which consumer is familiar with the brand (Keller 1993). With a smaller distance to the ceiling, we expect the ceiling effect of advertising to be weaker for brands with higher equity.

Figure 3.1 depicts graphically how and when platforms stores impact brick and mortar category sales.

Data

Natural-Experiment Setting

The purpose of this research is to identify the halo (spillover) effects of manufacturers' opening online marketplace stores on brick-and-mortar performance. Specifically, we investigate the effects of opening a store on Alibaba's Tmall by national brands (NBs) on retailers' category sales, as well as the focal brand's, rival NBs', and private label' (PLs) shares and prices in China between January 2011 and December 2014 across 45 consumer packaged goods categories at three leading China retailers: Carrefour, RT-Mart, and Walmart. These retailers represent the top three retailers in China with a market share of 8.18%, 8.02%, and 7.91%, respectively, within the time window that we study. The retailers vary in sales and price positioning as shown in Table 3.3. All three retailers use an umbrella branding strategy for their PLs in all categories in which they operate.

We use AiMark household panel data for the Chinese market from January 2011 to December 2014 which we aggregated to sales, share and price at the weekly level. The AiMark data track 63 product categories. We focus on the 45 categories as listed in Table 3.4. We drop the other categories for several reasons. Specifically, we exclude five categories (i.e., bean products, curry, hamburger, health pad, and insecticide/mosquito repellent) where no Tmall store openings were identified within our time window. We drop five categories (i.e., air fresheners, bottled water, cosmetics, dog food, and MSG) where we could identify store openings but were unable to identify the exact date of the openings. Moreover, we exclude three categories (i.e., adult diapers, cat food, and tampons/sanitary bolt) that are too infrequently purchased and five categories (i.e. malted milk/chocolate milk, mousse/hair spray, nutrition supplement, soymilk, and razor and shaving stand) were total volume sales are too low (i.e., most households did not make many purchases over the full length of the sample) leading to sparse series.

Next, we identify all brands with a market share of more than 1% (cf. Gordon et al. 2013), resulting in 404 NBs and 3 PLs (Carrefour's Carrefour brand, RT-Mart's RT-Thumb brand, and Walmart's Great Value brand) across three retailers in 45 categories[7]. For all brands, we obtained advertising data from CTR Market Research for each brand. Table 3.4 depicts the sales, price, advertising, and number of brands in 45 categories.

In addition, we use the household panel data to derive the brand's equity and price positioning. Specifically, we capture a brand's relative positioning as the ratio of the brand's regular price to the category price across all brands in category c at retailer r at time t (Sotgiu and Gielens 2015). We measure a brand's equity as the revenue premium -- the difference in revenue (i.e., net price × volume) between a branded good and a corresponding private label (Ailawadi et al. 2003).

Event Date

We define the event date as the day when a NB opens a store in the online marketplace -- Tmall. In order to capture the store opening date accurately, we retrieve the store opening date through two sources. The first source is the disclosures, press releases, and articles obtained from the Factiva and LexisNexis databases, which provide access to extensive documents from various news, and business sources as well as company website searches. The second source is the Internet Archive digital library (https://archive.org/web), which provides access to past online websites and allows us to track when a website was created (Babić Rosario et al. 2016). After comparing the store opening date from the two sources, we retain whichever is earlier as the final store opening date. In total, we track 195 Tmall stores openings by 140 unique NBs in 45 categories across 3 retailers (525 NB-NB own effects, 4103 NB-NB competitive effects, and 88 NB-PL competitive effects) during 208 weeks.

[7] PLs are not available in every category.

Methodology

In a first step, we quantify the effects of Tmall store openings on category sales, own and rival brand shares and prices in each of the 45 product categories covered in our dataset. In a second step, we focus on category-specific effects of these openings (i.e., parameter estimates of the step dummy variables with respect to category sales) to a set of variables that capture the brand's advertising spending and its equity and price positioning.

Step1: Quantifying the Impact of Tmall Store Opening

To capture a holistic picture of the impact of online marketplace stores on entrenched reselling channels, we evaluate their impact on category sales, market shares, and retail prices for every category-retailer combination. To account for potential simultaneity we use a system of equations that allows for simultaneous estimation of the dependent variables in different equations describing category sales, market share, and retail price, respectively (for a similar approach, see Petersen and Kumar 2009). For ease of explanation, we write down one price and market share equation per category, although separate equations are incorporated in the system for each brand in the category. We first discuss the category sales equation before elaborating on the market share and price equation.

Category sales. The category sales of category c at retailer r in time t are estimated as,

$$(1)\ \ln(\mathrm{CATSAL}_{c,r,t}) = \alpha_{c,r} + \rho_{c,r,1}\ln(\mathrm{CATSAL}_{c,r,t-1}) + \sum_{j=1}^{B}\varphi_{j,c,r}\mathrm{STORE}_{j,c,r,t} + \rho_{c,r,2}\ln(\mathrm{CATPRICE}_{c,r,t}) + \rho_{c,r,3}\ln(\mathrm{SKU}_{c,r,t}) + \sum_{j=1}^{B}\rho_{j,c,r,4}\mathrm{CF1}_{j,c,r,t} + \rho_{c,r,5}\mathrm{CF2}_{c,r,t} + \rho_{c,r,6}\mathrm{TREND} + \xi_{c,r,t}$$

where $\mathrm{CATSAL}_{c,r,t}$ a represent total volume category sales of all brands in category c at retailer r in time t and its lagged value is included to correct for the installed base in the category. The variable $\mathrm{STORE}_{j,c,r,t}$ is the focal construct in this analysis and is a step dummy variable that equals 1 if $t \geq t_{j,c}$ and 0 if otherwise, where $t_{j,c}$ refers to the moment when brand j in category c opens a Tmall store. This step dummy variable allows for a level shift at the time of Tmall store opening. In Eq. (1), if $\varphi_{j,c,r}$ is significant and positive, the Tmall store opened by j initiates an increase in the sales of category c at retailer r. $CATPRICE_{c,r,t}$ represents the average category price in category c at retailers r in time t. $SKU_{c,r,t}$ controls for the net outcome of SKU listing and delistings. $CF1_{j,c,r,t}$ represents a set of control function terms for the endogenous variables $STORE_{j,c,r,t}$ (see below for a more detailed discussion). $CF2_{c,r,t}$ represents the control function for the endogenous variable $CATPRICE_{c,r,t}$. TREND is a deterministic trend variable. Finally, $\xi_{c,r,t}$is a white-noise residual.

Market share. To add market shares to the system, we use an extended multiplicative competitive interaction market share attraction model (Cooper and Nakanishi 1988). The market share of brand b in category c at retailer r at time t is expressed as the attraction of the brand, $Attr_{b,c,r,t}$ relative to the summed attractions of the brands offered in the category, thereby ensuring that market share sum to unity and that the market share are between 0 and 1.

$$(2)\ MS_{b,c,r,t} = \frac{Attr_{b,c,r,t}}{\sum_{b=1}^{B} Attr_{b,c,r,t}}$$

where $MS_{b,c,r,t}$ represents the volume share of brand b within a specific category c and retailer r in week t. The attraction of each brand is expressed as a function of all Tmall store openings in the category, the brand mix instruments, and a set of control variables. The attraction of each brand in the category can be expressed as follows,

$$\begin{aligned}(3)\ \ln\left(Attr_{b,c,r,t}\right)\quad & \beta_{b,c,r} + \lambda_{b,c,r,1}\ln\left(MS_{b,c,r,t-1}\right) + \sum_{j=1}^{B}\theta_{b_j,c,r}STORE_{b_j,c,r,t} + \\ & \lambda_{b,c,r,2}\ln\left(PRICE_{b,c,r,t}\right) + \lambda_{b,c,r,3}\ln\left(ADV_{b,c,r,t}\right) + \lambda_{b,c,r,4}\ln\left(SKU_{b,c,r,t}\right) + \\ & \sum_{j=1}^{B}\lambda_{b_j,c,r,5}CF1_{b_j,c,r,t} + \lambda_{b,c,r,6}CF2_{b,c,r,t} + \lambda_{b,c,r,7}CF3_{b,c,r,t} + \\ & \lambda_{b,c,r,8}TREND + \varepsilon_{b,c,r,t}\end{aligned}$$

where the lagged value of the observed market share $MS_{b,c,r,t-1}$ is included to account for dynamics (Franses et al. 2002). In Eq. (3), if $\theta_{b_j,c,r}$ is significant and positive, the Tmall store opened by j initiates an increase in the attraction of brand b in category c at retailer r. Note that all own-effects are included in the model as well. For example, if $b = j$, $\theta_{b_j,c,r}$ expresses the extent to which Tmall store opened by j influences its attraction in category c at retailer r. $PRICE_{b,c,r,t}$ is the unit list price for brand b in category c at retailer r. $ADV_{b,t}$ is the advertising expenditures of brand b. $CF2_{b,c,r,t}$ represents the control function for $PRICE_{b,c,r,t}$. $CF3_{b,c,r,t}$ represents the control function for $ADV_{b,t}$. Finally, $\varepsilon_{b,c,r,t}$ is a white-noise residual.

After substituting Eq. (3) into Eq. (2), we linearize the attraction model by applying the log-centering transformation (Cooper and Nakanishi 1988).

Price. The price of brand b in category c at retailer r at time t is estimated as,

$$(4)\ \ln\left(PRICE_{b,c,r,t}\right) = \gamma_{b,c,r} + \delta_{b,c,r,1}\ln\left(PRICE_{b,c,r,t-1}\right) + \sum_{j=1}^{B}\pi_{b_j,c,r}STORE_{b_j,c,r,t} + \delta_{b,c,r,2}\ln\left(SKU_{b,c,r,t}\right) + \sum_{j=1}^{B}\delta_{b_j,c,r,3}CF1_{b_j,c,r,t} + \delta_{b,c,r,4}TREND + \zeta_{b,c,r,t}$$

where $PRICE_{b,c,r,t}$ and $PRICE_{b,c,r,t-1}$ represent unit retail price of brand b in category c at retailer r in time t and t-1, respectively. $\zeta_{b,c,r,t}$ is a white-noise residual.

To generate insights across introductions, categories, and retailers, meta-analytic z-statistics are computed that reflect whether, overall, these effects are significantly different from zero (Rosenthal 1991, p.93).

Endogeneity Issues

Tmall store opening and marketing mix (i.e., pricing and advertising) decisions are strategically made by firms. Moreover, not only do retailers care about the market share of individual brands in the category, they care about overall category performances as well. To control for these issues, we use a control function approach to handle endogeneity issues (Wooldridge 2002).

Store openings. With respect to the Tmall store opening decision, we need to find an instrument variable (IV) that meets two criteria: (i) the relevance criterion, that is, the IV must correlate with the endogenous STORE variable and (ii) the exclusion restriction, that is, IV cannot correlate with the unobserved determinants of brand performance (that form part of the error term) (Angrist and Pischke 2009).

To meet these criteria, we use the cumulative Tmall adoption rate among the manufacturer's peer firms as our primary IV (for a similar approach, see Germann et al. 2015). We define peer firms as those firms that operate in the same primary four-digit Standard Industrial Classification (SIC) code as the focal firm. Specifically, the cumulative Tmall adoption rate at time t is the number of firms that joined Tmall by time t divided by the total number of firms in the industry.

To verify that the cumulative Tmall adoption rate is a good IV, we need to, on the one hand, demonstrate instrument relevance (i.e., the IV predicts Tmall store opening) and, on the other hand, argue that the IV meets the exclusion restriction (i.e., establish that the IV does not correlate with the error term that contains the omitted variables). In terms of instrument relevance, we need to conceptually make the case that prevalence of entering Tmall among peer firms correlates with the Tmall store opening decision of the focal firm. Our argument here rests on two primary premises. First, we argue that the focal firm faces similar market conditions as the peer firms because they operate in the same industry. Second, we argue that the Tmall store opening decision of the focal firm is influenced by its peers in the same industry. Research in sociology and organizational behavior (for review, see Strang and Soule 1998; Wejnert 2002) lends support for our argument as they find that organizational actions are deeply influenced by those of other referent entities within a given social system (i.e., social contagion) (Angst et al. 2010; DiMaggio and Powell 1983). Nonadopters are influenced by adopters over time, and they influence the actions of other nonadopter after their own adoption of innovation. Thus, similar market conditions and social contagion among peer firms should make the instrument relevant.

What remains to be argued is why our instrumental variable meets the exclusion restriction. That is, why it is uncorrelated with the omitted variables that affect the focal firm's brand performance. There are firm-level variables such as organizational culture (similar argument, see Germann et al. 2015). Here, we argue that the peer firms collectively cannot observe or measure the focal firm's omitted variable(s) or cannot act on those variable(s) strategically. For example, organizational processes and cultures that are difficult to measure and quantify are embedded in an organization's fabric and thus become difficult to imitate (Granovetter 1985). Furthermore, we consider all the firms in the same industry all over the world to calculate the cumulative Tmall adoption based instrument. Thus, it seems highly unlikely that peer firms will take collective action against a single competitor and then also form other alliances similar in spirit to act against other competitors (which are also part of the other alliances these firms form). We conclude that it is unlikely that our instrument would relate to a focal firm's omitted variables (e.g., organizational culture) because (1) such variables may be difficult to observe and (2) collective action is difficult to manage. Therefore, the instrument should be uncorrelated with the omitted variable.

Price and advertising. Regarding retail price and advertising, we also need to find instruments that meet the relevance criterion and exclusion restriction. We follow Nevo (2001)'s approach of using price and advertising information from a similar but different market as instrumental variable. In general, prices and advertising are set by the cost and markup structure as determined by the nature of the product, category, and retail environment. The logic is that shocks that cause exogenous variation in marketing variables in one market will cause similar exogenous variation in the focal market. For example, costs of ingredients may drive price variation in a market in the same way that they drive price variation in a different and noncompeting market (Hausman 1997; Nevo 2001; for recent applications, see Dinner et al. 2014; Sotgiu and Gielens 2015). As such, we argue that marketing mix variables in a similar but different market meet the relevance criterion. In terms of exclusion restriction, costs shifters are expected to be correlated with prices and advertising but to be uncorrelated with demand and unobservable demand shocks. In other words, the prices and advertising in one market influence consumer demand in its own territory but not the other market. Thus, marketing variables in a similar but different market meet the exclusion restriction (Hausman 1997; Heerde et al. 2013; Nevo 2001; Sotgiu and Gielens 2015).

For these instruments to be valid, no common demand shocks may occur across markets, nor can price promotion and advertising activities be coordinated across markets. To that extent we use the CPG retail price and advertising of U.S. as the instruments. Specifically, for every brand in every category of our sample, we identified the leading NBs and PLs and matched them to the corresponding NBs and PLs in our sample for the same period (2011- 2014).

