TWO ESSAYS ON DIGITAL AND MULTI-CHANNEL MARKETING PRICING STRATEGY

BY

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DISSERTATION

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ABSTRACT

Pricing is the process whereby a business sets the price at which it will sell its products and must be considered as a core part of the business's marketing plan. In recent years, there has been a growing awareness of the complex nature of price as a determinant of consumer decision making process. Recent research indicates there is no simple explanation of how price influences firm performance and individual consumer purchase decisions. The pricing strategy in traditional brick-and-mortar stores has received consistent attention from both academia and industry. However, as the raising of digital technology, the evolving business circumstance changed, or even re-introduced, many practically and theoretically important questions. Given this importance, the two essays tackle the strategic pricing strategy in the two critical perspectives of marketing — advertising and retailing.

In the first essay, I explore the effects of displayed product price on keyword advertising performance in online shopping websites, as well as on consumers' decision processes. With a hierarchical Bayesian model using a unique data set from a leading electronic shopping platform and a simulated experiment, I empirically test the asymmetric effects of price rank on advertising performances (i.e., click-through rates and conversion rates) in study one and the underlying mechanism in study two. Specifically, I find that consumers tend to click more on extreme price options (i.e., highest or lowest) in the early phases of the purchase funnel, which serve as anchors to evaluate a broad range of options. Clicks at later stages, which tend to convert to purchases, instead are more likely for moderately priced options, which offer a compromise across different product features. The effects of price rank diminish among

advertisements sponsoring more specific keywords but grow for those sponsoring more popular keywords. This essay demonstrates that the keyword advertisements provides a context for price comparison, which further influences consumers' responses toward advertisements.

While the first essay focuses on gaining competitiveness through enhancing the price competition in digital advertising context, the second essay focuses on avoiding price competition in multi-channel retailing context through switching the business focus. The second essay explores the causal effects of multi-channel retailer implementing cross-channel price integration. Leveraging a revised pricing policy implemented by one of the leading house appliance retailers, I empirically investigate how cross-channel price integration affects product sales and consumer preferences. This change of cross-channel pricing strategy reveals varying impact across time, products, channels, and customer segments. In the short term, price integration leads to a 14.70% decrease in sales of products without services but a 14.68% increase in sales of products with services. The price integration effect is more positive in the long run, such that sales of products increase by 10.07% without services and 36.07% with services. Further, using a latent class model with zero-inflated Poisson framework, I empirically differentiated the effects of price integration on three consumer segments with different preferences (i.e., lovers, haters and adaptors). The findings of the second essay contribute to the multi-channel pricing literature by providing an empirical examine of the effectiveness of cross-channel price integration and consumer migration.

The findings of the two essays contribute to the pricing, keyword advertisements and multi-channel literature, and shed lights on the strategic implications of pricing

activities. Specifically, the first essay connects the pricing literature, consumer search and keyword advertising literature by exploring the effects of contrast among displayed product prices in the keyword advertising context. This essay is among the first few to investigate how advertised product price affects advertising performance. The study suggests the advertised product price display two contrasting effects on consumers' clicking and purchasing behaviors along their purchase funnel. In addition, the research extends understanding of two keyword characteristics by theoretically differentiating keyword specificity and keyword popularity. The second essay connects the multi-channel pricing literature and transaction value literature by empirically examine the effects of retailers implementing cross-channel price integration policy. Advancing prior research on perceived transaction value and multi-channel pricing literature, this research proposes two contrasting mechanisms (i.e., price change and pricing consistency), through which the cross-channel price integration affects the product sales and consumer sales. The empirical findings shed lights on managerial implications to multi-channel retailers.

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To My Family, My Mentors, and Anyone Expanding the Boundaries of Human Knowledge

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EXECUTIVE SUMMARY

> Price is the one element of the marketing mix that produces revenue; the other elements produce costs… [Price] also communicates to the market the company's intended value positioning of its product or brand.
>
> – Philip Kotler (2011, p. 383)

Pricing is the process whereby a business sets the price at which it will sell its products. In recent years, there has been a growing awareness of the complex role of price as a determinant of a purchase decision. The pricing strategy in traditional brick-and-mortar stores has received consistent attentions from both academia and industry (e.g., Phillips 2005; Varian 1980; Varian 1989; Winer 1986). However, as the raising of digital technology, the evolving business circumstance reshaped, and even re-introduced, many practically and theoretically important pricing questions (e.g., Ratchford 2009; Verhoef et al. 2015). Given the importance and ubiquity nature of pricing, it is important to extend our understandings in pricing strategy in the evolving marketing contexts.

In this dissertation, the two essays tackle the pricing issues across two important marketing domains — advertising and retailing, under the two emerging business contexts — online and multi-channel retailers. The first essay focuses on the competitively pricing strategy in digital advertising. I explored the effects of displayed product price on the advertising performances in keyword advertising. Relying on purchase funnel model (Hauser and Wernerfelt 1989; Roberts and Lattin 1991) and two behavioral heuristics, i.e., anchoring effect (Tversky and Kahneman 1974) and compromising effect (Simonson and Tversky 1992), the first essay investigates the effects of advertised product price rank on the advertising performances, i.e., click-through rates and conversion rates, along with the moderating effects of two keyword characteristics. This essay demonstrates that the sponsored lists in keyword advertising provides a context for consumer to compare prices, which further influences consumers' responses toward the advertisements. Managerially, the first essay sheds light on the competitively pricing strategy in the sponsored keyword advertising so that strategically pricing the products will improve the efficiency or overall traffic of search advertisements.

While the first essay focuses on direct price competition through strategic price contrast, the second essay focuses on reducing price competition through differentiating shopping experience. The second essay contrasts two prevalent pricing strategies among multi-channel retailing industry. Relying on the perceived transaction value framework (Zeithaml 1988), the second essay explores the causal effects of cross-channel price integration, through which the price of an identical product is kept consistent across channels, on the product and consumer sales. The results suggest that the cross-channel price integration initiate the immediate sales decreases and overtime sales increases, resulting from both the shift of target consumers (i.e., from price focused to experience focused consumers) and the attitude change of other consumers. In addition, the product associated with coordinated specialty services help the products to recover much faster from the immediate sales loss. This essay suggests that the two contrasting pricing strategies identify distinct strategic focuses, where channel-specific pricing strategy focus on the "better prices" while the consistent pricing strategy focus on the "smoother" and "easier" shopping experience. Based on the target consumer segments, product types and strategic focuses, the multi-channel retailers should select the corresponding pricing strategy.

The two essays contribute to the pricing, keyword advertisements and multi-channel literature, and offers insightful strategic implications. Specifically, the first essay proposes to connect the pricing and keyword advertising literature by exploring the effects of displayed product price along consumer purchase funnel in the keyword advertising context. This essay is among the first to investigate how the product prices of keyword advertisements affects consumer decision process and advertising performance. The empirical evidence suggests that the displayed product price display two contrasting effects depending on the consumers' decision process and heterogeneity. The second essay contributes to the multi-channel pricing strategy literature by empirically examine causal effects of retailer implementing cross-channel price integration, resulting in the switch from channel-specific pricing to consistent pricing strategy. This research is among the first few researches to empirically investigate the dynamic effects of adopting consistent pricing strategy, in contrast to channel-specific pricing strategy. The research suggests that all products suffer in the short run but benefit in the long run, as the results of consumer attitude evolvement and the changes of target consumer segments.

In sum, the two essays investigate theoretically and managerially important issues regarding pricing strategy under the emerging business contexts. The findings of the two essays jointly contribute to the pricing literature by building the bridge between classic pricing theories with the evolving business circumstances.

ESSAY ONE: The Effects of Price Rank on Clicks and Conversions of Sponsored Keyword Advertising in Online Retail Platforms

1.1 Abstract

Sponsored keyword advertising serves as a channel for firms to communicate with consumers. Noting the critical role of price information in consumers' decision making, this study investigates price as a factor that affects consumers' responses to such advertising throughout the purchase funnel, along with the moderating effects of two keyword attributes. With a hierarchical Bayesian model using a unique data set from a leading electronic shopping platform and a simulated experiment, the authors find that consumers tend to click more on extreme price options (i.e., highest or lowest) in the early phases of the purchase funnel, which serve as anchors to evaluate a broad range of options. Clicks at later stages, which tend to convert to purchases, instead are more likely for moderately priced options, which offer a compromise across different product features. The effects of price rank diminish among advertisements sponsoring more specific keywords but grow for those sponsoring more popular keywords. These findings provide new insights on the role of price information and managerial implications for devising effective sponsored keyword advertising strategies.