We formally assessed the validity and strength of our instruments. First, we ran a Sargan test for overidentifying restrictions (Wooldridge 2002). The Sargan test firmly confirmed their validity: we could not reject the null hypothesis that the residuals and the instruments are uncorrelated at any of the conventional significance levels. Second, we also checked the strength of the individual instruments and removed instruments for which the significance level exceeded

10. The p-values of our instruments are below .01, suggesting that the variables are sufficiently strong.

Step2: The Moderating Effects of Advertising and Brand Characteristics on the Impact of Store Openings on Category Sales

In a second step, the impact of the store openings on category sales as captured by the parameter estimates of the STORE effects ($\varphi_{j,c,r}$ in Eq. 1) is related to a set of variables that capture its annual advertising expenditures, marketing positioning, and control variables. To correct for a potential violation of the statistical independence assumption that exists because dependent variables are parameter estimates, we use robust standard errors (Lewis and Linzer 2005).

$$
\begin{aligned}
(5)\ \varphi_{j,c,r} = \quad & \omega_0 + \omega_{j,c,r,1}\mathrm{ADV}_{j,c,r} + \omega_{j,c,r,2}\mathrm{ADV}_{j,c,r}{}^2 + \omega_{j,c,r,3}\mathrm{ADV}_{j,c,r} \times \mathrm{BRDPOS}_{j,c,r} + \\
& \omega_{j,c,r,4}\mathrm{ADV}_{j,c,r} \times \mathrm{BRDEQY}_{j,c,r} + \omega_{j,c,r,5}\mathrm{ADV}_{j,c,r}{}^2 \times \mathrm{BRDPOS}_{j,c,r} + \omega_{j,c,r,6}\mathrm{ADV}_{j,c,r}{}^2 \times \\
& \mathrm{BRDEQY}_{j,c,r} + \omega_{j,c,r,7}\,\mathrm{BRDPOS}_{j,c,r} + \omega_{j,c,r,8}\,\mathrm{BRDEQY}_{j,c,r} + \\
& \textstyle\sum_{b=1}^{B} \omega_{j,c,r,8+l}\mathrm{RANK}_{j,c,r} + \sum_{r=1}^{R} \omega_{12+r}\mathrm{RETAILER}_{c,r} + \\
& \textstyle\sum_{c=1}^{C} \omega_{14+c}\mathrm{CATEGORY}_{c,r} + \varsigma_{j,c,r}
\end{aligned}
$$

where $\mathrm{ADV}_{j,c,r}$ represents annual advertising expenditures of brand j in category c at retailer r. $\mathrm{BRDPOS}_{j,c,r}$ represents brand j's relative price positing in category c at retailer r. $\mathrm{BRDEQY}_{j,c,r}$ represents brand equity of brand j in category c. We also include RANK -- brand ranking fixed-effects, RETAILER -- retailer fixed-effects, and CATEGORY -- category fixed-effects. All independent variables are measured in the year prior to Tmall store opening. Finally, all continuous independent variables are mean-centered to ease interpretation. $\varsigma_{b_j,c,r}$ is a robust standard error.

Results

Step 1: The Impact of Marketplace Store Openings on Category Sales, Own and Rival Share

To summarize the results of the Step 1 estimations across 45 categories we report in Table 3.5 meta-analytic z-statistics that reflect whether overall the effect of opening a store on an online platform are significantly different from zero and positive in case of the category sales, own market share, and rival NB market share and significant and negative in case of the rival PL share. Next to summarizing the effects across all brands in the category we also split them up depending on whether the store was opened by the leading brand in the category or a follower brand. We further report the frequency of cases in which online marketplaces result in a significant increase or decrease of the four metrics: category sales, focal NBs market share, rival NBs market share, and rival PLs share.

Overall, in 72%, 85%, 81%, and 77% of all marketplace store openings, not all NBs brands managed to significantly affect category sales, focal NBs market share, rival NBs share, and rival PLs share, respectively. This is not surprising because we include an almost full set of brands (brands with 1% market share or higher in each category) in this study to avoid potential sample selection biases. This finding is also consistent with previous findings that demonstrate that halo effects of online channels on offline channels only appear in specific settings (Pauwels et al. 2011). Given that we include a broad range of CPG categories and brands, these results make sense.

Still, online marketplaces, overall, seem to affect *category sales* positively ($z = 1.70$, $p < .05$), suggesting that online marketplaces increase category sales in brick-and-mortar stores. This result is mainly driven by non-leading brands ($z = 2.54$, $p < .01$). Thus, online marketplaces, overall, act as a "living billboard" and drive category sales in brick-and-mortar stores especially if a non-leading brand opens a store on an online marketplace.

With respect to the impact on *focal NB market shares*, online marketplaces positively affect own market share in the store (z = 2.17, $p < .05$). This result is consistent across all brands. Thus, the "living billboard effects" manifests itself for all brands. Turing to the competitive effects, in general, online marketplaces boost rival NBs' market share (z = 4.35, $p < .01$), indicating once again that the store opening may affect the category as a whole positively. This result is also consistent across all brands. However, with respect to PLs shares, online marketplaces hurt rival PLs market share (z = -2.03, $p < .05$). PLs are often used by retailers as a powerful weapon to achieve various strategic goals, including fighting back to NBs (Geyskens et al. 2010), increasing store loyalty (Ailawadi et al. 2008), and store differentiation (Marcel Corstjens and Lal 2000). Many PLs are still generics and copycats of NBs with the lowest price at which a product is available in the store (Kumar and Steenkamp 2007). Therefore, NBs and PLs are less likely to enter a consumer's narrow consideration set simultaneously on a given shopping trip (Gielens 2012). Consumers that patronize offline stores due to NBs' "living billboard effects" may be less likely to choose rival PL as alternatives. Rival NBs therefore may reap the benefits more easily while rival PLs do not.

Step 1: The Impact of Marketplace Store Openings on Price

Table 3.6 summarizes the meta-analytic z-statistics for the impact of marketplace store openings on retail prices. More specifically, it reports whether overall the effects are significantly different from zero and positive in case of focal NBs retailer price, and significant and negative in case of the rival NBs and PLs retail price. Overall, retailers raise up the retail price of focal NBs (z = 1.88, $p < .05$). This result is mainly found for non-leading brands, suggesting that retailers indeed retaliate through deteriorating the relative price positon of non-leading brands.

Turing to the competitive impact, retailers do not change the price of rival NBs but decrease the price of their PLs when market leaders enter online marketplaces (z = -1.72, $p < .05$). This finding suggests that retailers by no means treat all store openings equally: when leading brands enter, they use PLs as a weapon to fight back; when non-leading brands enter, they simply increase the price of focal brands to retaliate.

Step 2: The Moderating Effects of Advertising and Brand Characteristics on Store Openings Elasticities w.r.t. Category Sales

Table 3.7 reports the results for the Step 2 analyses and allows us to gauge insight into when and for what type of brand we manage to find positive billboard effects for the category.

As we expected, the relationship between advertising on marketplace store opening effectiveness is nonlinear ($\omega_{j,c,r,2}$ = .275, $p < .01$). Specifically, it follows a U-shaped curve, suggesting that the online platform presence is more likely to create billboard effects for brands that either advertise very little or a lot, whereby the former can create extra awareness through the platform and the latter manage to galvanize their platform presence through extensive communication. Being 'stuck in the middle' seems to be the worst-case scenario where brands do not create sufficient extra awareness to lift category sales in any notable way. Moreover these effects depend on the positioning of the brands as the interaction term of price positioning and advertising ($\omega_{j,c,r,3}$= -1.212, $p < .01$) as well as that of price positioning and advertising squared ($\omega_{j,c,r,5}$= .932, $p < .01$) are both significant.

To get a better understanding, we plot simple slopes at three levels: high (one standard deviation above the mean), average (mean), and low (one standard deviation below the mean) (Cohen et al. 2003).

As shown in Panel A of Figure 3.2, the billboard effects are strongest for premium brands when advertising spending is high, which is different from our expectation, suggesting that the signaling effects of price are additive to the signaling effects of advertising. Specifically, more premium brands can break away from the 'stuck-in-the-middle' zone by investing more in advertising (i.e., more than ¥1,780 million annually -- graphically depicted by the dot mark in Panel A of Figure 3.2). For example, a premium brand, like Tide, that spends about ¥1,657 million annually (and thus may incur negative spillover effects when opening a Tmall store) can cancel out these effects by spending ¥123 million more on advertising (an increase of 7.4%). Moreover, spending an additional ¥100 million more (an additional increase of 6.0%) the initial negative elasticity of -.075 becomes .143. In the washing powder category in which Tide operates this will lead to weekly additional sales of 21.8%, 21.3%, and 29.7%, at Carrefour, RT-Mart, and Walmart, respectively. More economy like brands, however, may want to be careful not to overshoot with advertising (i.e., no more than ¥1,230 million – as depicted by the triangle mark in Panel A of Figure 3.2) when operating on online platforms as a discrepancy between the price image and excess advertising may lead to negative spillover effects on the category. For instance, a non-premium brand, Jin Mai Lang, that chooses to increase its annual advertising spending from ¥1,549 million by ¥400 million (an increase of 26%) will curtail the elasticity from .244 to .193. In the instant noodle category in which Jin Mai Lang operates this will lead to a decrease in weekly sales of 5.1%, 4.6%, and 13.0%, at Carrefour, RT-Mart, and Walmart, respectively.

Turning to the role of brand equity, we find significant interaction terms of advertising with brand equity ($\omega_{j,c,r,4}$= -383.301, p < .01) as well as brand positioning ($\omega_{j,c,r,6}$= 99.549, p < .10). As shown in Panel B of Figure 3.2, advertising helps leverage the billboard effects for low equity brand supporting our expectation, suggesting that ceiling effects is strongest for high equity brand. The curve for low equity brands is non-decreasing, suggesting that ceiling effects are almost muted for low equity brands. In contrast, the curve for high equity brands is clearly U-shaped, indicating that ceiling effects are salient for high equity brands. Specifically, low equity brands, as long as they spend more than ¥780 million (depicted by the star mark in Panel B of Figure 3.2) in advertising, can enjoy positive spillover effects. For example, a low equity brand, like VV, has to increase its annual advertising spending from ¥611 million with ¥200 million (an increase of 33%) to end up with positive elasticity (from -.062 to .012). In the Milk/Soy milk/Infant formula category in which VV operates this will lead to an increase in weekly sales of 7.4%, 6.9%, and 15.3%, at Carrefour, RT-Mart, and Walmart, respectively. High equity brands, on the other hand, are likely to be 'stuck in the middle' when their advertising expenditures fall in the range of ¥780 million to ¥2380 million (the "stuck-in-the-middle" zone in Panel B of Figure 3.2). For instance, if a high equity brand, like Tsingtao, were to increase its annual advertising spending from ¥622 million to ¥200 million it would eradicate its elasticity from .113 to -.029. In the beer category in which Tsingtao operates this will lead to a decrease in weekly sales of 14.2%, 13.7%, and 22.1%, at Carrefour, RT-Mart, and Walmart, respectively.

To put these results in perspective, we interpret the results against the backdrop of category advertising spending (Table 3.4). With respect to price positioning, non-premium brands in categories with high advertising spending, such as skin care and shampoo/hair cream, should be cautious about the "overshoot" issue (i.e., excessive advertising leads to negative spillovers on category sales); premium brands in these category then should be aware of the "stuck-in-the-middle-zone" problem. Turing to brand equity, low equity brands in categories with low advertising spending, such as fabric softener and paper towels, can benefit from increasing their adverting budget, at least, to the "surface" point (i.e., the threshold of advertising spending switches spillover effects from negative to nonnegative). High equity brands in categories with high advertising spending, however, should pay more attention to the "stuck-in-the-middle-zone" problem.

Conclusion

Online marketplaces are gaining unprecedented popularity around the globe. Not only do these platforms allow CPG manufacturers to get direct access to consumers, they also allow them to build strong brands. Traditional routes to market often come with severe limitations. CPG manufacturers often find it hard to generate sufficient store traffic for a standalone brand site and the lack of one-stop shopping experience on these brand specific sites does not conform the way consumers shop for CPGs. Turing to reselling channel, CPG manufacturers often find themselves abused by powerful retailers (Gielens et al. 2017) as exemplified by the complaints about Amazon -- the largest online behemoth in the world – for being too aggressive in terms of controlling manufacturers (e.g., Chatterjee 2014; Harrison 2017).

A possible solution to these limitations may thus be offered by an online marketplace store. Still this begs the question whether a brand's success on online marketplaces can upset their entrenched resellers. So intrinsically CPG manufacturers need to find out whether and when platform stores can turn into truly brand building opportunities that allow them to expand their opportunities to get in touch with consumers without hurting entrenched brick-and-mortar retailers. That is, to what extent do online marketplaces lead to higher sales universally not just in the new channel? To address this question, we assessed the impact of CPG manufacturers' store openings at Alibaba's Tmall on entrenched brick-and-mortar stores. This particular context allows us not only to gauge insights in the success of these platforms in one of the most important emerging economies in the world but also to reflect on the potential of this route to market globally. Not only is Tmall the first online platform that is truly successful among consumers and brands with brand manufacturers often eager to partner with Tmall. Besides its access to a gigantic consumer base Tmall tries to treat manufacturers well, as evidenced by Tmall's commitment to clean up gray market on its platform, making many luxury brands, like Burberry, willing to join (Chu and Chiu 2014). Moreover, many brands -- not just local brands but also global brands -- learn how to do business on marketplaces successfully through Tmall – an experience which is often in stark contrast with what they encounter at other online platforms. On Tmall, manufacturers maintain control over the look and feel of their stores and implement whatever marketing strategy that aligns with their own interests, which is typically not the case on platforms such as Amazon.com or Walmart.com. The experience and learnings from operating on Tmall may thus create a pull effect from the brands for more similar operations on other markets/platforms. Last but not least, Alibaba is also looking across borders. For example, Alibaba is building logistics centers (Neerman 2018) and artificial intelligence (AI) data center (Kharpal 2018) in Germany. These cross-border movements may signal their eagerness to actively export the Tmall platform to other countries. From the perspective of CPG manufacturers that joined Tmall, the reverse marketing experiences -- ideas flowing from emerging markets to developed countries -- become extraordinarily valuable to help them leapfrog their peers without such experiences.

Still, for the online platform to become a truly viable gateway to consumers we need to demonstrate its potential for success. Based on our study we can answer to following questions.

Are Online Marketplaces A Winning Proposition? The answer is most definitely yes. Our results suggest that marketplaces may lift not only category sales in brick-and-mortar stores but also brand shares of those opt for online marketplaces. This finding provides clear evidence that online marketplaces may offer a win-win proposition -- creating synergies across channels and bringing positive spillovers to the entre supply chain system.

Are All Brands Created Equal? The answer is absolutely no. Our finding shows that while the market share of national brands increases, the market share of private labels shrinks. However, researchers and managers should be extremely cautious to interpret these results correctly because the total category sales in brick-and-mortar stores actually increase, making the sales of private labels not necessarily decrease. Still, the question can be asked why private labels do not gain share as their counterparts -- national brands -- do. A potential explanation is that national brands and private labels are usually in different consideration sets (Hauser and Wernerfelt 1990). Given that consumers traditionally consider a very limited set of alternatives (Putsis and Srinivasan 1994), the positive halo effects brought by national brands to brick-and-mortar stores may therefore not spill over to private labels.

Is the Brand's Price Positioning at Risk? We find evidence that the relative price positioning of focal brands deteriorates in brick-and-mortar stores. At first glance, manufacturers may feel anxious about this price retaliation from retailers who indeed feel threatened by marketplace activities. However, our results indicate that such concern may not be completely warranted -- their market shares actually increase after opting for marketplaces. That is, the billboard effects are stronger enough to wipe out the potential negative influences caused by increased price. Moreover, the lifted price in brick-and-mortar stores actually can reduce the risk of intra-channel price competition, making it much easier for manufacturers to manage the dual channel (marketplaces and reselling) system.

Does Advertising Help? Our findings indicate that advertising can reinforce the billboard effects built on online marketplaces, however, such reinforcement largely hinges on the manufacturers' brand characteristics, namely, price positioning and brand equity. Online marketplaces are more likely to create positive spillover effects on category sales for brands that either advertise very little or a lot. This finding indicates that manufacturers should be cautious about advertising investment. A thorough assessment of own brand characteristics before opting for online marketplaces is indeed the key lessons based on our study. For instance, more premium brands can break away from the 'stuck-in-the-middle' zone by investing more in advertising. More economy like brands, however, may want to be careful not to overshoot with advertising.

Future Research

First, we use Tmall -- the biggest online marketplace in emerging markets as the empirical context. Future research could generalize to other platforms as well as to other countries, for instance, eBay in the United States and Flipkart in India. Understanding the similarities and differences across different platforms may provide new insights to both academic researchers and industrial practitioners.

Second, although this study accounts for the reactions from retailers, future research may explicitly factor in the reactions from suppliers as well. Arya et al. (2007) show that suppliers may cut wholesale prices to soften the dual-channel competition with retailers.

Another interesting revenue of future research is to model the drivers of retailer reactions. Prior research shows that assortment overlap between the incumbent and new entrants plays an important role in the extent to which retailer perceive the seriousness of the threat (Gielens et al. 2008). Do retailers consider assortment overlap when making retaliation decisions? To what extent will retailers treat the overlap in assortment as a threat? Understanding the antecedents of retail retaliation will provide clear picture under the scene.

Finally, this study offers empirical generalizations that shed light on whether online marketplaces work and to what extent. However, this study does not allow for normative insights. For example, evaluating whether online marketplaces should not be launched in the first place cannot be done using the results from this study. Future research should try to implement a structural approach in the tradition of Nevo (2001) to derive insights.

Table 3.1: Three models of selling to consumers

Variable (label)	*Data Source*	*Measure*[a]
Market Position *(MKTPOS)*	Euromonitor, Mintel Oxygen	A firm's weighted market share in China (range is [0, 1]), whereby the weight is the percentage of a firm's total sales in the category.
Marketplace Experience *(CHLEXP)*	Factiva, Firm websites, Internet Archive Digital Library	Dummy variable that equals 1 when a firm launches a marketplace store on JD.COM, and 0 otherwise.
Portfolio Width *(PORWID)*	Euromonitor, Mintel Oxygen	Number of categories that a firm operates in China.
Brand Equity *(BRDEQY)*	BrandFinance.com	Dummy variable that equals 1 when a firm is listed in Brand Finance's Global 500 Most Valuable Brands list, and 0 otherwise.
Advertising *(ADV)*	Kantar Media	Annual advertising expenditure in China (Unit: Million Chinese Yuan).
Innovativeness *(INV)*	Compustat	Logarithm of annual R&D expenditure (Unit: Million US Dollar); Item: XRD.
Foreign Firm *(FOREIGN)*	Compustat	Dummy variable that equals 1 when a firm does not originate from China, and 0 otherwise; Item: LOC.
Total Assets (*TOA*)	Compustat	Annual total assets; Item: AT.
Return on Assets *(ROA)*	Compustat	A firm's net income divided by total assets; Items: NI/AT.
Financial Leverage *(LVG)*	Compustat	A firm's total liabilities divided by shareholder equity; Items: LT/SEQ.
Service *(SEV)*		Dummy variable that equals 1 when a firm's two digit SIC code is between 70 and 89, and 0 otherwise.
GDP of Home Country *(GDP)*	Compustat	GDP of a firm's home country j.
SGA*(SGA)*	Compustat	A firm's sales and general administrative expenses (SGA); Item: SGA.
Adoption Rate *(ADPRAT)* [b]	Compustat	Percentage of firms from the focal firm's home country j that adopted Tmall.

[a] All variables are measured in the year prior to event year.

[b] Variable featuring exclusively in the selection equation.

Table 3.2: (Exemplary) Empirical research on interaction between online and offline channels

		Intra Firm	Inter-Firm	
New channel owner		*Retailer*	*Retailer*	*Manufacturer*
New channel type	*Add offline channel*	• Avery et al. (2012) • Wang and Goldfarb (2017) • Bell et al. (2018) • Qian et al. (2013)	• Brynjolfsson et al. (2009) • Forman et al. (2009)	
	Add online channel	• Gallino and Moreno (2014) • Pauwels et al. (2011)	• Goldmanis et al. (2010)	• Branded website: Van Crombrugge et al. (2018) • Online platform: ***This study***

Table 3.3: Market share and price by retailer

Table 3.3A: Market share

	Market share by retailers		
Year	Carrefour	RT-Mart	Walmart
2011	8.56%	6.70%	7.04%
2012	8.51%	6.89%	8.50%
2013	8.31%	7.61%	8.18%
2014	8.18%	8.02%	7.91%

Table 3.3B: Relative price (Carrefour is the reference)

	Relative price by retailers		
Year	Carrefour	RT-Mart	Walmart
2011	1.00	1.07	1.15
2012	1.00	1.08	1.15
2013	1.00	1.09	1.13
2014	1.00	1.07	1.12

Table 3.4: Sales, price, advertising spending, number of brands, and pl share by category

Category Name	Share of Wallet (2011-2014)	Average price (Value sales/Unit sales)	Annual category advertising spending (2011-2014, Unit: Billion CNY)	Number of brands that opened Tmall store	Number of NBs in the category
Baby diapers/Pants	1.10%	76.85	6.62	4	4
Beer	1.40%	4.56	7.54	4	10
Biscuit	4.32%	8.58	4.25	5	12
Bread	0.71%	5.22	4.25	5	11
Butter/Cheese/Honey/Jam	1.81%	15.55	0.00	5	14
Cake/Pie	0.88%	9.40	4.25	5	9
Candy	0.94%	7.18	11.03	5	8
Cereals	0.96%	15.79	0.32	5	8
Chewing gum	1.04%	7.55	6.16	4	6
Chocolate	2.05%	14.65	11.03	5	9
Conditioner	0.81%	20.22	0.88	5	9
Edible vegetable oils	9.50%	52.20	3.71	5	10
Fabric softener	0.35%	18.26	0.01	4	5
Facial cleaning products	1.69%	20.69	3.24	5	8
Family special detergent	1.69%	11.47	0.98	4	15
Frozen dessert	2.41%	10.46	5.70	4	10
Hair dye	0.38%	40.33	0.58	4	6
Hand lotion	0.23%	11.45	0.35	4	5
Household cleaning	0.48%	8.37	0.10	4	6
Ice cream	0.56%	5.23	2.47	4	8
Instant noodles	1.68%	5.60	5.70	4	6
Jelly pudding	0.22%	3.98	4.25	4	6
Laundry detergent	0.79%	5.00	0.35	5	12
Laundry soap	2.13%	20.68	0.18	5	8
Liquid beverage	5.55%	4.41	11.69	4	13
Milk	7.50%	8.17	3.96	5	8
Milk/Infant formula	4.74%	65.00	0.74	5	9
Other solid beverage	0.96%	15.49	0.22	4	6
Paper towels	4.87%	8.13		4	12
Rice	3.92%	47.79		3	8
Salty snack	2.12%	5.77	2.04	4	10
Sanitary napkins	2.25%	8.35	3.24	5	14
Sausage/Ham/Bacon	2.27%	7.13	0.14	4	9
Shampoo/Hair cream	3.38%	30.44	21.72	4	7
Shower gel	1.23%	22.16	0.74	5	9
Skin care	4.08%	29.48	119.03	4	10
Solid beverage	2.15%	13.99	5.84	4	8
Soup	0.64%	5.84	0.09	4	7
Soy sauce/Oyster sauce	1.87%	7.86	2.32	4	9
Spirit	3.77%	41.50	7.54	4	7

Toilet soap	0.66%	5.80	1.71	4	7
Toothbrush	0.68%	6.07	1.71	4	13
Toothpaste	2.11%	8.62	16.54	4	13
Washing powder	1.07%	14.11	2.46	4	9
Yogurt/Yogurt drink	6.06%	6.10	1.78	4	11
Total (or Average)	1	10.49	287.92	195	404

Table 3.5: Effects of online marketplaces on category sales and market share

		Marketplace Entries By	
Effect On	All	Market Leaders	Other Brands
Category sales			
z-value	**1.70****	-1.28	**2.54*****
% + (p < .05)	14.72	8.40	16.40
% - (p < .05)	13.65	22.69	11.24
Focal brand market share			
z-value	**2.17****	**1.90****	**1.98****
% + (p < .05)	7.57	6.72	7.80
% - (p < .05)	7.38	9.24	6.86
Rival NB market share			
z-value	**4.35*****	**1.75**	**4.22*****
% + (p < .05)	9.42	10.29	9.20
% - (p < .05)	9.92	10.06	9.89
Rival PL market share			
z-value	**-2.03****	-.22	**-2.01****
% + (p< .05)	7.61	9.01	7.14
% - (p < .05)	15.22	18.18	14.29

***$p < .01$, **$p < .05$

Notes: [a] Cases refer to brand–category–retailer combinations. In total, we follow the Tmall entries by 195 unique brands. Not all 195 brands are available across all retailers. To avoid confusion, we report the total number of brand–category–retailer combinations.

[b] The meta-analytic z-values are obtained by the method of adding weighted Zs (Rosenthal 1991); z-values that are significant at $p < .05$ (one-sided) are in bold. For effects on category sales, focal NBs market share, and rival NBs market share, these effects are tested to determine whether they are significantly different from zero and positive. Competitive effects on rival PLs market share are tested to determine whether they are significant and negative.

Table 3.6: Effects of online marketplaces on retail price

		Marketplace Entries By	
Effect On	All	Market Leaders	Other Brands
Focal NB retail price			
z-value	**1.88****	.18	**1.87****
% + (p < .05)	7.47	.03	8.89
% - (p < .05)	6.73	.08	6.25
Rival NB retail price			
z-value	-.81	-.13	-.80
% + (p < .05)	5.96	6.72	5.69
% - (p < .05)	7.02	6.95	7.10
Rival PL retail price			
z-value	-.07	**-1.72****	.86
% + (p < .05)	10.87	4.76	9.86
% - (p < .05)	7.61	14.29	8.45

***p < .01, **p < .05

Notes: [a] Cases refer to brand–category–retailer combinations. In total, we follow the Tmall entries by 195 unique brands. Not all 195 brands are available across all retailers. To avoid confusion, we report the total number of brand–category–retailer combinations.

[b] The meta-analytic z-values are obtained by the method of adding weighted Zs (Rosenthal 1991); z-values that are significant at $p < .05$ (one-sided) are in bold. Effects on focal NBs retail prices are tested to determine whether they are significantly different from zero and positive. Effects on rival NBs and rival PLs retail prices are tested to determine whether they are significant and negative.

Table 3.7: Explaining store opening elasticities w.r.t. category sales

Dependent Variables: $\boldsymbol{\varphi_{j,c,r}}$	**Estimate**	***t*-value**
Intercept	.066	.14
Main Effects: Advertising		
Advertising	-.314	1.28
Advertising Squared	**.275**	**2.81*** **
Moderating Effects		
Advertising × Brand Positioning	**-1.212**	**3.18*** **
Advertising × Brand Equity	**-383.301**	**3.81*** **
Advertising Squared × Brand Positioning	**.932**	**5.33*** **
Advertising Squared × Brand Equity	**99.549**	**1.68* **
Control Variables		
Brand Positioning	-.192	1.27
Brand Equity	104.842	1.53
Market Position Dummy Variables	Included	
Category Fixed Effects	Included	
Retailer Fixed Effects	Included	
R-square		.18

***$p < .01$, **$p < .05$, * $p < .10$

Figure 3.1: Conceptual framework

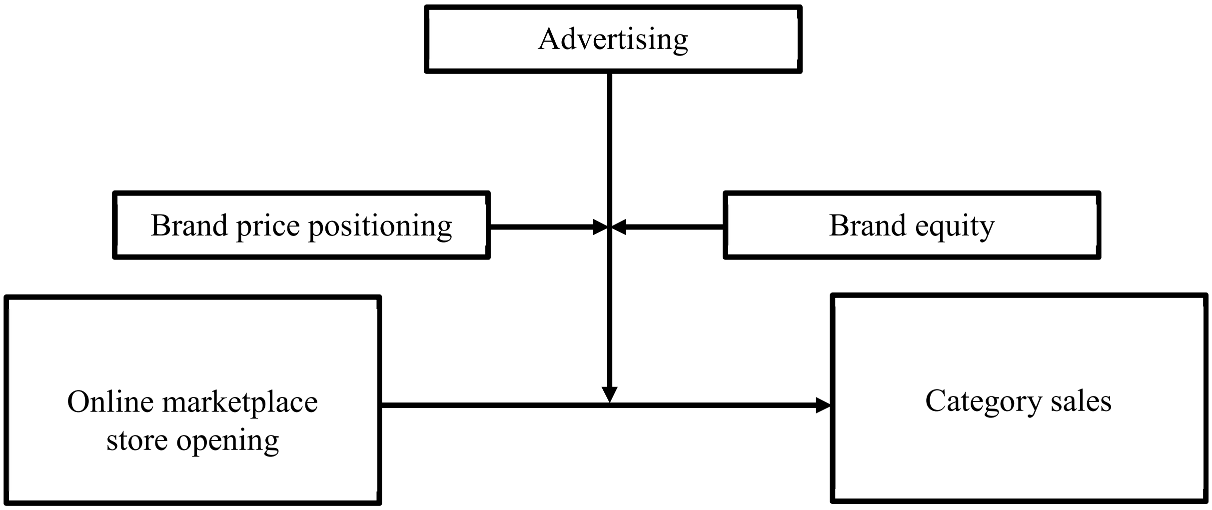


Figure 3.2: Simple slope for predicted store opening elasticities with respect to category sales