Keywords: sponsored keyword advertising, price rank, keyword specificity, keyword popularity, click-through rate, conversion rate, consumer purchase funnel

1.2 Introduction

Consumers rely on price as a critical input to assess the value of products in choice sets (Kalwani et al. 1990; Rajendran and Tellis 1994). In online retailing settings, firms' pricing strategies often are particularly dedicated to consumers who are sensitive to price information (Chevalier and Goolsbee 2003; Lynch Jr and Ariely 2000), such that retail search engines frequently offer sponsored search advertising display results that also feature price comparison tools. They thus support comparison shopping, in that the search engines collect product information, including prices, from retailers, then display the collected, comparative information in response to shoppers' queries. Prior research notes the influences of rank positions (Agarwal et al. 2011; Narayanan and Kalyanam 2015; Rutz et al. 2012; Xu et al. 2011), competition (Yang et al. 2013), and budget allocations (Sayedi et al. 2014) on the outcomes, but despite potentially meaningful implications, limited search advertising literature addresses how product prices in a display list affect the performance of sponsored keyword advertising. In this sense, firms' pricing strategies, especially as they relate to the prices of competing products, remain unexplored.

This gap is particularly relevant because firms predict what prices their competitors will charge in their advertisement and then adjust their own prices in order to get the desired price rank. Using purchase funnel and dynamic models of consumer choice (Hauser and Wernerfelt 1989; Nedungadi 1990; Roberts and Lattin 1991; Simonson and Tversky 1992), I propose that clicks can be driven by different motivations of consumers, including exploratory searches to develop anchors and the need for compromise among product features across the phases of the purchase funnel. Specifically, consumers develop anchors for comparison by exploring extreme priced options first, then make actual purchase decisions by evaluating moderately priced options, to achieve an appealing compromise between product quality and price. I accordingly conduct two complementary studies.

In the first, I investigate aggregated keyword search advertising responses (i.e., click and conversion), depending on the price rank of the search results in an online retailer's website. Using detailed information about 207,407 keyword advertisements from a leading electronic shopping platform, I show that the price rank functions as an anchor that consumers use to develop their expectations and assess alternatives; it also helps them find a compromise between price and quality before making a purchase decision. I include moderating effects of two keyword attributes (specificity and popularity), which can identify consumer segments and reflect different preferences associated with search topics (Jeziorski and Segal 2015). Greater specificity indicates that consumers have developed more detailed preferences (Adaval and Wyer 2011); popularity reveals the extent to which consumers' needs and preferences are common in the market (Jerath et al. 2014). Depending on the specificity and popularity of keywords, consumers likely react differently to product prices displayed on a keyword search result page.

In Study two, I conduct an experiment to verify the within-consumer variations across groups with different orientations in keyword search behaviors. Clickstream data from 310 consumers reveal that for *search-and-buy* consumers, consumers' focus shifts along the purchase funnel that early-stage clicks are more likely to be driven by searches that aim to build anchors with extremely priced options, whereas this tendency diminishes for late-stage clicks, which often convert to purchases and thus are driven more by the need to find a compromise between product price and quality with moderately priced options. For *search-only* consumers, they have a tendency to click extremely priced items across the search process. Clickstream data also shows that the conversion rate is higher for moderately priced products than for extremely priced ones.

With this novel investigation of advertised product prices in sponsored keyword advertising, I make several contributions. The analysis of price ranks within a sponsored listing in Study 1 reveals how the price information contained in sponsored keyword advertising affects advertising performance. The experiment in Study 2 confirms the mechanisms that the preferences for extreme priced options are dominant in early phases of the purchase funnel, but moderately priced options are more prevalent when consumers have a specific purchase goal, as in the later phases of the purchase funnel when they seek to choose the most feasible alternative. Furthermore, this paper expands understanding of how keyword specificity and popularity each interact with price ranks to influence the performance of sponsored keyword advertisements. Both keyword attributes reflect market characteristics, in terms of the development of consumer preferences and potential market size.

Since firms have control of their own pricing policy, they can adjust their own prices to get desired price rank. Once there are changes in the prices of competitors' sponsored listings, they could react in real time without the limitation of the ad platform. Using the theoretical foundation and empirical findings of this paper, firms can develop more nuanced sponsored keyword advertising strategies. In a post hoc analysis, I determine that for firms that target consumers who search for popular and general keywords and that want to increase the absolute number of clicks and conversions, achieving an extremely low price rank should be a primary consideration. If instead these firms seek efficiency and enhanced profitability, they should pursue a moderate price rank. Finally, firms that target a segment of consumers using niche and specific keywords do not need to consider price rank.

1.3 Relevant Literature

Search advertising literature primarily addresses two aspects: display and keyword attributes (see Table 1). General research questions focus on the effects of page rank positions and keyword attributes on consumers' choices and purchases (Agarwal et al. 2011; Animesh et al. 2011; Chan and Park 2015; Ghose and Yang 2009; Jerath et al. 2014; Jerath et al. 2011; Narayanan and Kalyanam 2015; Rutz et al. 2012; Xu et al. 2011; Yang et al. 2013). For example, a ranking in the top position prompts the highest click-through and conversion rates (Animesh et al. 2011; Jerath et al. 2011; Narayanan and Kalyanam 2015; Rutz et al. 2012; Xu et al. 2011), but the high costs of reaching this position reduce its economic benefits (Ghose and Yang 2009). In studies of keyword attributes, keyword specificity has emerged as a moderator between advertising position and consumer choice (Table 1), because the specificity of search queries signals the customer's involvement and segment; more specific queries weaken position effects (Agarwal et al. 2011; Narayanan and Kalyanam 2015). In addition, keyword popularity may offer another moderator; though it has received somewhat less attention, Jerath et al. (2014) find that the search volume of a keyword decreases consumers' focus on sponsored, relative to organic, search results.

Other display attributes require further consideration though. In particular, I know little about the effect of product prices on adverting performance, even though consumers take price into consideration carefully when making purchase decisions (Chevalier and Goolsbee 2003; Lynch Jr and Ariely 2000). The influence of product prices on consumers' behaviors might be predicted by the keywords that those consumers use for their searches. Therefore, I investigate product price as a display attribute and consider its interaction with keyword attributes to uncover the effects on consumers' responses to sponsored keyword advertising. Furthermore, prior literature mainly investigates behavioral variations among consumer segments (i.e., between-consumer variations) (Animesh et al. 2011; Chan and Park 2015; Jerath et al. 2014), but little is known about behavioral variations within individual searches (i.e., within-consumer variations). I investigate mechanisms underlying the empirical patterns of advertising responses by considering both between-consumer variations across consumer segments and within-consumer variations in individual search processes.

TABLE 1
Review of Selected Prior Research and the Contributions of this Study

Authors	Research Context	Key Variables	Research Focus	Findings
Jerath et al. (2004)	Analytical models and 15-day records from a leading search engine firm in Korea in July 2008	Advertising position, firm quality and advertising cost	Economic value of advertising position and firms' bidding strategy	A superior firm may bid lower than an inferior firm and obtain a position below it, yet it still obtains more clicks than the inferior firm. The inferior firm wants to be at the top where more consumers click on its link, whereas the superior firm is better off by placing its link at a lower position under both pay-per-impression and pay-per-click mechanisms.
Ghose and Yang (2009)	Six-month panel data set from a large nationwide retailer that advertises on Google in 2007	Click-through rates, conversion rates, advertising cost, and advertising position	Economic value of advertising position and firms' bidding strategy	Click-through rate and conversation rate are positively related to advertising position. But topmost position might not be economic optmized, whereas middle position usually has higher economic return
Agarwal, Hosanagar, and Smith (2011)	Field experiment on Google.com for 45 days in 2009	Click-through rate, conversion rate, advertising position	Economic values of advertising position and moderating effect of keyword specificity	Click-through rate decreases with position, conversion rate increases with position and is even higher for more specific keywords.
Animesh, Viswanathan, and Agarwal (2011)	Field experiment in conjunction with a firm in the mortgage industry	Advertising position, click-through rate, advertising creativity and competitive intensity	Consumer segmentation, performance of advertising position, and competition	Sponsored search listings can act as an effective customer segmentation mechanism, and the effects on click-through rate advertising rank are strongly moderated by the seller's ability to differentiate itself from its rivals.
Jerath, Ma and Park (2014)	Individual-level click data from a leading search engine firm in Korea.	Keyword popularity and clicks	Organic and sponsored search displays and search advertising strategy	Consumers'click activity after a keyword search is low and heavily concentrated on the organic list. However, searches of less popular keywords (i.e.,keywords with lower search volume) are associated with more clicks per search and a larger fraction of sponsored clicks.

TABLE 1 (Cont')

Yang, Lu and Lu (2014)	Aggregate data on 1,573 keywords from a leading online market maker outside the United States	Click-throughs, CPC, Number of advertisers	The effects and determinants of competition on click volume and CPC	The number of advertisers has a positive effect on the baseline click volume, has an inverse-U relationship with the mean decay factor, and has a negative and convex effect on the mean value of clicks; competition generally hurts advertisers but benefits the paid-search host.
Chan and Park (2015)	Data from a leading search engine in Korea in 2008	Clicks and advertising position	Consumer segmentation and economic value of advertising position	Users in the larger, low-involvement segment are less likely to click sponsored links but more likely to stop the search. In contrast, users in the smaller, high-involvement segment are more likely to click multiple links and less likely to stop the search.
Narayanan and Kalyanam (2015)	Data from a large online retailer of consumer durables.	Advertising position, click-through rate, sales order, seller size, prior experience and brand equity	Performance of advertising position and its moderators	Advertising position positively affects Click-through rates, but has similar effect on sales order on the advertisements on the first page. The position effect further depends on seller size, prior experience, and brand equity.
Agarwal and Mukhopadhyay (2016)	360 keywords with 1,267 advertiser keyword in Yahoo 2008	Advertising position, click-through rate, conversion rate, keyword specificity and ad quality	The impact of competing ads on the click performance	First, competing high-quality ads have a lower negative effect on the click performance as compared to competing low-quality ads. Second, the negative effect of competing high-quality ads decreases at low positions as compared to high positions. Furthermore, this decrease in the negative effect of competing high-quality ads is more substantial for specific keywords.
Im et al. (2016)	Search transactions of 11,001 keywords from a sponsored search engine channels in 2010.	brand-seeking vs. deal-seeking, search vs. experience goods	The effects of keyword type (deal- vs. brand-seeking) and product type on advertising performances	First, search queries containing deal-seeking keywords are associated with higher click-through rates and conversion rates than are search queries without such keywords. Second, the positive effect of deal-seeking keywords on click-through rates is more pronounced for experience goods than for search goods.

TABLE 1 (Cont')

Du, et al. (2017)	Daily aggregates of sponsored search advertising from a major Chinese online B2C retailer that advertises on Google	Advertising position, click-through rate, conversion rate, cost-per click, and keyword characteristics	Performances of different keyword categories and match types.	First, relativetogenerickeywords, focal-brand keywords are associated with higher CTRs and higher CRs, while competing-brand keywords are associated with lower CTRs; Second, keyword match types are also important and that their effects differ for the three keyword categories.
Gong, Abhishek and Li (2018)	4.6 million search impressions of 12,790 keywords in Google 2007.	Advertising position, click-through rate, keyword ambiguity	The effect of keyword ambiguity on ad performance	Higher keyword ambiguity is associated with higher CTR on top-positioned ads, but also a faster decay in CTR with screen position.
This study	Display-level data from a leading online shopping platfrom in 2014	Price ranks, click-through rates, conversion rates, keyword specificity and keyword popularity	Influence of price rank on advertising performance, and the moderators	Consumers tend to click the advertising display with extremely high or low prices and purchase the product of the advertising display with middle prices. These effect further depends on keyword specificity and popularity.

1.4 Theoretical Background

1.4.1 Purchase Funnels of Search Advertisements

Consumers develop and modify their preferences on the basis of a choice set, such as the list of sponsored advertisements obtained from a search (Bettman et al. 1998; Payne et al. 1992). Consumers' responses to price ranks in keyword search advertisements likely shift, depending on whether they are conducting exploratory information searches that build expectations, actively engaging with a specific advertising sponsor, or approaching an actual purchase (Bettman et al. 1998; Kalwani et al. 1990). The purchase funnel model and dynamic views of consumer choice suggest that consumer behaviors vary across purchase stages (Hauser and Wernerfelt 1989; Nedungadi 1990; Roberts and Lattin 1991; Simonson and Tversky 1992), due to the complexity of the decision process and consumers' efforts to reduce that complexity. Prior literature also specifies that to simplify complex decision-making processes, consumers alter their behaviors according to phases (Shocker et al. 1991), such that their multi-phase decision process involves a series of hierarchical or nested choice sets. In different phases, consumers express different preferences and behave according to various patterns (Alba and Chattopadhyay 1985).

Building on consumer decision literature, I consider two specific behavioral patterns and the corresponding mechanisms for search and purchase decisions that in turn affect consumers' responses to sponsored keyword advertisements. That is, I expect that the prevalence of the two mechanisms varies across different phases of the purchase funnel during the search process and for consumers with different orientations or goals.

1.4.2 Anchoring Effects for Information Searches

When consumer preferences are ambiguous, preferences evolve through an anchoring-and-adjustment process (Carpenter and Nakamoto 1989; Hoch and Deighton 1989). Both anchoring and adjustment processes, as postulated by Tversky and Kahneman (1974), occur when people judge a stimulus along an attribute dimension with some uncertainty. Given the vastness of a universal set and their limited information processing capability, consumers usually select extreme values along this dimension as anchors, then adjust their expectations to arrive at a value that seems plausible. The extremes serve as anchors that help consumers learn the large universal set efficiently at the first glance; then they might gradually move to non-extremes to further their search process. That is, extreme prices, whether at the highest or lowest point, anchor consumers' price perceptions (Kalwani et al. 1990), such that consumers use them as reference points for searches made with uncertainty (Epley and Gilovich 2006). Krishna et al. (2006) show that extremely priced products, among a set of more moderately priced options, affect the reservation price for a moderately priced target product in the same category. This anchoring effect is particularly influential when the products are more closely related and presented contiguously (Krishna et al. 2006). An explicit comparison of products against the price anchor activates consideration of product features available at this price, which then influences consumers' willingness to pay (Adaval and Wyer 2011). After reviewing the extreme options, consumers identify key product features that they want to compare and develop expectations about those identified features to inform their purchasing decisions.

1.4.3 Compromise Effects for Purchases

Starting from a universal set, consumers interested in buying a product narrow down their consideration set and focus on a subset of plausible alternatives. In contrast with an anchoring effect, a compromise effect implies that brands gain more share when they represent an intermediate rather than extreme option in a choice set (e.g., Chernev 2004; Dhar et al. 2000; Kivetz et al. 2004b). When consumers are closer to a purchase decision, they likely pay more attention to moderately priced products, which represent viable options along the entire spectrum of available products and enable consumers to make compensatory trade-offs among the available options (Chernev 2004; Dhar et al. 2000).

1.4.4 Consumer Responses: Click-Through Rates and Conversion Rates

Consumers' responses to sponsored keyword advertising include clicking and converting (Jerath et al. 2014). Consumers search alternatives and select one with the highest utility. By clicking the sponsored links, consumers retrieve information from the sponsored advertisement, using exploratory searches to find generic information about products, which they can leverage to develop their expectations and evaluate alternatives. Conversion implies more active, engaged purchase behaviors.

Clicks for building anchors versus compromising. The intrinsic purpose of keyword searches (i.e., seeking information about a topic) implies that consumers develop anchors to evaluate the alternative products displayed in the keyword search results. Clicking behaviors support the development of anchors particularly in the early stages of the purchase funnel. Clicking a sponsored display involves minimal engagement, and the basic information allows consumers to derive expectations about products of interest. According to anchoring effect theory (Krishna et al. 2006), consumers pay more attention to extreme prices to develop references, because these extreme options are more informative as anchors, enabling consumers to identify desired quality or prices and compare products along those features (Epley and Gilovich 2006). The high price of a product can reflect high quality, whereas the low price of a product can compensate for low quality. Thus, the extremely priced products, either high or low, may or may not be considerable choices for clicks, depending on consumers' preferences and budgets.

In contrast, consumers might click moderate options to find a compromise between product price and quality at the stages closer to the decision in the purchase funnel. The net effect then depends on the relative strength of these two contrasting roles for clicks. In general, it takes more time and more clicks to conduct exploratory searches, whereas clicks for purchase decisions likely occur only at the last stage of the purchase funnel. Previous findings similarly establish that conversion rates are much lower than click-through rates (Agarwal et al. 2011; Rutz et al. 2012; Yang and Ghose 2010). Therefore, I anticipate that clicking behaviors are driven more by the exploratory need to build anchors, rather than a need for compromise, and consumers click on extreme-priced displays more than moderately priced ones to develop these anchors. Formally,

H_1: Price rank has a U-shaped effect on consumers' click-through rate on a displayed list of sponsored keyword advertising, such that the click-through rate is higher for extremely priced products than for moderately priced ones.