Figure 3.2A: Price positioning

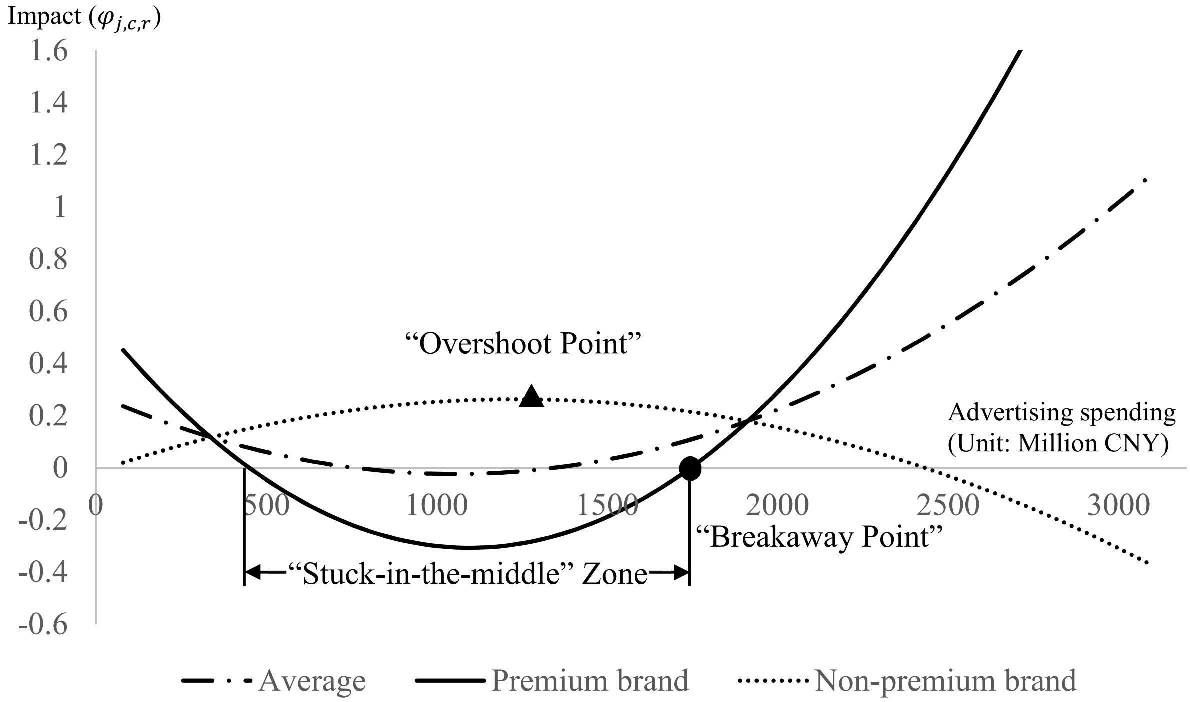
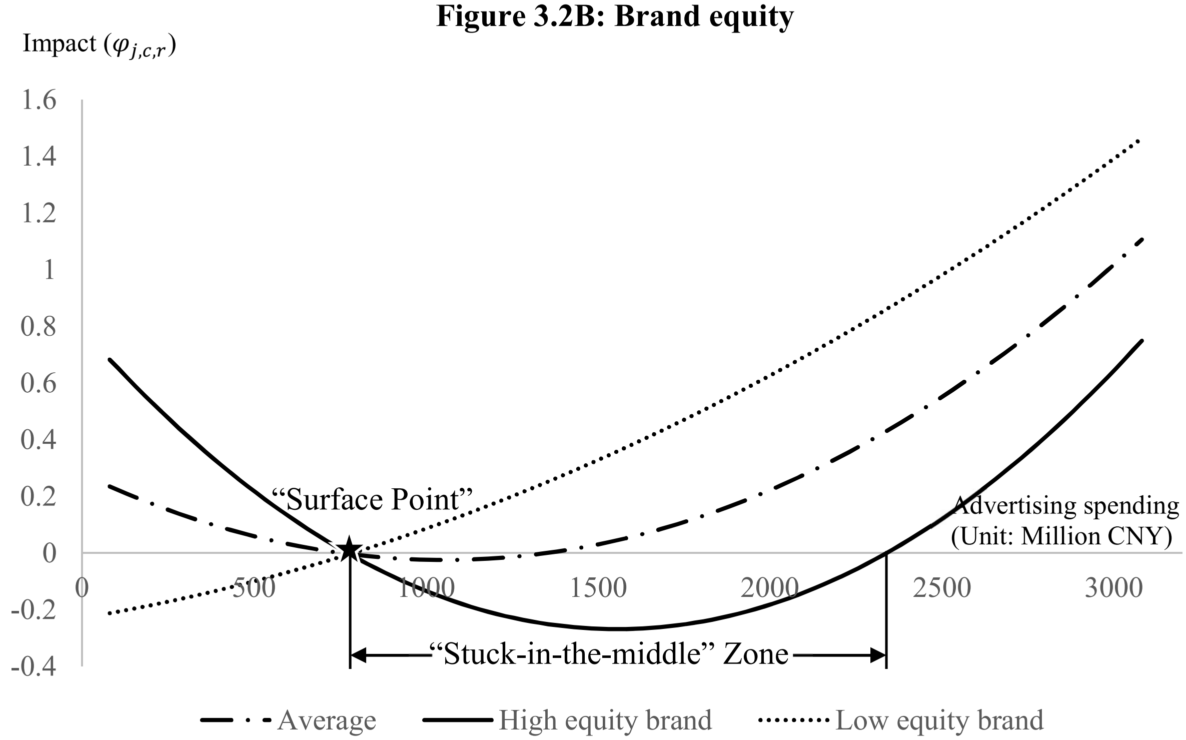


Figure 3.2B: Brand equity



CHAPTER 4: WHEN STORES LEAVE: THE IMPACT OF WALMART SUPERCENTER CLOSURE ON RETAIL PRICE

Abstract

In this paper, we seek to understand the impact of store closures on local communities. More specifically, we examine how retail prices change following the exit of a local retailer. To that extent, we focus on Walmart supercenter closures in local U.S. markets. By using a difference-in-difference estimator with correction for selection bias, we find that, on average, consumers have to pay a higher price (+1.6%) after a Walmart supercenter' exit. This suggests that the benefits remaining retail stores harness due to decreased competition outweigh the loss of agglomeration benefits. Moreover, our study shows that the pricing effects of supercenter closures differ by the type of consumers. Specifically, the pricing effects are stronger for Walmart loyal consumers and households who spend more on fresh products and produce. More importantly, we find that the pricing effects highly depend on the level of overlap between remaining and exiting stores. In particular, the pricing effects are most salient at remaining retailers that are highly overlapping with supercenters in terms of assortment and positioning rather than retailers that are highly differentiated from supercenters. Interestingly, our results suggest that the pricing effects are quite robust (rather than decline quickly) with distance: The magnitude of the price increase at the discount stores that are close to the exiting supercenter is similar to that of discounts stores that are farther away from the exiting supercenter.

Keywords: Walmart, retail exit, retail price

Introduction

The retail industry has witnessed unprecedented change over the past five years. Not only do many established retailers find it hard to satisfy the demanding customers, they also face rising competition from e-commerce and hard discounters. Under such pressure, many retailers decide to scrutinize their finance and shut down their stores. In 2018, for example, Walmart, the world's largest retailer closed 60 stores across the U.S. (Thomas and Wells 2018). Meanwhile, Sears and Best Buy closed 142 and 250 unprofitable stores by the end of the same year, respectively (Timmermann 2018). These are just some conspicuous examples representing more than 5,000 retail store closures in the U.S. (Tokosh 2018). A similar story is unfolding in Britain, where the media regularly forecasts "the end of the high street". In 2018 alone, major UK retailers closed 1,267 retail stores (Wilson and Scott 2019). Whether these closures indicate the permanent death of brick-and-mortar stores or are they merely painful, but necessary transformations is not known yet. Interestingly, however, is the fact that at the same time consumers are spending more (Gielens and Gijsbrechts 2018). According to a report by Reuters, consumer spending, which accounts for more than two-thirds of the U.S. economy, increased at a 3.6 percent annualized rate in the third quarter of 2018 (Mutikani 2018). The retail pie, therefore, is not shrinking at all.

This raises the question whether the market is becoming more oligopolistic and consumers are simply paying higher prices. Or, does it mean that prices have remained unchanged but consumers are buying more? Despite its prevalence and complexity, relatively little is known about store closures and its relationship with retail price. In this paper, we seek to address this question -- how do retail closures influence retail price. On the one hand, as a market becomes less competitive, remaining stores are able to raise the price as the number of competitors decreases in the local market (Ozturk et al. 2016). In contrast, remaining stores may not have the luxury to increase the price because they lose the co-location benefits when their rival exits (Rosenthal 1980). The co-location or *agglomeration effects* arise when differentiated retailers choose to cluster around their rivals as the increased demand due to co-location exceeds the decreased demand due to competition (Zhu et al. 2011). In the presence of the two opposing effects, the pricing effects of retail closures become hard to predict.

To complicate things even further, not all consumers in the local market stand to be affected equally by the retail store closure. The extent to which a consumer is vulnerable to the *post-exit* price surge at remaining stores depends on his or her *prior-exit* retail patronage and socio-demographic profile. The intuition is that consumers of the exiting store need to choose a new place to shop after the exit and the store decision is often determined by their retail patronage and social demographics (Bell and Lattin 1998; Ellickson and Misra 2008; Lal and Rao 1997). As we discussed before, some remaining stores tend to increase the price following store exits due to decreased competition, while some others may decrease price because of diminished agglomeration. If consumers tend to patronize the remaining stores that gain considerable deduction in competition, they are likely to pay a higher price. By contrast, consumers who deflect to the retailers that loss tremendous amount of agglomeration benefits, tend to pay less.

To add another layer of complexity, pricing effects may also vary by the overlap between the remaining and exiting stores, whereby overlap refers to the similarity in store assortment and price positioning (Gielens et al. 2008; Zhu et al. 2011). When the overlap between retailers is high, agglomeration benefits are typically limited and competition is more fierce, keeping prices lower in such markets (Anderson and Neven 1991). When a similar competitor leaves such a market, the tendency to compete on price will become weaker and prices may increase.

In summary, in this paper we tackle three research questions. First, how do retail store closures affect the retail price in a local market? Second, does this impact differ by the type of consumers? Third, does the pricing effect vary by the overlap between the remaining and exiting stores? To address these questions, we study the implications of Walmart supercenter closures in January 2016. On January 15, 2016, Walmart announced to close 269 stores across the world, which includes 12 Walmart supercenters in the US[8]. Figure 4.1 graphically depicts the locations of these stores.

The context of these Walmart supercenter closures fits the research purpose very well. First, as the largest retailer in the world, Walmart's entry been studied extensively. For example, prior research finds that the entry of Walmart affects market structure (Ellickson and Grieco 2013; Jia 2008), retail price (Basker 2005b), competitors' firm value (Gielens et al. 2008), supplier profits (Huang et al. 2012), labor markets (Basker 2005a), consumer surplus (Hausman and Leibtag 2007), obesity rate (Courtemanche and Carden 2011), and housing price (Pope and Pope 2015). Accordingly, we expect the closure of Walmart stores to create notable impact. Second, Walmart supercenters, an average 180,000 square feet, are retail stores that combine a discount department store with a full-service supermarket. They offer a wide variety of general merchandise and food items, including meat, produce, deli, and other perishables (Singh et al. 2006). In addition, many supercenters include ancillary services such as pharmacy, dry cleaning, and vision center. The wide spectrum of business lines not only enables Walmart supercenter to

[8] We exclude a closed supercenter in Alaska from the treatment pool because we do not have information on local market structure.

compete directly with retailers of different assortment and positioning, but also allows us to capture various remaining retailers' reactions following a supercenter exit.

We use a unique data set compiled from three main sources in our empirical analysis. Specifically, we combine U.S. household panel data, covering all packaged food, fresh produce, and nonfood purchases from all retail formats one year before and one year after the supercenter closures, with (1) detailed Walmart supercenter geographic information and supercenter closure dates, and (2) five-digit zip-code-level U.S. social demographic data. Using a difference-in-difference framework with a correction for selection bias, we estimate the pricing effects of store closures in depth to address the three research questions in this study.

We find that, on average, consumers have to pay a higher price (1.6%) after Walmart supercenters exit. This suggests that the benefits that remaining retailers harness due to decreased competition outweigh the loss of agglomeration gains. Moreover, our study shows that the pricing effects of supercenter closures differ by the type of consumers. Specifically, the pricing effects are stronger for Walmart loyal consumers. In addition, such effects are also stronger for households who have a high share of wallet (SOW) in fresh produce. More importantly, we find that the pricing effects highly depend on the level of market overlap between remaining retailers and exiting stores. In particular, the pricing effects are most salient in remaining retailers that are highly overlapped with supercenters in terms of assortment and positioning (i.e., discount stores) rather than retailers that are highly differentiated from supercenters (e.g., drug store). Interestingly, our results suggest that the pricing effects are quite robust (rather than decline quickly) with distance: The magnitude of price increase at the discount stores that are proximate to the exiting supercenter (0-10 miles) is similar to that of discounts stores that are farther away from the exiting supercenter (20-30 miles).

Conceptual framework

We first reflect on the overall pricing effect of store closures before elaborating on moderating consumer and retailer effects as shown in Figure 4.2.

The Pricing Effect

So far, the effects of market exits have been largely unexplored. To that extent, we mainly draw upon the entry literature to postulate the nature of the pricing effects in local markets when retail stores close.

The empirical entry literature mainly suggests that prices decrease following the entry of big chains (Ailawadi et al. 2010; Basker 2005b; Basker and Noel 2009; Hausman and Leibtag 2007; Singh et al. 2006; Zhu et al. 2011; Zhu et al. 2009). For example, Basker (2005b) finds that a Walmart entry leads to lower average retail prices, with a decrease of 1.5-3% in the short run and four times as much in the long run, even though the magnitudes vary considerably by product and specification. Relatedly, Basker and Noel (2009) explore the variation in the price reductions and find that competitors' response to entry by a Walmart Supercenter is a price reduction of 1-1.2%, mostly due to smaller-scale competitors rather than big-chain rivals. In addition, Hausman and Leibtag (2007) find that consumers benefit from the entry of a Walmart supermarket both through a direct price effect that arises from the lower prices at the Walmart supercenters themselves and through an indirect price effect that arises from the competitive pressure that Walmart exerts on traditional food outlets. Specifically, average prices paid by consumers fall by 3% over four years or .75% per year as shopping shifts to the lower-priced supercenters, mass merchants, and club stores (SMCs). In contrast, Ailawadi et al. (2010) show that incumbents show little reaction in many stores and categories when Walmart enters a market. Yet, the question remains whether store exit effects will take the exact mirror image of these entry effects. Currently, the literature on the pricing effects of retail exits is extremely limited. One exception is the work by Ozturk et al. (2016). In the context of car dealership exits the authors report that prices increase by about 1% following an exit relative to the price change in the absence of an exit. Given that their study is based on durable goods (i.e., car), it is unclear whether the predictions from this literature translate directly to the case of frequently purchased grocery products.

To gain insight in the potential impact of retail store exits, we turn to insights on competition versus agglomeration effects in local retail markets.

Competition vs. Agglomeration

Although empirical exit studies are rare, the analytical literature provides us the framework to predict the potential pricing outcomes of retail closures (Zhu et al. 2011). The key factor to determine a remaining store's *post-exit* response depends on the *prior-exit* bilateral relationship between the remaining and exiting store. The bilateral relationship consists of two opposing forces: competition versus agglomeration effects. If two retailers are highly overlapping in terms of assortment and positioning they are essentially targeting the same, or at least very similar, consumer segment. An increase in sales at one retailer is very likely at the expense of a sales decrease at the other retailer. In this case, the bilateral relationship is competition-dominant. Abundant empirical studies document this competitive relationship (e.g., Ellickson and Grieco 2013; Jia 2008; Shields and Kures 2007; Vias 2004; Watson 2009). Not too surprisingly, many of them are in the context of Walmart. When the bilateral relationship is competitive, the exit of any player monotonically de-escalates the intense competition. As a result, the remaining player obtains the luxury to charge a higher price.

By contrast, when two retailers are very distinct from each other with respect to assortment and positioning, they are intrinsically catering to different groups of consumers or to the same group of consumers under different demand occasions. For example, a consumer in need of groceries and durables on the same shopping trip may bypass a nearby grocery store but instead visit a supermarket (for groceries) located near a discount store (for durables). In this example, the supermarket and the discount store create sales for each other rather than steal from each other. The intuition behind it is that the presence of rival stores in close geographic proximity leads to a decline in consumers' search costs and an increase in aggregate demand. In this case, the bilateral relationship is agglomeration-dominant. Empirical research reports the agglomeration effects in the lodging industry (Chung and Kalnins 2001), shopping center industry (Vitorino 2012), and retail industry (Datta and Sudhir 2013). When the bilateral relationship is mainly driven by agglomeration, the exit of any retailer unavoidably curtails the clustering benefits. Consequently, the remaining store has to reduce the price to retain consumers.

In grocery retailing settings overlap in positioning and assortment are reflected by differences in the retail format. To further reflect on the differences in retail prices found at different retailers following a competitor's exit, we elaborate in the following on the role of store format and physical distance.

Store Format

The rapid growth of alternative retail formats, in the form of mass discounters, wholesale clubs, drug stores, and supercenters, has transformed not only the competitive structure of the industry, but also the way in which consumers shop (Singh et al. 2006). Retailers of the same format often compete with each other because they are very similar in terms of store size, product assortment, and pricing strategy (Briesch et al. 2009). By contrast, retailers of different formats are more immune from each other's competition as they target distinct consumer segments or shopping trips. Supercenter formats, which mostly target lower-income consumers with larger families, are retail stores that combine a discount department store with a full-service supermarket. They offer a wide variety of general merchandise and food items at low price (Singh et al. 2006). On the other hand, grocery stores, which target time-constrained, service-seeking customers, often differentiate from discounters by opening stores in convenient residential areas and providing a higher level of service. (Gauria et al. 2008). Moreover, drug stores, a highly specialized format, mainly sell medicines and miscellaneous items, such as food, cosmetics, and film. In addition, warehouse clubs target consumers who are willing and able to buy in bulk because the package sizes sold at club stores are over three times larger than those in other formats (Ailawadi et al. 2018).

Using the framework we discussed before, the bilateral relationship between the same formats is likely to be competition-dominant, while the bilateral relationship between the different formats tends to be agglomeration-dominant. Existing studies lend empirical support for this prediction. For example, Ailawadi et al. (2010) study the entry effects of Walmart on incumbents of various formats such as mass stores, supermarkets, and drugstores. They find that incumbents that have greater proximity or assortment overlap with Walmart suffer more: mass stores suffer a median sales decline of 40%, supermarkets suffer a median sales decline of 17%, and drugstores experience a much smaller median decline of 6%. Similarly, Igami (2011) studies the entry of large supermarkets in Tokyo, and finds that their entry induces the exit of existing large and medium-sized competitors, but improves the survival rate of small supermarkets. The latter position themselves in a differentiated product space to avoid/reduce direct competition with the big entrant. In the context of Walmart store closures, retailers adhering to a discount format, like Walmart, will be Walmart's closest competitors. Accordingly, when a Walmart supercenter leaves the market, we expect the remaining discount retailers to experience more reduction in prior-exit competition. As a result, these remaining discount stores are able to charge a higher price. By contrast, we expect the remaining retailers adhering to other store formats to lose the highest amount of agglomeration benefits. Consequently, these retailers are more likely to cut prices.

Physical distance

Retail stores, big or small, usually have a specific trading area -- the geographic area from which a store generates the majority of its customers (Huff 1964). Retailers therefore do not open too many stores in the same neighborhood or pinpoint their stores too close to its competitors in order to avoid own-business-stealing or cross-business-competition effects, respectively (i.e., spatial competition). Extant research lends support for the existence of spatial competition (Nishida 2014; Ozturk et al. 2016; Pancras et al. 2012). However, the majority finds the magnitude of the spatial competition is either small or the effects decline with distance very fast. For example, Pancras et al. (2012) studied the net impact of a US fast food store's opening/closure on overall chain performance. They conclude that the majority (86.7%) of the sales generated by each store comes from incremental demand, whereas cannibalized sales from nearby stores belonging to the chain only take a small portion (13.3%). Moreover, they also find a significant decay in cannibalization with distance: when the distance between stores increases by one mile, the sales lost due to cannibalization decrease by 28.1%. Similar findings have been reported by Nishida (2014), who finds that the cannibalization effects decay significantly with distance by analyzing the convenience store industry in Okinawa, Japan.

Turning to the setting of our study, these insights imply that we need to factor in physical distance between the remaining stores and exiting store when evaluating how pricing effects vary when Walmart pulls out from the local market. For remaining stores that mainly have a competitive relationship with the exiting store (i.e., discount stores), the nearby stores get a more pronounced reduction in competitions effects than the more distant ones, lending the nearby retailers more room to raise prices following a Walmart exit. As a result, we expect price increases more at nearby (discount) stores than at more distant (discount) stores. By contrast, for remaining stores that mainly have an agglomeration relationship with the exiting store (e.g., drug stores), the nearby stores lose a greater amount of agglomeration benefits than the more distant ones, which forces the nearby retailers to cut prices more following a Walmart exit. Consequently, we expect more price decreases at nearby stores than at more distant stores.

Shopper Characteristics

When store exits, consumers face the decision to either pick up a new place to shop or increase the purchase at remaining stores. Such post-exit store decision is often determined by consumer retail patronage and socio-demographic profiles (Bell and Lattin 1998; Ellickson and Misra 2008). Given that not all remaining stores increase/decrease post-exit prices to the same extent, we need to factor in consumer characteristics in order to determine what types of consumers suffer more from a potential post-exit price surge. As we discussed before, highly overlapping remaining stores are more likely to increase prices following store exits due to decreased competition. When consumers choose remaining stores that are highly overlapping with Walmart supercenters as their new store to shop, they may end up having to pay a higher price. In contrast, highly differentiated remaining stores are likely to cut prices after store closures because of weakened agglomeration benefits. When consumers pick up such remaining stores that are highly distinct from Walmart supercenters as their new shopping alternative, they may pay a lower price. To that extent we need to consider what type of consumers are more likely to prefer the discount format. Overall, discount formats tend to be characterized by "Everyday Low Price" (EDLP) pricing strategy (Ellickson and Misra 2008). As such, discount channels tend to be preferred by shoppers who want to minimize the fixed cost of shopping, namely, large family households, low-income households (Ellickson and Misra 2008), and large basket shoppers (Bell and Lattin 1998). In sum, we expect:

Household size (+). Large households tend to be large basket shoppers because the consumption need is intrinsically large. They have a relatively high probability of purchase for any given category per shopping trip. Therefore, they become less capable to respond to prices in individual product categories but will be more sensitive to the expected cost of the overall portfolio (the market basket) when choosing a store (Bell and Lattin 1998). Discount stores usually implement EDLP pricing strategy across a wide assortment of product categories. When a Walmart supercenter exits, large households that purchase products from a wide range of categories therefore will prefer discount stores (i.e., EDLP store) where the overall expected price across a wide variety of categories is lower. Since discount stores are highly overlapping with Walmart supercenters, we expect large households to be more vulnerable to the post-exit price surge.

Household income (-). High-income households have high opportunity costs of time and are likely to be more price sensitive (Blattberg et al. 1981). This segment is willing to pay for added convenience at a store, which helps them save time. They therefore are likely to shop at "High-Low" (HiLo) grocery stores with convenient locations in residential areas (closer to their households) and a high level of service (Gauria et al. 2008). In contrast, low-income households are less time-sensitive and experience low disutility for travel costs. They therefore prefer to patronize discount stores or supercenters, which occupy large areas and are located in areas with low rents, usually outside the city limits (Ellickson and Misra 2008; Gauria et al. 2008). When Walmart shuts down a supercenter, low-income households are likely to choose another discount store that uses an EDLP pricing strategy as the new place to shop. Given that discount stores tend to raise prices following a Walmart exit, we expect low-income households to be more vulnerable to the post-exit price surge.

Share of wallet at Walmart (+). Using an EDLP pricing strategy, Walmart mostly aimed at lower-income consumers with larger families (Ellickson and Misra 2008; Gielens et al. 2008). Consumers with a high SOW at Walmart are very likely to be the segment that Walmart is targeting at, namely, a low-income and large-family segment. When a Walmart supercenter exits, this low-income and large-family segment tends to pick up another discount store as the alternative due to low disutility for travel costs and high sensitivity to expected basket cost, respectively. As we discussed previously, incumbents that are highly overlapped with Walmart supercenters in terms of assortment and position (e.g., pricing strategy) stand to increase price following a Walmart supercenter closure. We therefore expect consumers with a high SOW at Walmart to be more vulnerable to the post-exit price increase as well.

Share of wallet in fresh produce (-). HiLo grocery stores that targeting at the time-constrained consumers often compete against EDLP discounters by including a rich assortment, such as fresh produce and fruits, higher quality meats and fish, delis and other specialty goods (Lal and Rao 1997). Consumers with a high SOW in fresh produce are very likely to be the consumers that HiLo stores are targeting at. When Walmart shuts down the supercenter, this segment tends to choose HiLo stores rather than EDLP discounters as the new alternative. Since

HiLo grocery stores are substantively distinct to EDLP discounters in terms of assortment and service, the former is very unlikely to increase the price when the latter quits. As such, we expect the households with a higher SOW in fresh produces to be less vulnerable to the post-exit price increase.

Data

Setting: Walmart Supercenter Closures

On January 15, 2016, Walmart announced it would close 269 stores across the world, including 12 supercenters in the U.S. (Walmart 2016). Since we want to assess the impact of Walmart supercenter closures on local retail prices paid by the consumer, these closed supercenters become the treatment stores in our analysis[9]. Although the location of the closed Walmart supercenters varies across the U.S., 10 out of 12 the supercenters were closed on the same day (i.e., January 28, 2016)[10]. Therefore, the exit variation in our data is mainly cross-sectional and the endogeneity of the exit-timing decision is unlikely to be a concern is our study. This, combined with the panel structure of the data, allows us to account for strategic selection of the exiting stores and for other time-invariant, household-specific unobservables, via the inclusion of household fixed effects.

Retail Market Definition

Walmart supercenters usually have a trading radius of 15 miles. Accordingly, we use a 15-mile boundary to define the local retail market (for a similar approach, see Ailawadi et al. 2010). Hereafter, we use the word "market" and "vicinity" interchangeably. A specific

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[9] We exclude a closed supercenter in Alaska from the treatment pool because we do not have information on local market to implement correction for selection bias.

[10] The two exceptions are supercenter #2837 in Las Vegas, NV is closed on January 17, 2016 and supercenter #3814 in Juneau, AK is closed on February 5, 2016.

household is assumed to be “treated” by a Walmart supercenter closure if the household lives within the vicinity of a closed supercenter. Similarly, we use a 15-mile boundary in our selection of control households. After household selection, we include the purchase made by the treatment and control households at all retail stores, regardless of the distance, in our analysis (Hwang and Park 2015).

Data Description

We compile a data set from three resources for this research. The primary source is the nationwide home-scan panel data set from A.C. Nielsen, which consists of approximately 61,500 randomly selected households across the U.S. and includes purchases as well as demographic information for all households in the sample (Hausman and Leibtag 2007). Households scan their purchases of all-bar-coded packaged goods (food and nonfood) at home. Unlike retail scanner data that usually do not include the sales of Walmart, the Nielsen home-scan panel data set enables us to observe actual purchase choices by consumers at both Walmart and competing retail channels (Hwang and Park 2015). Specifically, this data set records household’s purchases from all grocery retail formats, including discount stores, grocery stores, warehouse clubs, drug stores, convenience stores, and department stores. The data cover the period of January 2015 to December 2016, which is approximately one year before and one year after the Walmart supercenters closure date. We aggregate the households’ trip-level data into weekly data and compute the weekly average price paid by each household across all retail channels as well as individual channel.

Along with the records on shopping trips, the Nielsen home-scan panel data set also provides us the details on households’ location (i.e., five-digit zip codes of household’s home addresses). By using Google’s geocoding service, we first obtain the longitudes and latitudes of five-digit zip code centroids for each household. We then use the GEODIST function in SAS to computes the geodetic distance in miles between each household to Walmart stores. The distance variable is of great importance in our identification strategy because it enables us to tell whether a household is within the vicinity of a closed/open Walmart store.

The second data source is the geographic information on Walmart supercenters in the U.S. This data set comprises the address, store numbers (store ID), store type, and closure date (if the store is closed in January 2016) for each Walmart supercenter. We obtain the data from Walmart's website using Python Scrapy (https://scrapy.org/), an open-source web-crawling framework. We supplement this data set by combining longitude and latitude coordinates of each Walmart store using Google's geocoding service. In total, our sample includes the detailed information on 3,066 Walmart supercenters in the U.S. It is worth to mention that Walmart rarely opens more than one Walmart supercenter in the same zip code outside of Arkansas (i.e., the home state of Walmart) to avoid business-stealing effects between stores (for a detailed discussion, see Holmes 2011). This enables us to use the geographic region defined by the five-digit zip code as a proxy of the vicinity of each supercenter. As a result, we can use the five-digit-zip-code-level market information (e.g., social demographics and retail competition structure) to correct for potential selection biases due to observables for each closed supercenter in our empirical analysis (see below for a further discussion).

The third source pertains to market-level information on social demographics and retail competition structure. With respect to the social demographics, we harness the data from the American Community Survey (ACS)[11], an annual survey by the U.S. Census Bureau. This survey gathers rich information on social demographics, such as ancestry, educational

[11] Website: https://census.gov/programs-surveys/acs/.

attainment, income, language proficiency, migration, disability, employment, and housing characteristics. The survey collects the details on participants' location (i.e., 5-digit zip codes of participants' home addresses). We aggregate the individual-level data and compute the demographic variables at the 5-digit zip-code level. Regarding the retail competition structure, we obtain the retail store data from A.C. Nielsen. This data set contains the detailed information (e.g., retail format and geographic location) on retail stores in the U.S. We aggregate the store-level data and compute the retail competition structure (e.g., the number of discount stores) at 3-digit zip-code level[12]. Moreover, we link the retail store data to the home-scan panel data set and compute the annual sales growth rate of individual retail channel for each market. The information on the number of stores along with the annual growth rate provides us the required knowledge on the local market structure.