Conversions with compromises. Consumers consider products with different features from among the results of their keyword searches, though all the products likely represent the same category. Conversion requires deep customer engagement, beyond exploratory searches, because consumers seek to determine if a product option meets their specific needs or which needs a specific option might serve. According to compromise effect theory (Chernev 2004; Dhar et al. 2000; Kivetz et al. 2004a), consumers seek trade-offs among product features to make a purchase decision, for which product prices and quality are two primary concerns (Feinberg and Huber 1996; Mehta et al. 2003). However, product quality is difficult to observe in a sponsored search advertising context, so consumers might infer quality from product prices, with the belief that a higher price indicates better quality (Feng and Xie 2012). Thus, conversions involve more compromise than exploratory searches, and they should be more likely in response to moderately priced products than extremely priced options with the highest or lowest prices. I predict:

H_2: Price rank has an inverted U-shaped effect on consumers' conversion rate for the displayed list of sponsored keyword advertising, such that the conversion rate is higher for moderately priced products than for extremely priced ones.

1.4.5 Moderating Effect of Search Keyword Characteristics

Keyword attributes could provide a basis for consumer segmentation. Keywords that a consumer uses for online searches reveal his or her shopping stages and goals as well as the breadth of the market (niche vs. mass) (Jeziorski and Segal 2015). In particular, searches reflect two aspects of consumers' preferences. First, consumers differ in their specific needs and shopping goals, so they use different search keywords (Chan and Park 2015; Du et al. 2015; Jerath et al. 2014; Rutz and Bucklin 2011; Rutz et al. 2011). The specificity of the search keywords signals consumer traits, according to the level of detail associated with those keywords (Narayanan and Kalyanam 2015). Second, search keywords can provide estimates of the size of the market that might be interested in the related topics (e.g., niche vs. mass). Keyword popularity, or the extent to which the keywords are used commonly by consumers in their searches (Jerath et al. 2014), thus can indicate the size of the market segment.

Keyword specificity. I argue that keyword specificity reflects the depth of search, and deeper search reduces the influence of product prices on decision making. Because more specific keywords cover a narrower range of products, searchers likely have a clear idea of the products they want (e.g., “automatic neck massager”), whereas less specific keywords contain only a rough product description (e.g., “massager”). The use of more specific keywords corresponds to more specific preferences for the products for which consumers are searching, as reflected in the additional constraints on the search queries. In contrast, less specific keywords imply searches for information without specific shopping goals (Jerath et al. 2014; Rutz and Bucklin 2011). In preference construction, extreme-priced products have a more critical anchoring function when consumers lack specific preferences or are not familiar with the topic (Biswas and Blair 1991). In terms of decision making, consumers with specifically defined preferences have less need to compromise among the product features to choose the product that meets their already specific preferences (Dhar et al. 2000). That is, consumers using specific keywords have a weaker need for anchors to evaluate a wide spectrum of options, and they are more reluctant to compromise product features to avoid uncertainty. In contrast, consumers with general or no preferences, reflected in general keywords, rely more on the product price to anchor the market spectrum or compromise among product features to avoid risks. I thus predict a moderating effect of keyword popularity, such that the U-shaped effect of price ranks on clicks and the inverted U-shaped effect of price ranks on conversion rates grow flatter with greater keyword specificity.

H_3: Keyword specificity weakens the U-shaped effect of price ranks on the click-through rate, making the effect flatter.

H_4: Keyword specificity weakens the inverted U-shaped effects of price ranks on the conversion rate, making the effects flatter.

Keyword popularity. A keyword's popularity relates directly to its advertising value, which determines competition in the display list. Greater popularity means that more consumers are interested in the topic, so advertisers compete more intensely for this large market. The intense competition in turn drives marketers to advertise their best-selling products and design advertisements in the most attractive way, such that consumers encounter all-attractive choice sets. With all these attractive alternatives, it becomes difficult for consumers to narrow down the consideration sets efficiently, and consumers have a greater need for signals to guide product searches and purchases. Product price, which are likely in accordance with operational costs and product positioning strategies, offers an intuitive, efficient indicator that consumers can use to develop their expectations across the purchase funnel (Bagwell and Riordan 1991; Monroe 1973). In contrast, less popular keywords likely imply a niche market, in which consumers already encounter a clearly distinguishable choice set with products that offer varying non-price quality signals (Dalgic and Leeuw 1994), so their need to use price as an indicator decreases. That is, consumers using more popular keywords have stronger needs to develop anchors for search and to compromise. Thus, the U-shaped effect of price ranks on click-through rates and the inverted U-shaped effect of price ranks on conversion rates should be steeper with greater keyword popularity.

H_5: Keyword popularity increases the U-shaped effect of price ranks on the click-through rate, making the effects steeper.

H_6: Keyword popularity increases the inverted U-shaped effect of price ranks on the conversion rate, making the effect steeper.

1.5 Study One: Evidences from a Retail Search Engine

1.5.1 Research Context and Data

The data set comes from one of the world's largest electronic shopping platforms. It only maintains online stores, serves more than 18 million buyers and sellers from more than 240 countries and regions, and showcases products in categories ranging from raw materials to finished goods. The platform offers certain keywords in auctions, for which sellers bid to earn a position on the sponsored display list of keyword search results. The automatic bidding process runs daily, and the content and position of the advertisements remains the same for that one-day period. The platform determines the position of the sponsored advertisements using various elements, including the cost per click (CPC), product relevance, and seller reliability. Its ranking algorithm ensures that products included in the sponsored list are relevant and comparable. The sponsored advertisements also are displayed alongside organic search results, and each page holds eight sponsored advertisements (see Appendix A for the example page). The sponsored advertisements disclose basic information about the products, including their name, small pictures, unit prices, and past sales. The displayed product prices are not affected by this bidding process, so sellers can price their products regardless of their rankings or CPC. If they click a sponsored advertisement, consumers are directed to the product pages, which disclose more detailed information (e.g., multiple pictures, customer reviews, original and actual prices, seller information).

I collected advertising records and responses over a one-month period (June 2017) of the most active 969 keywords across 91 subcategories in four industries: 100 keywords in home decoration and design (e.g., “decorative design”), 602 keywords in health care (e.g., “foot massagers”), 212 keywords in DIY tools (e.g., “ultrasonic cleaner”), and 55 keywords in gym equipment (e.g., “yoga pad”). The 207,407 observations of sponsored advertisements feature 5,724 products and 189 sellers. On average, each day, a keyword receives 7,692 searches, 2,775 clicks, and 201 clicks that convert into purchases.

1.5.2 Measures

Searches, clicks, and conversions. I measured the three key response variables daily. Following prior literature (Jerath et al. 2014; Rutz and Bucklin 2011; Rutz et al. 2012; Yang and Ghose 2010), I measured *search* as the daily number of searches for the focal keywords, *click* as the number of clicks that the keyword advertisements received, and *conversion* as the number of purchases generated through clicks.

Price rank and display rank. The price rank is the magnitude of the product price, relative to all displayed advertisements, coded with a discrete number range from 1 (lowest price) to 8 (highest price). A higher price ranking (smaller number) indicates that the focal product has a relatively lower product price. For convenience, I divide *PriceRank* by the total number of sponsored advertisements on the same pages, so the variable ranges from .125 to 1.000. Display rank refers to the position of the advertisements, and the topmost position is considered the most advantageous (Agarwal et al. 2011; Jerath et al. 2011). For this measure, I divided the rank of the advertisements by the total number of sponsored advertisements; it ranges from 0 to 1, where the topmost position has the smallest value and the bottom-most position has the largest value.

Keyword specificity and popularity. Following prior literature that measures keyword specificity (Agarwal et al. 2011; Yang et al. 2013), I note the number of modifiers, which might describe a feature, version, brand name, or function. For example, "massager" has no modifier and thus a 0 specificity score; "Phillips feet massager" has two modifiers and a score of 2 on the specificity measure. For keyword popularity, I adapt Jerath et al. (2014)'s measure, which uses a global rank of search volume. Because this measure risks multicollinearity, in that popular keywords tend to be less specific, I instead assess keyword popularity using the local rank of search volume, conditional on keyword specificity. That is, for keyword *i* with specificity *k*, I measure the popularity of the focal keyword as its rank among keywords with same specificity, such that $Popularity_i = SearchRank_{ik}/N_k$, where $SearchRank_{ik}$ is keyword *i*'s rank in terms of the search volume among the keywords with specificity *k*, and N_k is the number of keywords with specificity *k*. Thus, $Popularity_i$ represents market popularity relative to other keywords with the same specificity. This modified approach reduces multicollinearity concerns between keyword specificity and popularity. In Table 2, I summarize the variables, definitions, and operationalizations for Study 1 and Study 2. Table 3 presents the descriptive statistics.

TABLE 2
Variables, Definitions, and Operationalizations

	Definitions	Operationalizations
Study 1		
1. Click	The number of times that consumer clicking sponsored ad to view product webpage	Number of Clicks received by the advertisement per day
2. Conversion	The number of purchases converted from clicks	Number of Conversations received by the advertisement per day
3. Search	The number of times that consumers search the keyword	The number of searches received by the keyword per day
4. Specificity	The specificity of the keywords	The specificity is coded in terms of their specificity toward a certain category
5. Popularity	The popularity of the keywords	Rank of searches received by the keyword within the keyword with same length
6. Price Rank	The relative order of displayed product price of search advertisements in a after-search page	PriceRank=Price ranking/number of prices in display list, ranging from 0.125 to 1
7. Display Rank	Advertising position in a vertical listing setting	Display position from 1 to 8, 1 represents topmost position
8. Ave. Sponsored Price	The displayed price of sponsored search results	The average displayed prices of the products appeared in the sponosred search results
9. Keyword Length	The length of the keyword	Number of characters included in the keywords
10. Title Length	The length of the title of the sponsored advertisement	Number of characters included in the sponsored advetisement title
11. Ave. Organic Price	The displayed price of organic search results	The average displayed prices of the products appeared in the organic search results

TABLE 2 (Cont')

12. Past Sales	Units sold in the past 30 days, observable to consumers in click and conversion	Number of units sold in the past 30 days
13. Price	The advertised unit price displayed in the sponsored advertisements	The advertised unit price of the product in local currency
14. Sponsored Product Number	Sellers' strategic focus on the advertised products in searh advertising	Total number of products the seller sponsored in one day
15. Sponsored Keyword Number	Sellers' strategic focus on the advertised keywords in searh advertising	Total number of keywords the seller sponsored in one day
16. Review Number	The popularity of the sellers, observed by consumers reviews toward the focal seller	Number of customer reviews for the advertised products
17. Brand	Whether the keyword involves certain brand names	Dummy variable, Brand=1 indicating the keyword include a brand name and Brand=0 otherwise
18. Discount Rate	The extent of promotion, observed by consumers in conversion stage	Discount Rate=1-Sale Price/Original Price
Study 2		
1. Click	The click decisions of participants on the sponsored advertisements	Dummy variable, click=1 indicating the advertisement is clicked at focal click, and 0 otherwise
2. Conversion	The purchase decisions of participants on the sponsored advertisements	Dummy variable, conversion=1 indicating the advertisement is purchased, and 0 otherwise
3. Rank (from 1 to 7)	The relative order of displayed product price of search advertisements among the 7 advertisements	Measured as a categorical variable with the lowest priced as 1 and highest as 7
4. Stream	The sequence of clicks along the participant's search process	Normalized to one with the first click as 0, and the last click prior purchase is 1
5. Design	Participants' interests toward the design of the product regardless of product price	Measured by a 7-point scale with “not interested/ extremely interested”
6. PreClick	Participants' interests toward the design of the product regardless of product price	Dummy variable, PreClick=1 indicating the advertisement has been clicked prior the focal click, and 0 otherwise

TABLE 3
Study 1: Descriptive Statistics

Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Click	282.59	859.99	0.00	28299.00	1.00																	
2. Conversion	20.46	143.34	0.00	7129.00	0.52	1.00																
3. Search	7645.83	14089.93	3.00	320940.00	0.57	0.11	1.00															
4. Specificity	1.18	0.67	0.00	3.00	-0.03	0.02	-0.13	1.00														
5. Popularity	0.48	0.31	0.00	1.00	0.23	0.09	0.40	-0.04	1.00													
6. Price Rank	0.53	0.29	0.13	1.00	-0.01	-0.01	0.00	0.01	0.00	1.00												
7. Display Rank	0.50	0.34	0.00	1.00	-0.04	0.01	0.00	0.00	0.00	0.06	1.00											
8. Ave. Sponsored Price	1312.86	2390.34	1.05	25015.85	0.16	0.02	0.13	-0.02	-0.07	0.02	0.00	1.00										
9. Keyword Length	5.29	1.53	2.00	11.00	0.00	0.03	-0.10	0.79	-0.01	0.01	0.00	0.00	1.00									
10. Title Length	28.41	2.22	1.00	30.00	0.01	0.01	0.01	-0.01	-0.02	-0.12	-0.05	-0.06	-0.02	1.00								
11. Ave. Organic Price	897.69	2259.17	0.00	50000.00	0.10	0.00	0.09	-0.08	-0.07	0.00	0.00	0.44	-0.05	0.00	1.00							
12. Past Sales	860.55	2836.87	0.00	21235.00	0.01	0.01	-0.02	0.01	0.01	-0.15	-0.09	-0.05	0.00	0.19	-0.05	1.00						
13. Price	1312.86	3607.62	0.50	179900.00	0.13	0.01	0.09	-0.01	-0.05	0.25	0.02	0.66	0.00	-0.09	0.29	-0.08	1.00					
14. Sponsored Product Number	117.17	125.47	4.00	680.00	-0.02	0.00	-0.01	-0.03	-0.01	-0.05	0.06	-0.16	-0.02	-0.01	-0.03	-0.08	-0.12	1.00				
15. Sponsored Keyword Number	27.00	26.91	1.00	186.00	0.02	-0.01	-0.01	0.04	0.01	-0.07	-0.15	0.13	0.02	0.10	-0.01	0.08	0.06	-0.30	1.00			
16. Review Number	6530.50	23238.10	0.00	221136.00	0.01	0.01	-0.02	0.01	0.00	-0.16	-0.07	-0.04	0.00	0.18	-0.05	0.75	-0.07	-0.07	0.06	1.00		
17. Brand	0.07	0.25	0.00	1.00	0.00	0.01	-0.04	0.10	-0.02	0.00	0.00	0.02	0.13	-0.05	0.06	0.03	0.01	0.01	0.01	0.04	1.00	
18. Discount Rate	0.48	0.27	0.00	0.99	0.02	0.01	0.00	0.02	0.03	-0.19	-0.04	0.03	0.01	0.29	-0.04	0.22	-0.09	-0.08	0.10	0.24	0.01	1.00

1.5.3 Model Specification

I cast our simultaneous model in a hierarchical Bayesian framework. Assume that for keyword *i* at time *t*, the sponsored advertising display of advertisement *j* receives n_{ijt} clicks and m_{ijt} conversions out of N_{ijt} searches, where $0 \leq \mathrm{n_{ijt}} \leq \mathrm{N_{ijt}}$. Furthermore, among the n_{ijt} clicks, there are m_{ijt} conversions, such that $m_{ijt} \leq n_{ijt}$. I define the probability of a click as p_{ijt} and the probability of a conversion as q_{ijt}, conditional on $n_{ijt} > 0$. In our model, the consumer faces two decisions, click and conversion, that lead to three outcomes. First, a consumer might click the keyword advertisement and make a purchase ($p_{ijt}q_{ijt}$). Second, a consumer can click the keyword advertisement but not make a purchase ($p_{ijt}\,(1 - q_{ijt})$). Third, a consumer can choose not to click ($1 - p_{ijt}$). These decisions depend on differences in individual keywords, both observed and unobserved, and the observed characteristics of the seller and the product. The probability of observing (n_{ijt}, m_{ijt}) is given by

(1) $$f(m_{ijt}, n_{ijt}, p_{ijt}, q_{ijt}) = \frac{N_{ijt}!}{(N_{ijt}-n_{ijt})!(n_{ijt}-m_{ijt})!m_{ijt}!}(1-p_{ijk})^{N_{ijt}-n_{ijt}}\,[p_{ijk}(1-q_{ijk})]^{n_{ijt}-m_{ijt}}\,(p_{ijk}q_{ijk})^{m_{ijt}}$$

Consumers' decisions to click. The click rates a sponsored advertisement receives vary across keywords, according to the corresponding audience (Jerath et al. 2014; Rutz and Bucklin 2011) and the rank of search advertisements (Rutz et al. 2012; Yang and Ghose 2010). Therefore, I model the click-through rate as a function of observed heterogeneities *Specificity*, *Popularity*, and *DisplayRank*; a vector $\boldsymbol{X_{ijt}}$ containing observed covariances; and unobserved keyword-level, seller-level, and time-level heterogeneities. The probability of click p_{ijt} by the latent consumer utility function U_{ijk}^{click} is given as:

(2) $p_{ijt} = \frac{\exp(U_{ijt}^{click})}{1+\exp(U_{ijt}^{click})}$, and

(3) $U_{ijt}^{click} = \alpha_{0i} + \alpha_{1i}\, PriceRank_{ijt} + \alpha_{2i} PriceRank^{2}_{ijt} + \alpha_{3} Specificity_{i} + \alpha_{4} Popularity_{i} +$

$\alpha_{5} DisplayRank_{ijt} + \alpha_{6\text{-}15}\boldsymbol{X_{ijt}} + \delta_{t}^{click} + \theta_{j}^{click} + \eta_{ijt}$.