Household Selection: Treatment and Control Households

To attribute any pricing effects to Walmart supercenter closures and not to other confounding events, we compare the price paid by the households in markets where a Walmart supercenter exits i.e. treatment households, with the price paid by the households in markets where a Walmart supercenter does not exit, i.e. control households. Therefore, we need to identify the treatment and control households that are identical, apart from the treatment. As such, the deviation in the difference in price for treatment households from that of the control households provides a causal estimate of the treatment effect.

[12] A.C. Nielsen only provides store information at 3-digit-zip-code level to avoid store identification.

We use the 11 Walmart supercenters that are closed at the end of January 2016 as the treatment supercenters[13] to select treatment households. More specifically, we select treatment households on the basis of the following conditions:

(1) The household's distance from any treatment Walmart supercenter is less than 15 miles.

(2) The household stays in the panel from January 2015 to December 2016.

(3) The household records at least 10 shopping trips every calendar year.

Condition 1 ensures that the treatment household is within the vicinity of the treatment Walmart supercenter (Ailawadi et al. 2010). Condition 2 ensures that we have sufficient shopping records of the household before and after the supercenter closures. Condition 3 ensures that we exclude the households that may not have faithfully reported their shopping trips (for a similar approach, see Hwang and Park 2015).

To identify the control household, we use a random sample of 1,500 households from the Nielsen home-scan pool (for a similar approach, see Gill et al. 2017; Shi et al. 2017). We then only retain the households that meet the following conditions:

(1) The household's distance from any treatment Walmart supercenter is more than 15 miles.

(2) The household's distance from the closest non-treatment Walmart supercenter is less than 15 miles.

(3) The household stays in the panel from January 2015 to December 2016.

(4) The household records at least 10 shopping trips every calendar year.

Condition 1 ensures that the impact of treatment store on control household is limited. Condition 2 ensures that the control household is within the vicinity of the non-treatment Walmart supercenter. Condition 3 ensures that we have sufficient shopping records of the

[13] The Walmart supercenters that remain open become the non-treatment supercenters.

household before and after the supercenter closures. Condition 4 ensures that we exclude the households that may not have faithfully reported their shopping trips.

In total, we have 1,157 treatment households and 1,185 control households.

Descriptive Statistics

Table 4.1 summarizes the panel households' shopping behavior at Walmart stores. In our data, the sample households shopped at Walmart stores in approximately 39.9% of observed sample weeks, and the average weekly spending conditional on purchase is approximately $118.

In Table 4.2, we compare two key demographic variables that might influence households' shopping behavior: household income and household size. The table indicates that households in the treatment and control group are very similar in terms of income and household size. This ensures the validity of our difference-in-difference approach.

Methodology

Identification Strategy

Our goal is to examine whether the closure of Walmart supercenter changes local retail prices. In an ideal setting (i.e., a random field experiment), we would randomize the treatment (i.e., supercenter closure), then observe the retail price paid by the households within the vicinity of treatment (i.e., closed) Walmart (P_1) and the retail price paid by the households within the vicinity of non-treatment Walmart (P_0). With such a random assignment, the difference in the average price, ($\overline{P}_1$- $\overline{P}_0$), represents the treatment effect -- the price change due to a Walmart exit. However, Walmart closure decisions are not random, and we need to account for such non-randomness. We, as researchers, are unable to observe all the variables that influence the exit decision. Omitted variables that drive a store closure decision could correlate with the price paid by the households who live in the vicinity of that store, leading to an endogeneity bias. For example, unobservables like consumers' preference for organic food may affect the closure decision[14] as well as the retail price (Krystallis and Chryssohoidis 2005)[15]. Therefore, we consider three potential solutions to correct for selection biases in order to establish the causal link between store closure and retail price: (1) we use a difference-in-difference approach, (2) we augment the difference-in-difference approach with selection on observables, and (3) with selection on unobservables.

Difference-in-differences. The difference-in-differences approach compares the price differential (post-treatment price - pre-treatment price) paid by the households in the treatment group with the households in the control group. Thus,

$$[1]\ ln\left(Price_{h,s,t}\right) = \beta_0 + \beta_1 Treat_{h,s} + \beta_2 After_t + \beta_3 Treat_{h,s,} \times After_t + \epsilon_{h,s,t}$$

where $ln\left(Price_{h,s,t}\right)$ is the natural logarithm of average price paid by household h in the vicinity of Walmart supercenter *s* at week t. $\epsilon_{h,s,t}$ is a random error term. $Treat_{h,s}$ is a dummy variable, which equals 1 if household h is in treatment group and 0 otherwise. It picks up mean differences in the retail price between treatment group and the control group, referred to as group fixed effects and indicated by the coefficient β_1. $After_t$ is a dummy variable, which equals 1 if the week *t* is after the store closure week and 0 otherwise. The corresponding coefficient β_2 captures the mean differences in post-treatment relative to pre-treatment period price, similar to time fixed effects. Finally, β_3 represents the difference in the change in retail price (difference-

[14] Walmart is likely to exit a market where consumers prefer organic products if consumers find the number of organic products is very limited at Walmart and, as a result, prefer to visit other retail chains.

[15] Consumers prefer organic products may be willing to pay a higher price for other products.

in-differences) across the treatment and control groups, after controlling for permanent differences across groups and the time shocks common to both groups. Since we use the natural logarithm of price as the dependent variable, β_3 can be interpreted as price elasticity.

A key identification assumption of the difference-in-differences approach is that the treatment and control groups are identical, so the time trends in price for the treatment and the control group are also identical ("*parallel trends assumption*"), apart from the treatment. Under this assumption, the change in the difference in prices for the treatment group from that of the control group provides a causal estimate of the treatment effect. In addition, group fixed effects also eliminate time-invariant, group-specific unobservable variables and thus selection-bias -- to the extent that this bias is due to time-invariant, group-specific unobservables (Gill et al. 2017).

However, the critical parallel trends assumption could be violated in our study because household-specific unobservables (which influence both Walmart closure decisions and retail price) could vary across household, resulting in heterogeneous, dissimilar groups. The group fixed effects, meant to smooth out the permanent differences between groups, then would not eliminate buyer unobservable variables that are distinct from the group-specific, time-invariant unobservables. Therefore, we augment the difference-in-differences analysis.

Difference-in-differences with selection on observables. Compositional differences between the control and treatment groups (thus violating the parallel trends assumption) arise because unobservables may influence the store closure decision as well as retail prices. For example, the household characteristics of the local market may affect the probability of the Walmart closure decision as well as the retail price. Selection on observables correct for this selection bias by assuming that we as researchers observe all variables that Walmart consider while closing a store.

In this study, household characteristics such as household size and household income may influence both the store closure decision and retail price. A selection-on-observables strategy includes these observables as a control, such that the treatment and control groups look similar and the parallel trends assumption is preserved (Angrist and Pischke 2009). We therefore operationalize this approach by augmenting the difference-in-differences model from Equation 1 with all the observed (and unobserved) household characteristics variables as follows:

$$[2]\ ln(Price_{h,s,t}) = \beta_0 + \beta_3 Treat_{h,s} \times After_t + \mu_{h,s} + \upsilon_t + \varepsilon_{h,s,t}$$

where the added $\mu_{h,s}$ are the household fixed effects, which capture the (observable and unobservable) household-specific, time-invariant characteristics. υ_t are the time fixed effects. We no longer include $Treat_{h,s}$ and $After_t$ because the effects are already absorbed by $\mu_{h,s}$ and υ_t, respectively.

Difference-in-differences with selection on unobservables. The assumption that we can observe all the important variables is very strong, so we also need to account for unobservable variables. We augment the difference-in-differences analysis with a formal Heckman-style selection model, in which the errors in the selection equation (required to model the Walmart store closure decision) and the errors in the outcome equation (i.e., difference-in-differences model) correlate and follow a bivariate normal distribution. In turn, we can derive the inverse Mills ratio (IMR) to account for unobservable variables in the outcome equation (Heckman 1979). Adding this ratio to the outcome equation accounts for omitted unobservable variables, so this strategy is called selection on unobservables.

We first model Walmart's decision to close a supercenter in a specific local market as a function of all the observables with a probit model ("exit equation"), and calculate the IMR for supercenters in treatment and non-treatment markets. We discuss the exit decision model in more detail in the following section. Next, we augment the difference-in-difference approach as follows:

$$[3]\ ln\left(Price_{h,s,t}\right) = \beta_0 + \beta_3 Treat_{h,s} \times After_t + \gamma IMR_s + \mu_{h,s} + \upsilon_t + \xi_{h,s,t}$$

In addition, in order to test the moderating effects of household characteristics, we modify Equation 3 by adding the interaction terms as follows:

$$[4]\ ln\left(Price_{h,s,t}\right) = \beta_0 + \beta_3 Treat_{h,s} \times After_t + {}_1^4\Sigma\theta_i Treat_{h,s} \times After_t \times \left(X_{h,s,i} - \bar{X}_i\right) + \gamma IMR_s + \mu_{h,s} + \upsilon_t + \varepsilon_{h,s,t}$$

where $X_{h,s,i}$ represents the vector of household characteristics, namely, household size, household income, share of wallet at Walmart, and the share of fresh and produce in the household's grocery basket.

Finally, In order to test the moderating effects of store format, we need to assess how pricing effects differ by different retail formats. As we discussed previously, the treatment effect (i.e., pricing effects) is the net effect of the two forces -- competition and agglomeration. In order to test the moderating effects of store, we estimate Equation 3 per format as follows:

$$[5]\ ln\left(Price_{h,s,f,t}\right) = \beta_0 + \beta_3 Treat_{h,s} \times After_t + \gamma IMR_s + \mu_{h,s} + \upsilon_t + \xi_{h,s,t}$$

where $ln\left(Price_{h,s,t}\right)$ is the natural logarithm of average price paid by household h in the vicinity of Walmart supercenter *s* in retail format *f* at week *t*.

Finally, Nishida (2014) shows that potential business-stealing effect (i.e., competition effects) decline quickly with distance (no more than 1 km, which equals .62 mile) by analyzing the convenience store industry in Okinawa, Japan. In the spirit of his work, we decide to test whether the competition and agglomeration effects decay quickly with distance as well. Specifically, we re-estimate Equation 3 for each different retail formats, namely, discount stores, grocery stores, drug stores, and warehouse clubs at three separate distance bands, namely, 0-10 miles, 10-20 miles, and 20-30 miles[16]. The price variable $ln\left(Price_{h,s,d,f,t}\right)$ now captures the natural logarithm of the average price paid by a household, who lives within distance *d* to the exiting store *s*, in a specific channel *f* at time *t*. Specifically, we include four types of retail channels -- discount stores, grocery stores, drug stores, and warehouse clubs, in our analysis.

$$[6]\ ln\left(Price_{h,s,d,f,t}\right) = \beta_0 + \beta_3 Treat_{h,s} \times After_t + \gamma IMR_s + \mu_{h,s} + \upsilon_t + \xi_{h,s,t}$$

The Exit Model

When deciding to close certain stores, Walmart has relevant private information that is not fully known to the researchers but that influences their decision to close a supercenter in a specific market. Specifically, we estimate Walmart's decision to close a supercenter as a function of cost drivers and controls with a probit model as follows:

[16] Since A.C. Nielsen only provides the detailed location (at 5-digit-zip-code level) of the households (rather than that of the stores), we draw the three separate distance bands based on the distance between the closing store and the households. For example, we calculate the retail price of discount stores at 0-10 miles band by using the discount store purchase data of households who live within 0-10 miles radius of the closing store. We calculate the retail price of drug stores at 10-20 miles band by using the drug store purchase data of households who live within 10-20 miles radius of the closing store.

$$[7]\ \text{Prob}(Exit_s) = \delta_0 + \delta_1\, Dis2HQ_s + \delta_2\, GrwDis_s + \delta_3\, CntDis_s + \delta_4\, CntWmt_s + \delta_5\, MdnInc_s + \delta_6\, PctMor_s + \delta_7\, GrsRnt_s + \delta_8\, PctCol_s + \delta_9\, Pct65_s + \delta_{10}\, PctBlk_s + \delta_{11}\, PctHsp_s + \zeta_s$$

where *Exit* is the focal variable of interest and equals 1 if the supercenter *s* is closed in January 2016 and 0 otherwise. We include the natural logarithm of distance in miles from the supercenter *s* to the Walmart headquarter in Bentonville, AR (*Dis2HQ* is) as an important cost driver and an instrument. We motivate below why this is a valid instrument. We further include the annual growth rate of the discount store channel in the local market (*GrwDis*), the number of discount stores (*CntDis*) in the local market, and the number of Walmart stores (*CntWmt*) in the same 3-digit-zip-code region[17]. Combined these capture the market competition structure in the vicinity of supercenter *s.* We also include some social demographics variables as controls: The median household income (*MdnInc*), the percentage of housing units with mortgage (*PctMor*), the median gross rent (*GrsRnt*), and the percentage of population with a bachelor's degree or graduate degree *(PctCol*) capture the financial characteristics of households who live in the vicinity of supercenter *s*. The percentage of population over age 65 (*Pct65*), the percentage of African-American (*PctBlk*), and Hispanic residents (*PctHsp*) capture the population characteristics of households who live in the vicinity of supercenter *s*.

Instrument motivation. We expect the instrument (*Dis2HQ*) to affect Walmart's decision to close a store but not to affect the outcome equation. This instrument must be relevant; that is, it must be able to predict the endogenous exit decision strongly enough. In addition, it should

[17] A.C. Nielsen only provides store information at 3-digit-zip-code level to avoid retailer identification.

satisfy the exclusion restriction; that is, it should not affect prices set in the market directly, (see Germann et al. 2015; Rossi 2014). We believe the distance can serve as a valid instrument (for a similar approach, see Courtemanche and Carden 2011; Neumark et al. 2008). It is correlated with the *Exit* variable because long distances to the headquarter imply high logistic and administrative costs (i.e., distance costs) (McCann 2010). As a result, a distant store with high distant costs is more likely to be shut down than a nearby store. However, the distance to the headquarter should not directly affect retail prices in a local market. Therefore, we argue that the distance to the Walmart headquarter satisfies the exclusion constraint.

Variable Operationalization

Table 4.3 lists measures of all the variables in our empirical analysis.