To capture unobserved seller-level and time-level heterogeneities, I include two random effects: δ_{t}^{click} is the random effect for time t, and θ_{j}^{click} is the random effect for a seller of advertisement j. In turn, $\boldsymbol{X_{ijt}}$ is a vector of observed covariances, including the average sponsored prices of keyword i at time t, the length of keyword i, a dummy variable indicating whether the keyword i contains certain brand names, the length of advertisement j's title at time t, cumulative past sales of the advertised product j at time t, the price of the product j at time t, the number of keywords that advertisement j's seller sponsored at time t, and the number of products that advertisement j's seller sponsored at time t. To capture keyword-level heterogeneity, I use random coefficients for the intercept and *PriceRank*. The random coefficients are modeled as:

(4) $$\begin{bmatrix}\alpha_{0i}\\ \alpha_{1i}\\ \alpha_{2i}\end{bmatrix} = \begin{bmatrix}\bar{\alpha}_{0}\\ \bar{\alpha}_{1}\\ \bar{\alpha}_{2}\end{bmatrix} + \begin{bmatrix}0 & 0\\ \alpha_{11} & \alpha_{12}\\ \alpha_{21} & \alpha_{22}\end{bmatrix} \times \begin{bmatrix}Specificity_{i}\\ Popularity_{i}\end{bmatrix} + \begin{bmatrix}\xi_{0i}^{\alpha}\\ \xi_{1i}^{\alpha}\\ \xi_{2i}^{\alpha}\end{bmatrix}$$

(5) $$\begin{bmatrix}\xi_{0i}^{\alpha}\\ \xi_{1i}^{\alpha}\\ \xi_{2i}^{\alpha}\end{bmatrix} \sim \text{MVN}\left(\begin{bmatrix}0\\0\\0\end{bmatrix}, \begin{bmatrix}\Sigma_{11}^{\alpha} & \Sigma_{12}^{\alpha} & \Sigma_{13}^{\alpha}\\ \Sigma_{21}^{\alpha} & \Sigma_{22}^{\alpha} & \Sigma_{23}^{\alpha}\\ \Sigma_{31}^{\alpha} & \Sigma_{32}^{\alpha} & \Sigma_{33}^{\alpha}\end{bmatrix}\right).$$

Consumers' decisions to convert. Keyword advertising literature suggests that conversion rates vary across keywords (*Specificity* and *Popularity*) and positions

(*DisplayRank*) (Rutz et al. 2012; Yang and Ghose 2010). In addition, review volume provides a quality signal that influences consumers' purchase decisions (Chevalier and Mayzlin 2006; Zhu and Zhang 2010). In our research context, review volume and discount rate can be observed only on the product page, so they are exogenous to click decisions. Furthermore, it takes some time for products to be delivered, so review volume can be considered predetermined. Thus, I model the conversion rate as a function of *Specificity*, *Popularity*, *Display Rank*, $\boldsymbol{X_{ijt}}$, *ReviewVolume, DiscountRate,* and random effects at the keyword-, seller-, and time-levels. The probability of conversion q_{ijt} determined by the latent consumer utility function U_{ijk}^{conv} is given as:

(6) $q_{ijt} = \frac{\exp(U_{ijt}^{conv})}{1+\exp(U_{ijt}^{conv})}$, and

(7) $U_{ijt}^{Conv} = \beta_{0i} + \beta_{1i}PriceRank_{ijt} + \beta_{2i}PriceRank^2_{ijt} + \beta_3 Specificity_i + \beta_4 Popularity_i +$

$\beta_5 DisplayRank_{ijt} + \beta_6 Review_{ijt} + \beta_7 DiscountRate_{jt} + \beta_{8\text{-}17}\boldsymbol{X_{ijt}} + \delta_t^{conv} + \theta_j^{conv} + \varepsilon_{ijt}.$

To capture unobserved heterogeneity in terms of time and the seller, I include two random effects: δ_t^{conv} is the random effect for time *t*, and θ_j^{conv} is the random effect for a seller of advertisement *j*. I again capture unobserved heterogeneity with a random coefficient, specified on both the intercept and the *PriceRank*, as follows:

(8) $\begin{bmatrix}\beta_{0i}\\ \beta_{1i}\\ \beta_{2i}\end{bmatrix} = \begin{bmatrix}\bar{\beta}_0\\ \bar{\beta}_1\\ \bar{\beta}_2\end{bmatrix} + \begin{bmatrix}0 & 0\\ \beta_{11} & \beta_{12}\\ \beta_{21} & \beta_{22}\end{bmatrix} \times \begin{bmatrix}Specificity_i\\ Popularity_i\end{bmatrix} + \begin{bmatrix}\xi_{0i}^{\beta}\\ \xi_{1i}^{\beta}\\ \xi_{2i}^{\beta}\end{bmatrix}$, and

$$(9)\ \begin{bmatrix}\xi_{0i}^{\beta}\\ \xi_{1i}^{\beta}\\ \xi_{2i}^{\beta}\end{bmatrix} \sim \mathrm{MVN}\left(\begin{bmatrix}0\\0\\0\end{bmatrix}, \begin{bmatrix}\Sigma_{11}^{\beta} & \Sigma_{12}^{\beta} & \Sigma_{13}^{\beta}\\ \Sigma_{21}^{\beta} & \Sigma_{22}^{\beta} & \Sigma_{23}^{\beta}\\ \Sigma_{31}^{\beta} & \Sigma_{32}^{\beta} & \Sigma_{33}^{\beta}\end{bmatrix}\right)\ .$$

Advertiser's decision on price rank. Next, I model the advertiser's strategic price rank decision. Advertisers adjust their strategy to obtain competitive advantages, so I expect that sellers determine their pricing strategy on the basis of their expectations about competitors' pricing strategies, their own previous advertising performance (i.e., click-through and conversion rates), and their current product status (i.e., review volume). The advertisement's position is not determined by product prices and discounts, so I also expect advertisers to adjust the advertised prices according to the current display rank. Thus, I model *PriceRank* as a function of *DisplayRank, Review, DiscountRate,* and $\boldsymbol{X_{ijt}}$; the lagged click-through rate (p_{ijt-1}), conversion rate (q_{ijt-1}), and price rank of the same keyword ($PriceRank_{ijt-1}$); and the random effects for time *t* (δ_t^{price}) and for seller *j* (θ_j^{price}). Then $PriceRank_{ijt}$ is modeled as:

$$(10)\ PriceRank_{ijt} = \psi_0 + \psi_1 PriceRank_{ijt-1} + \psi_2 Specificity_i + \psi_3 Popularity_i + \psi_4 Review_{ijt}$$
$$+\psi_5 DisplayRank_{ijt} + \psi_6 DiscountRate_{jt} + \psi_7 p_{ijt-1} + \psi_8 q_{ijt-1} + \psi_{9\text{-}18}\boldsymbol{X_{ijt}}$$
$$+\delta_t^{Price} + \theta_j^{Price} + v_{ijt}.$$

Advertiser's decision on display rank. Finally, sellers observe prior advertising performance, achieved through their previous bidding activity, and seek an optimal advertising position. The platform also considers the advertiser's previous click-through rate and product popularity to determine bidding results. Thus, I use the lagged click-through rate p_{ijt-1}, conversion rate q_{ijt-1}, and advertising position $DisplayRank_{ijt-1}$; *Reviews,* *DiscountRate*, and keyword characteristics (i.e., *Specificity* and *Popularity*); and the random effects δ_t^{rank} for time *t* and θ_j^{rank} for seller *j* when I model *DisplayRank*.

(11) $DisplayRank_{ijt} = \varphi_0 + \varphi_1 DisplayRank_{ijt-1} + \varphi_2 Specificity_i + \varphi_3 Popularity_i + \varphi_4 Review_{ijt} + \varphi_5 DiscountRate_{jt} + \varphi_6 p_{ijt-1} + \varphi_7 q_{ijt-1} + \varphi_{8\text{-}17}\boldsymbol{X_{ijt}} + \delta_t^{rank} + \theta_j^{rank} + u_{ijt}$.

Finally, to model unobserved covariances, I let the four error terms correlate as follows:

(12) $$\begin{bmatrix}\eta_{ijt}\\ \varepsilon_{ijt}\\ v_{ijt}\\ \mu_{ijt}\end{bmatrix} \sim \text{MVN}\left(\begin{bmatrix}0\\0\\0\\0\end{bmatrix}, \begin{bmatrix}\Omega_{11} & \Omega_{12} & \Omega_{13} & \Omega_{14}\\ \Omega_{21} & \Omega_{22} & \Omega_{23} & \Omega_{24}\\ \Omega_{31} & \Omega_{32} & \Omega_{33} & \Omega_{34}\\ \Omega_{41} & \Omega_{42} & \Omega_{43} & \Omega_{44}\end{bmatrix}\right).$$

1.5.4 Identification

To identify endogeneity and the proposed system of the simultaneous equation model, I provide a sketch of the model, which boils down to the following simultaneous equations:

(13) $p_{ijt} = f(Pricerank_{ijt}, DisplayRank_{ijt}, X_{ijt}^p, \eta_{ijt})$,

(14) $q_{ijt} = f(Pricerank_{ijt}, DisplayRank_{ijt}, X_{ijt}^q, \varepsilon_{ijt})$,

(15) $Pricerank_{ijt} = f(DisplayRank_{ijt}, X_{ijt}^{price}, v_{ijt})$, and

(16) $DisplayRank_{ijt} = f(X_{ijt}^{rank}, \mu_{ijt})$

where X_{ijt}^p, X_{ijt}^q, X_{ijt}^{price}, and X_{ijt}^{rank} are exogenous variables from the four equations. The error terms (η_{ijt}, ε_{ijt}, μ_{ijt}, and v_{ijt}) capture information observed by decision makers (consumers, sellers, and the platform) but not researchers. The endogeneity of *PriceRank* and *DisplayRank* can be identified by correlation among the error terms, such that *PriceRank* is endogenous if v_{ijt} correlates with η_{ijt} or ε_{ijt}, and *DisplayRank* is endogenous if u_{ijt} correlates with η_{ijt}, ε_{ijt}, or v_{ijt}.

A triangulation system can be identified too, by modeling *DisplayRank* as exogenously determined by the advertiser's past performance with the same keyword, other keyword-related characteristics, and a latent instrumental variable. Given *DisplayRank* and the advertiser's past performance with the same keyword, advertisers determine their pricing strategy, which determines the effects of the advertisements' *PriceRank*. Finally, *PriceRank* and *DisplayRank* affect both click-through and conversion probabilities.

1.5.5 Estimation Results

To ensure the model is empirically identified, I pretest it with a simulated data set. I randomly generated a set of parameters to be estimated, then calculated the clicks and conversions using a sample from the data set and the proposed distributions. When I estimated the proposed model with the simulated data, I were able to recover the true parameter values. This result mitigates concerns about the empirical identification of the proposed model.

I adopt a Bayesian approach and use the Markov chain Monte Carlo (MCMC) method to estimate our proposed model. I draw samples from the posterior distribution of 40,000 iterations following a burn-in of 40,000 iterations and save every 40th draw to avoid potential autocorrelations (see Appendix B for details of the MCMC algorithm and Appendix C for the MCMC diagnosis). To avoid the influences of first-page biases (Agarwal et al. 2011) and the incomparability of the sponsored advertisements in later pages, I used samples containing only advertisements displayed in the first page of search results (i.e., top 8 positions). Table 4 presents the results of our main effects tests regarding the influences of price ranks and keyword attributes on click-through and conversion rates. In addition, I report the estimated, unobserved, keyword-level heterogeneities and estimated variance–covariance matrix in table 5 and 6. Price rank has a U-shaped effect on the click-through rates, such that the first-order term has a negative effect ($\bar{\alpha}_1$ = -1.483, $p < .01$), but the second-order term has a positive effect ($\bar{\alpha}_2$= 1.319, $p < .01$). Advertisements that feature product prices that are relatively high or low receive more clicks from keyword searches, in support of H_1. In addition, price rank has a positive first-order effect ($\bar{\beta}_1$ = .824, $p < .01$) and a negative second-order effect ($\bar{\beta}_2$= -.760, $p < .01$) on conversion rates, in support of H_2.

Table 4 also reveals moderating effects of keyword specificity and popularity. For click-through rates, the U-shaped effect of price ranks is weakened by keyword specificity (α_{11} =.979, $p < .01$ first-order interaction; α_{21} = -.921, $p < .01$ second-order interaction) and enhanced by keyword popularity (α_{12} = -.724, $p < .01$ first-order interaction; α_{22} = .610, $p < .01$ second-order interaction), in support of H_3 and H_5. For conversion rates, the inverted U-shaped effect is enhanced by keyword popularity (β_{12} = .390, $p < .01$ first-order interaction; β_{22} = -.434, $p < .01$ second-order interaction) but weakened by keyword specificity (β_{11} = -.563, $p < .01$ first-order interaction; β_{21} = .524, $p < .01$ second-order interaction), in support of H_4 and H_6.

Figure 1 further illustrates the effects of the price ranks on click-through and conversion rates, along with the moderating effects of keyword specificity and popularity. The high and low values of specificity and popularity are one standard deviation above and below the means, respectively. As illustrated, when the price rank moves from extreme to moderate values, the click-through rate decreases by around 21.03% (i.e., from 5.08% to 4.01%), and the conversion rate increases by 15.05% (i.e., from 1.43% to 1.65%).

Keyword specificity weakens consumers' tendency to click extreme-priced displays (Figure 1, Panel A) and thus minimizes the differences between moderate and extreme prices, such that the click-through rate decreases by 33.09% (from 5.31% to 3.55%) for low specificity keywords and by 6.89% (from 4.86% to 4.52%) for high specificity keywords as the price rank moves from extreme to moderate values. Keyword popularity expands the differences between extremely priced alternatives and moderately priced alternatives though (Figure 1, Panel B), such that the click-through rate decreases by 11.90% (from 5.06% to 4.46%) for low popularity keywords and by 29.26% (from 5.10% to 3.60%) for high popularity keywords when the price rank of the target product moves from the extremes to a moderate position.

For conversion rates, keyword specificity weakens (Figure 1, Panel C) but keyword popularity enhances (Figure 1, Panel D) the advantages of the moderately priced displays. As the price rank moves to the middle, the conversion rate increases by 4.45% (from 1.57% to 1.64%) if keyword specificity is high and by 26.73% (from 1.31% to 1.66%) if keyword specificity is low. In addition, the conversion rate increases by 24.50% (from 1.28% to 1.60%) when keyword popularity is high and by 6.15% (from 1.60% to 1.70%) when keyword popularity is low as the price rank moves from the extremes to the middle.

TABLE 4
Estimated Results

Dependent Variable	Click-through Rate	Conversion Rate	Price Rank	Display Rank
Main Effects				
Price Rank	**-1.483(.079)**	**.824(.122)**		
Price Rank^2	**1.319(.067)**	**-.760(.101)**		
Moderating Effects				
Price Rank × Specificity	**.979(.056)**	**-.563(.105)**		
Price Rank^2 × Specificity	**-.921(.055)**	**.524(.096)**		
Price Rank × Popularity	**-.724(.059)**	**.390(.112)**		
Price Rank^2 × Popularity	**.610(.057)**	**-.434(.102)**		
Control Variables				
Specificity	**-.467(.035)**	**.332(.069)**	-.001(.001)	**-.004(.001)**
Popularity	**.324(.034)**	**-.271(.067)**	.000(.001)	.000(.001)
Ave. Sponsored Price	**-.033(.006)**	**.049(.010)**	.003(.003)	.003(.003)
Keyword Length	**.100(.025)**	**.144(.034)**	**-.001(.001)**	**.004(.001)**
Brand	.006(.051)	-.022(.071)	**-.005(.002)**	**-.001(.003)**
Title Length	**.027(.007)**	**.060(.011)**	-.003(.003)	.004(.003)
Ave. Organic Price	**.013(.005)**	**.026(.009)**	**-.015(.001)**	-.001(.001)
Display Rank	**-1.119(.044)**	**-.763(.054)**	-.008(.010)	
Past Sales	**.060(.012)**	**.099(.023)**	.002(.004)	**-.033(.005)**
Product Price	**.041(.007)**	**-.096(.013)**	**.041(.001)**	.000(.001)
Product Number	**-.027(.012)**	**-.028(.016)**	-.001(.008)	**-.022(.010)**
Keyword Number	**.011(.006)**	**.042(.009)**	**.005(.001)**	**-.033(.002)**
Review Volume		.052(.022)	.002(.012)	.005(.022)
Discount Rate		**.077(.010)**	.004(.007)	-.006(.012)
Price Rank$_{t-1}$			**.133(.002)**	
Click Rate$_{t-1}$			-.008(.013)	**-.119(.019)**
Conversion Rate$_{t-1}$			.018(.011)	**.057(.016)**
Review Volume$_{t-1}$			**.012(.001)**	**.010(.001)**
Display Rank$_{t-1}$				**.151(.002)**
Intercept	**-2.281(.070)**	**-4.586(.245)**	**.458(.027)**	**-1.861(.052)**
DIC		229696.653		

Note : In table 4-7, 1) Specificity and Popularity are mean-centered; 2) Posterior means and posterior standard deviations (in parentheses) are reported, and estimates that are significant at 95% are bolded.