Exit equation. *Exit* is a step dummy variable equals 1 if the supercenter *s* is closed in January 2016 and 0 otherwise. Distance to headquarter (*Dis2HQ*) is the natural logarithm of distance (in miles) from the supercenter *s* to the Walmart headquarter in Bentonville, AR. Specifically, we use the GEODIST function in SAS to computes the geodetic distance in miles between any two latitude and longitude coordinates. Growth rate of discount stores (*GrwDis*) is the annual growth rate of discount store format (dollar sales) of 2015 in the vicinity of store *s* (at 3-digit-zip-code level). Number of discount stores (*CntDis*) is the number of discount stores in the vicinity of store *s* (at 3-digit-zip-code level). Number of Walmart stores (*CntWmt*) is the number of Walmart stores in the vicinity of store *s* (at 3-digit-zip-code level). Median income (*MdnInc*) is the median household income in the vicinity of store *s*. Percent of home mortgage (*PctMor*) is the percentage of housing units with mortgage in the vicinity of store *s* (at 5-digit-zip-code level). Gross rent (*GrsRnt*) is the median gross rent in the vicinity of store *s* (at 5-digit-zip-code level). Percent of people with college degree or higher (*PctCol*) is the percentage of population with a bachelor's degree or graduate degree in the vicinity of store *s* (at 5-digit-zip-code level). Percent of senior citizen (*Pct65*) is the percentage of the population over age 65 in the vicinity of store *s* (at 5-digit-zip-code level). Percentage of Afro-american population *(PctBlk*) is the percentage of the Afro-american population in the vicinity of store *s* (at 5-digit-zip-code level). Percent of Hispanic population (*PctHsp*) is the percentage of the population who are Hispanic in the vicinity of store *s* (at 5-digit-zip-code level).

Outcome Equation. The dependent variable *ln(Price)* is the natural logarithm of average price paid by household *h* in the vicinity of store *s* at week *t*. We compute the average price as dollar purchases divided by number of units. Household size is the number of people in the household *h.* Household income is the income of household *h*. Share of wallet at Walmart is the percentage of purchase at Walmart of household *h*'s total purchase (dollar sales) in 2015. Share of wallet in fresh produce is the percentage of fresh-produce (dairy, deli, fresh produce, and packaged meat) purchase of household *h*'s total purchase (dollar sales) in 2015, the year preceding Walmart's store closures.

Results

Model-Free Evidence

Figure 4.3 shows the average weekly prices for the treatment and control households over time. The weekly price trends before the Walmart store closure date (=treatment date) in the treatment and control groups are very similar, which further ensures the propriety of the difference-in-difference approach in our study. We further observe an increase in the average price after the closure of the Walmart supercenter in the treatment group. This model-free evidence suggests the positive price effect following a Walmart closure.

In Table 4.4, we report the households' average weekly spending, average weekly store trips, average weekly per-trip expenditure, and average weekly price before and after Walmart closure. For the control households we see no significant change in weekly prices. By contrast, for the treatment households an increase in prices can be reported ((3.93-3.87)/3.87 = 1.6%). The magnitude of this price effect is in line with the price decreases following a Walmart entry as reported by Basker and Noel (2009) -- competitors' response to entry by a Walmart Supercenter is a price reduction of 1-1.2%.

Model-Based Results

We begin by presenting the average treatment effect before adding the moderating effects of consumer characteristics. Next, we look at the treatment effect across different retail formats.

Difference-in-differences

Model 2 (Table 4.5) represents the estimates of the treatment effect from the difference-in-differences specification without any household-specific characteristics. The treatment effect was significant (β_3 = .016, $p < .01$) indicating a statistically significant price increase (1.6%) at remaining retailers after Walmart store closures.

Difference-in-differences with selection on observables

We augment the simple difference-in-differences model with household fixed effects in Model 3 in Table 4.5. Again, the treatment effect was significant (β_3 = .016, $p < .01$), indicating a statistically significant positive pricing effect of Walmart store closures. This estimate is very similar to that of Model 2, suggesting that household-specific, time-invariant characteristics may not be an endogeneity concern in our study.

Difference-in-differences with selection on unobservables

We first discuss the exit (selection model) before discussing the results of the outcome model.

Exit model. In the selection model, we capture the store closure decision using key drivers and a probit specification: The distance in miles from the supercenter *s* to the Walmart headquarter in Bentonville, AR (*Dis2HQ*), the annual growth rate of discount store channel (*GrwDis*), the number of discount stores (*CntDis*), and the number of Walmart stores (*CntWmt*), so we included these covariates as predictors of store closure in the first-stage model. For identification, the covariate set affecting store closure choice should contain at least one variable that provides an exclusion restriction, such that it affects closure decision but does not directly influence retail price. We use the distance in miles from the supercenter *s* to the Walmart headquarter in Bentonville, AR (*Dis2HQ*) as the instrument. Sargan test for overidentifying restrictions confirms the validity of the instrument ($p > .10$). Moreover, the incremental F-value of instrument exceeds the common threshold of 10, indicating that the IV is sufficiently strong.

Table 4.6 presents all parameters for the exit model. The likelihood ratio test shows good model fit ($\chi^2(11) = 50.7$, $p < .001$). In terms of variance inflation factors (VIFs), none of the variables exceeds the commonly used threshold of 10 (maximum VIF = 4.26) (Hair et al. 2010). The instrument variable (*Dis2HQ*) is significant and positive ($p < .05$) thereby indicating that long distance to Walmart headquarter involves high costs in logistics and administration. As a result, a distant supercenter is more likely to be closed by Walmart than a nearby supercenter. Moreover, Walmart tends to remove the supercenter located in a community with a low rate of discount store growth ($p < .05$) as well as many discount stores ($p < .01$).

Outcome/price model. The results, in Model 4 (without household effects), reveal that the selection correction term is significant, and the treatment effect is statistically significant (β_3 = .016, $p < .01$). The final model -- Model 5 (with household effects) confirms these results (β_3 = .016, $p < .01$), except that the selection correction term is statistically nonsignificant. Thus, the selection-on-unobservables strategy indicates positive pricing effects of Walmart supercenter closure.

The moderating effects of household characteristics. None of the VIFs exceeds 10 (maximum VIF = 1.11) (Hair et al. 2010). Thus, multicollinearity is not likely to be a problem. Model 6 in Table 4.5 contains the estimates of moderating effects of household characteristics. The interaction term of household size (θ_1 = -.001, *n.s.*) is not significant, suggesting that large households do not necessarily pay a higher price than small households following a Walmart supercenter closure. With respect to household income, we do find directional support (i.e., negative) but without significance (θ_2 = -.0003, *n.s.*). By contrast, the results lend support for the moderating role of share of wallet at Walmart (θ_3 = .037, $p < .05$). This suggests that Walmart loyal consumers are more vulnerable to the post-exit price surge. Specifically, Walmart loyal consumers (i.e., shoppers scoring 1 standard deviation above the mean of SOW at Walmart) have to pay a 2.3% higher price following a Walmart supercenter exit, compared to the average price increase of 1.6%. Furthermore, we find the interaction term of share of wallet in fresh produce is statistically significant (θ_4 = .129, $p < .01$), which is different from our expectation. This indicates that households with a high SOW in fresh produces have to pay a higher price after store closure. Specifically, households with a high SOW in fresh produce (i.e., shoppers scoring 1 standard deviation above the mean of SOW in fresh produce), have to pay a 3.7% higher price following a Walmart supercenter exit, compared to the average price increase of 1.6%.

The moderating effects of store format. Table 4.7 presents whether and how the pricing effects (β_3) differ by retail format. As hypothesized, the pricing effects are most salient at similar discount stores, indicating that highly overlapping retailers harness the benefits due to decreased competition and therefore increase the price following a Walmart exit. By contrast, the pricing effects are almost mute at the other retail formats, namely, grocery stores, drug stores, and warehouse clubs. This suggests that highly differentiated retailers mainly lose the agglomeration gains and thus do not have the luxury to increase price.

The moderating effects of physical distance. Turing to the distance metric, we find the magnitude of the treatment effects at discount stores do not decline quickly with distance (discount stores at 0-10 miles, β_3 = .0079, p < .05; discount stores at 10-20 miles, β_3 = .082, p < .01; discount stores at 20-30 miles, β_3 = .0077, p < .01). This contradicts the work by (Nishida 2014), in which he shows the competition effects decline quickly with distance in a setting of convenience store industry of Japan. A potential explanation is that Walmart supercenters have a much larger trading area (a radius of about 10 miles) than convenience store (a radius of about 500 to 700 in meters or .31 to .43 in miles) and therefore the decay of competition effects is much slower with distance for Walmart supercenters. Moreover, besides discount stores, we do not find statistically significant price change at other retail formats except for drug stores at 10-20 miles (β_3 = .0052, p < .05) and warehouse clubs at 20-30 miles (β_3 = .0060, p < .01). A potential explanation is that the pre-exit bilateral relationship is competition dominant for drug stores and warehouse clubs at further distance. When Walmart pulls out from the local market, more distant drug stores and warehouse clubs can afford to raise prices.

Robustness Check

Alternative bias correction strategy. Instead of the Heckman two-stage selection model to correct for unobservables, we use a propensity score matching (PSM) to correct for observables. We first identify a control supercenter for each treatment supercenter. We then assign the households within the vicinity of the control supercenter as the control households. Finally, we rerun the difference-in-difference model. The significance of the treatment effect remained unchanged when we used a PSM framework.

Alternative instrument. As a robustness check, we use the distance from Walmart's nearest food distribution center as the instrument. Food distribution center locations and entry dates were obtained from Holmes' website (for a similar approach, see Courtemanche and Carden 2011). The significance of the treatment effect remained unchanged when we using an alternative instrument.

Alternative dependent variable. As a robustness check, we use the absolute retail price as the dependent variable in the price equation. The significance of the treatment effect remained unchanged.

Conclusion

The competitiveness of the retail industry has never dwindled. As noted by Greg Foran -- President and CEO of Walmart U.S. – "You don't have to look far to see how competitive the retail industry is… As I look to the future, I don't see any signs suggesting this will change. If anything, the challenges will only become greater."[18] Not too surprisingly, thousands of retail stores are forced to close over the past few years. Given the prevalence of retail closures, it is

[18] https://news.walmart.com/2019/02/28/a-note-from-greg-foran-to-walmart-stores-regarding-people-greeter-changes

still unclear how this evolution will impact retail prices in local markets. To address this question, this paper investigated the pricing effects following Walmart supercenter closures in the U.S. Using a unique consumer panel data set along with complete information of Walmart store location, we provide empirical evidence on the price effects of Walmart exits in a setting with a rich set of product categories, and a complex market structure.

Theoretical Implications

We find that Walmart supercenter closures result in a significantly higher local retail price (1.6%) for the average household, suggesting that remaining retailers realize higher pricing power from decreased competition. This suggests that the exit of Walmart supercenters causes a welfare loss and consumer have to spend extra \$1.6 assuming an average weekly spending of 100.50 or \$83.6 ($100.50 \times 1.6\% \times 52$) per year on grocery purchase following a Walmart supercenter exit. This is in line with previous welfare studies on Walmart's entry in local markets. For example, Basker (2005b) reports consumer welfare increases following a Walmart entry as prices decrease with 1.5 to 3%.

To separate out the competition and agglomeration effects, we also investigate how the pricing effects differ by store format. We find that store formats that overlap with supercenters (i.e., discount stores) have the luxury to raise the price, regardless of their locations. This supports analytical work by Zhu (et al. 2011), in which they find that retailers tend to compete with the incumbents that are highly similar in terms of product assortment and store positioning. Moreover, we find that these pricing effects at discount stores do not decline with distance from the focal exiting store. This result differs from the findings by Nishida (2015) -- the business-stealing effects decline quickly with distance in the setting of the convenience-store industry in

Okinawa, Japan. A potential explanation is that the supercenters carry a much larger assortment than convenience stores and therefore affect a larger retail market in a wider radius.

In addition, we also find evidence to support the moderating role of consumers' pre-exit shopping behavior on pricing effects. Specifically, we find that households that tend to spend more of their of their grocery budget at the focal exiting retailer, i.e. Walmart, and who spend more on fresh products and produce are more vulnerable to the post-exit price increase (i.e., a 2.3% price increase for Walmart loyal segment, and a 3.7% price increase for high spenders in the fresh & produce segment). This is a substantial increase above the average price surge of 1.6%, indicating an additional welfare loss for these two segments. Translating the results into consumer spending, Walmart loyal consumers (one standard deviation above the mean) have to spend an additional \$2.3 (100.50 × 2.3%) per week or \$120.2 (100.50 × 1.6% × 52) per year on grocery following a Walmart supercenter exit. Moreover, households with a high SOW in fresh produce (one standard deviation above the mean) have to spend \$3.7 (100.50 × 3.7%) extra per week or \$193.4 (100.50 × 1.6% × 52) per year on grocery after Walmart pulls out from the market.

Managerial Implications

Being unique is not always beneficial. By unique, we mean retailers who try to differentiate themselves from their competitors in terms of store positioning, assortment, and location. In the case of the retail entry, it is most definitely correct to be unique (or at least somewhat different) compared with the incumbent retailers. By doing so, differentiated retailers actually target a different consumer segment and as a result, may benefit from the agglomeration effects. However, in the case of a retail exit, it becomes "bad" news for the differentiated retailers. As shown in our study, a distinctive format has no power to lift the price. This echoes the Hotelling's law (Hotelling 1929) in a sense that being somewhat similar to your competitors is not always bad.

Competition may be broader than you think. Practitioners often believe brick-and-mortar competition is a local thing. However, our study shows that the competition boundary in the industry is not that local. The pricing effects of supercenter closures do not decay too much as the magnitude is very similar in different geographic bands. It is worth to mention that, we, by no means, believe the results can be generalizable to every setting. For example, the convenience store industry has a quite different competition boundary.

Are consumers in the hot seat? The answer is yes and no. We find that whether a consumer is vulnerable actually depends on his or her shopping preferences. When consumers tend to be more fervent Walmart shoppers or spend more on fresh products and produce, they tend to be more vulnerable to the post-exit price surge. From the perspective of consumers, we suggest they change their store patronage and even format preference. For example, visiting a nearby grocery store is not a bad choice because we do not find a significant price increase at nearby grocery stores following a Walmart closure.

Limitations

Our results are based on the exits of Walmart supercenters. Future research can investigate and contrast the pricing effects of other formats (e.g., drug stores, warehouse clubs). In the current study, our channel exits are rooted in the case of permanent closures. We also hope that future research will investigate whether and how remaining retailers differentially respond to market structure changes induced by other forms of closure (e.g., store downsizing, distribution closure, entire banner closure).

Table 4.1: Panel households' shopping behavior at Walmart stores

Parameter	Value
No. of total households (HH)	2342
No. of treatment households (HH)	1157
No. of control households (HH)	1185
Observations (weeks)	245910
Purchase observations (weeks)	98044 (39.9%)
Weekly spending ($, excluding no purchases)	
Average	118.23
SD	104.64
Median	91.50
Max	1745.98
Min	0.19

Table 4.2: Demographic variables of treatment and control group households

	Income		Household size	
Group	Mean	SD	Mean	SD
Treatment	21.10	5.95	2.29	1.22
Control	20.12	6.05	2.33	1.28

Notes. In the panel data, income is recorded as an ordinal variable with 16 categories with near-equal intervals: 3 represents under $5,000, 4 represents $5000–$7999, and so on. The highest income level, 27, represents $100,000 and over. We treat the ordinal variable as a continuous variable and report means and standard deviations here.

Table 4.3: Variable operationalization

Variable	Source	Measure
<u>*Exit equation*</u>		
Exit	Walmart	A step dummy variable equals 1 if the supercenter *s* is closed in January 2016 and 0 otherwise
Distance to headquarter (*Dis2HQ*)	Google	The natural logarithm of distance (in miles) from the supercenter *s* to the Walmart headquarter in Bentonville, AR
Growth rate of discount stores (*GrwDis*)	A.C. Nielsen	The annual growth rate of discount store format (dollar sales) in 2015 in the vicinity of store *s* (at 3-digit-zip-code level)
Number of discount stores (*CntDis*)	A.C. Nielsen	The number of discount stores in the vicinity of store *s* (at 3-digit-zip-code level)
Number of Walmart stores (*CntWmt*)	Walmart	The number of Walmart stores in the vicinity of store *s* (at 3-digit-zip-code level)
Median income (*MdnInc*)	ACS survey	The median household income in the vicinity of store *s* (at 5-digit-zip-code level)
Percent of home mortgage (*PctMor*)	ACS survey	The percentage of housing units with mortgage in the vicinity of store *s* (at 5-digit-zip-code level)
Gross rent (*GrsRnt*)	ACS survey	The median gross rent in the vicinity of store *s* (at 5-digit-zip-code level)
Percent of people with college degree or higher (*PctCol*)	ACS survey	The percentage of population with a bachelor's degree or graduate degree in the vicinity of store *s* (at 5-digit-zip-code level)
Percent of senior citizen (*Pct65*)	ACS survey	The percentage of the population over age 65 in the vicinity of store *s* (at 5-digit-zip-code level)
Percentage of Black people *(PctBlk*)	ACS survey	The percentage of the population who are black in the vicinity of store *s* (at 5-digit-zip-code level)
Percent of Hispanic people (*PctHsp*)	ACS survey	The percentage of the population who are Hispanic in the vicinity of store *s* (at 5-digit-zip-code level)
<u>*Outcome equation*</u>		
Price	A.C. Nielsen	The natural logarithm of average price paid by household *h* in the vicinity of store *s* at week *t*.
Household size	A.C. Nielsen	The number of people in the household *h*
Household income	A.C. Nielsen	The income of household *h*
Share of wallet at Walmart	A.C. Nielsen	The percentage of purchase at Walmart of household *h*'s total purchase (dollar sales) in 2015
Share of wallet in fresh produce	A.C. Nielsen	The percentage of fresh-produce (dairy, deli, fresh produce, and packaged meat) purchase of household *h*'s total purchase (dollar sales) in 2015

Table 4.4: Walmart supercenter closure and retail price

	Weekly spending ($)		Weekly visits		Weekly basket size (items per trip)		Weekly price ($)	
Group	Before closure	After closure	Before closure	After closure	Before closure	After closure	Before closure	After closure
Treatment	100.39	100.68	2.86	2.88	9.36	9.38	3.87	3.93
Control	100.95	99.95	2.97	2.97	9.11	9.15	3.85	3.86

Table 4.5: Treatment effect estimation results

Variables	Model 1 Only treatment	Model 2 Without HH fixed effects	Model 3 With HH fixed effects	Model 4 Heckman model without HH fixed effects	Model 5 Heckman model with HH fixed effects	Model 6 Heckman model with HH fixed effects and interactions
Intercept	1.393(.045)***	1.349(.002)***	1.229(.046)***	1.391(.007)***	1.169(.583)***	.955(.289)***
Treatment effect		.016(.004)***	0.016(.004)***	.016(.005)***	.016(.004)***	.033(.015)***
Time dummy	0.011(.003)***	-.005(.003)***		-.005(.003)***		
Treatment group dummy		.019(.003)***		.019(.003)***		
Interactions:						
Household size						-.001(.002)***
Household income						-.0003(.0005)*
Share of wallet at Walmart						.037(.015)***
Share of wallet in Fresh Produce						.129(.018)***
IMR				.016(.005)***	.012(.113)***	.165(.111)***
Household fixed effects	Yes	No	Yes	No	Yes	Yes
Time fixed effects	No	No	Yes	No	Yes	Yes
R^2	.376	.001	.372	.001	.372	.362

***$p < .01$, **$p < .05$, * $p < .10$

Table 4.6: Exit model results

Exit Model Component	Coefficient	Standard Errors
Intercept	-6.653	3.12**
Distance to headquarter (*Dis2HQ*)	.888	.45**
Growth rate of discount stores (*GrwDis*)	-3.557	1.46**
Number of discount stores (*CntDis*)	.099	.03***
Number of Walmart stores (*CntWmt*)	-.036	.01
Median income (*MdnInc*)	.00002	.00001*
Percent of home mortgage (*PctMor*)	-.039	.02**
Gross rent (*GrsRnt*)	-.002	.001**
Percent of people with college degree or higher (*PctCol*)	.026	.02
Percent of senior citizen (*Pct65*)	-.091	.05*
Percentage of Black people *(PctBlk*)	.035	.01***
Percent of Hispanic people (*PctHsp*)	.015	.01**
Hit Rate	96.3%	
LR-χ^2	50.7***	

***$p < .01$, **$p < .05$, * $p < .10$

Table 4.7: Pricing effects differ by format and distance (Using model 5 - Heckman model with HH fixed effects)

The radius of vicinity	Discount Store	Grocery Store	Drug Store	Warehouse club
0-10 miles	.0079 (.0031)**	.0028 (.0032)	-.0045 (.0033)	.0026 (.0025)
10-20 miles	.0082 (.0025)***	.0030 (.0026)	.0052 (.0026)**	-.0003 (.0021)
20-30 miles	.0077 (.0025)***	.0013 (.0026)	.0043 (.0027)	.0060 (.0021)***

***$p < .01$, **$p < .05$, * $p < .10$

Notes. Standard errors are reported in parentheses.

Figure 4.1: Locations of closed Walmart supercenters

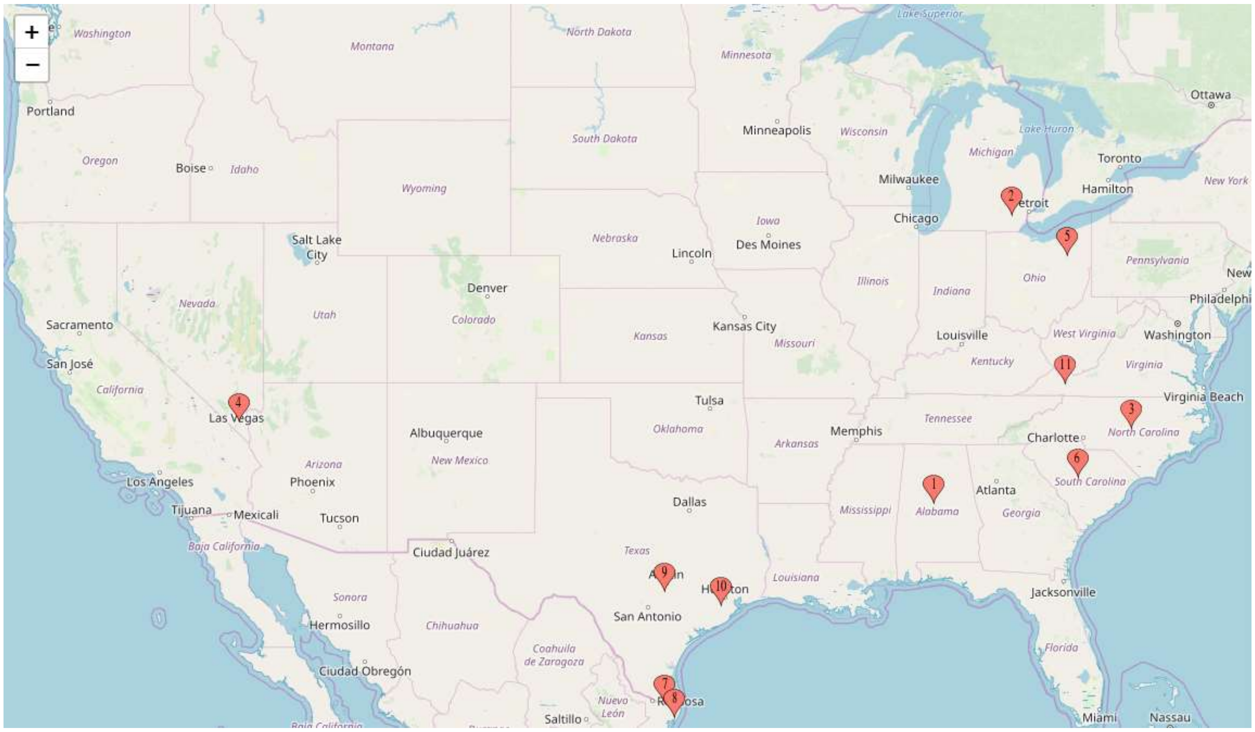


Figure 4.2: Conceptual framework

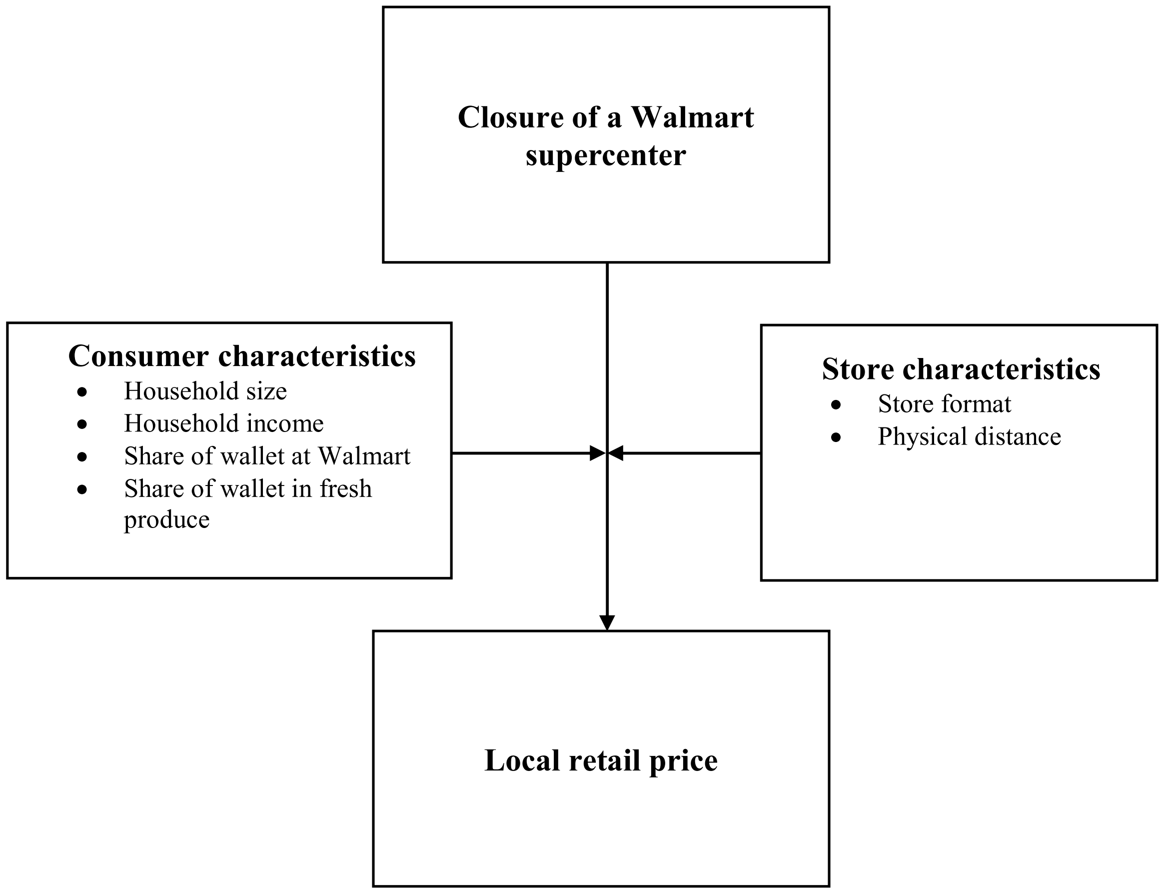
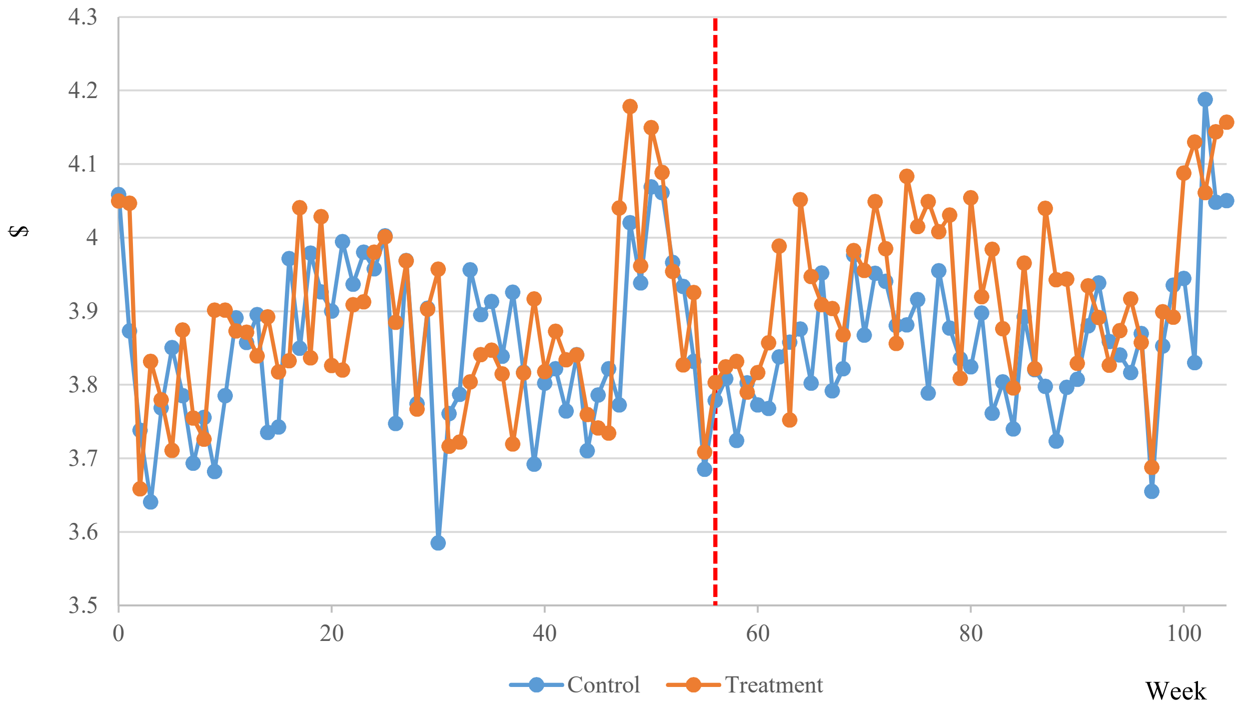


Figure 4.3: Weekly average price before and after supercenter closure



Notes. The vertical line in the center of the panel denotes the supercenter closure week.

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