TABLE 5

Study 1: Unobserved Heterogeneity Estimates

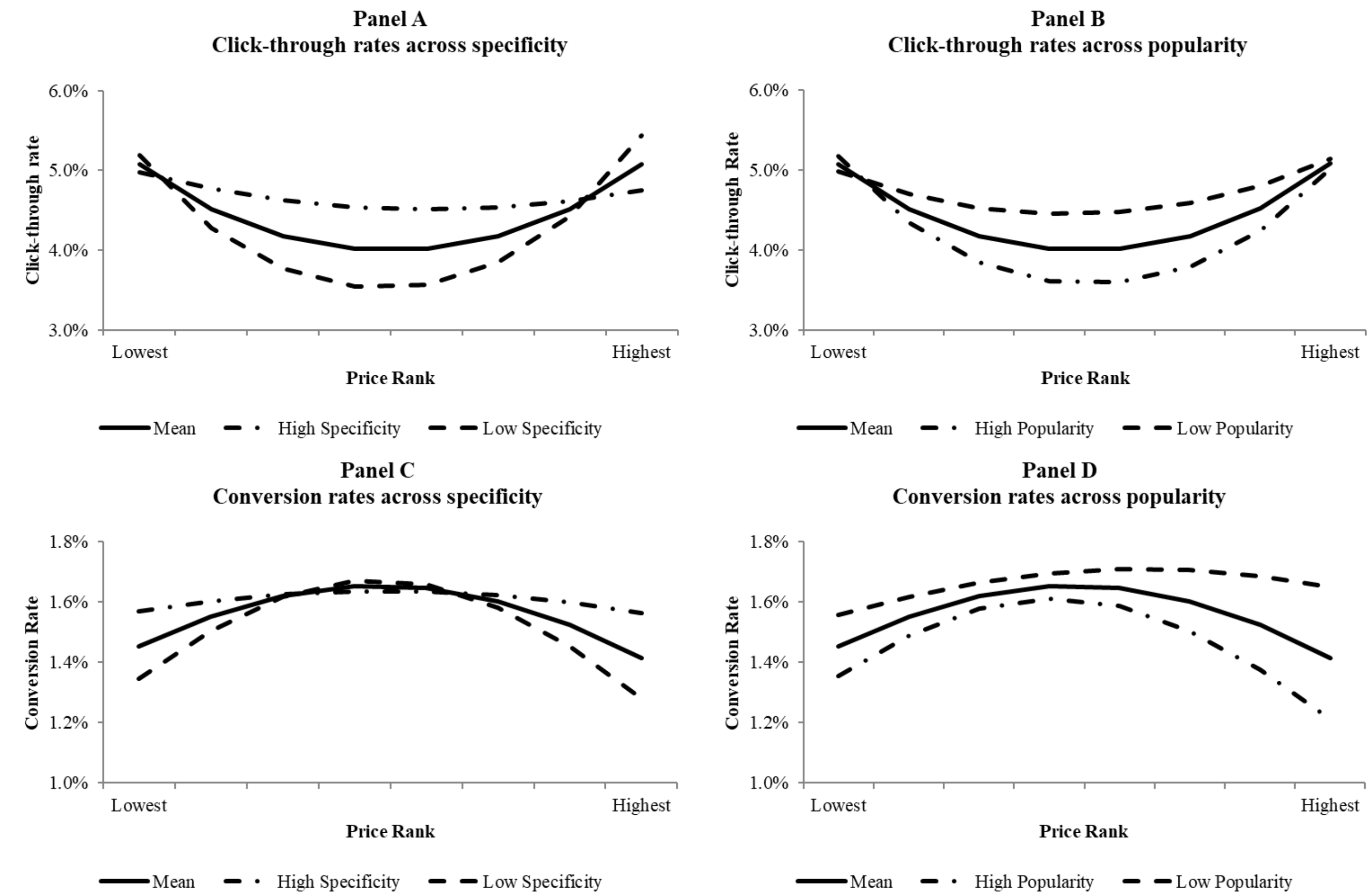
	Unobserved Heterogeneity Estimates (S^{α})		
	α_{0i} *(Intercept)*	α_{1i} *(Pricerank)*	α_{2i} *(Pricerank^2)*
α_{0i} *(Intercept)*	**1.340(.121)**	**-1.373(.117)**	**-.587(.065)**
α_{1i} *(Pricerank)*	**-1.373(.117)**	**1.490(.117)**	**.571(.063)**
α_{2i} *(Pricerank^2)*	**-.587(.065)**	**.571(.063)**	**.474(.040)**
	Unobserved Heterogeneity Estimates (S^{β})		
	β_{0i} *(Intercept)*	β_{1i} *(Pricerank)*	β_{2i} *(Pricerank^2)*
β_{0i} *(Intercept)*	**2.750(.296)**	**-2.568(.272)**	**-1.577(.176)**
β_{1i} *(Pricerank)*	**-2.568(.272)**	**2.487(.256)**	**1.493(.162)**
β_{2i} *(Pricerank^2)*	**-1.577(.176)**	**1.493(.162)**	**1.242(.115)**

TABLE 6

Study 1: Estimated Variance and Covariance Matrix

	η_{ijk} *(Click)*	ε_{ijk} *(Conversion)*	ν_{ijt} *(Pricerank)*	$_{ijt}$ *(DisplayRank)*
η_{ijk} *(Click)*	**.752(.004)**	**.526(.006)**	**-.003(.001)**	**.016(.004)**
ε_{ijk} *(Conversion)*	**.526(.006)**	**1.331(.012)**	**-.007(.002)**	**.014(.004)**
φ_{ijt} *(Pricerank)*	**-.003(.001)**	**-.007(.002)**	**.036(.000)**	**.002(.001)**
μ_{ijt} *(DisplayRank)*	**.016(.004)**	**.014(.004)**	**.002(.001)**	**.079(.000)**

FIGURE 1
The Effects of Price Ranks



1.5.6 Post Hoc Analysis: Economic Values of Price Ranks

I derive implications for the economic performance of each price rank by applying the estimated model. Specifically, I calculate, counterfactually, the number of clicks, number of conversions, and profitability of each price rank across different types of keywords. I divide the keywords into four categories: niche general, niche specific, popular general, and popular specific, such that niche or popular reflects the level of keyword popularity, and general or specific indicates the level of keyword specificity.

First, the first column of Table 7 illustrates the number of clicks received by the advertisements per day, given the price ranks. The results suggest that optimal price rank for gathering clicks are extreme prices, either low or high, for popular general keywords, popular specific keywords and niche general keywords; while consumers have a neutral preference toward products of all price ranks when they search for niche specific keywords. For niche specific keywords, the intermediately priced alternative receives the most clicks, though the gap is trivial.

Second, optimal price rank for conversions are high or low ones. Second column of Table 7 illustrates conversions received by advertisements per day across price ranks. The lowest priced alternative receives the most conversions for popular general keywords and popular specific keywords. While the highest priced alternative receives the most conversions for niche general keywords and niche specific keywords, although the differences are smaller.

To investigate the profitability of each price rank, I used profitable Cost-per-Click (*Profitable CPC*). *Profitable CPC* measures the highest Cost-per-Click that the advertiser can pay if its profit from each conversion is $1

($Profitable\ CPC = \$1 \times \frac{Number\ of\ conversions}{Number\ of\ clicks}$). A higher *Profitable CPC* indicates the better profitability of the advertisement. Column 3 of Table 5 shows that intermediate priced alternatives offer the highest *Profitable CPC* for niche general keywords, popular general, and popular specific keywords. For niche specific keywords alone, the optimal price rank is the highest priced alternative.

Overall, these analyses show that in order to generate consumer interests reflected in clicks and total transactions reflected in conversions, being high and/or low-price rank helps, while being intermediate price rank generates the highest dollar return of investment. These patterns are particularly strong for general and/or popular keywords.

TABLE 7
Study 1: Post-Hoc Analysis

Price rank	(1) Clicks	(2) Conversions	(3) Profitable CPC
	Niche general keywords		
Low	189.075	2.726	\$0.014
Median	146.980	2.523	\$0.017
High	204.689	3.057	\$0.015
	Niche specific keywords		
Low	160.462	2.698	\$0.017
Median	165.364	2.791	\$0.017
High	158.009	2.880	\$0.018
	Popular general keywords		
Low	684.669	8.594	\$0.013
Median	413.747	6.671	\$0.016
High	696.251	7.638	\$0.011
	Popular specific keywords		
Low	442.681	6.482	\$0.015
Median	355.388	5.635	\$0.016
High	409.365	5.486	\$0.013

Notes. Profitable CPC represents the highest Cost-per-Click the advertiser should pay if the profit per conversion is \$1.

1.5.7 Robustness Checks

To check the robustness of our estimation results, I conducted additional tests and the results are reported in Table 8.

Model specifications. I use fixed effects for keywords, sellers, and time instead of the current model specification. I find no significant differences in the estimation results.

Alternative predictors. A potential concern about the price rank measure is that the distances across the prices of the different products are not evident. Therefore, I divide the price range in the display list into five intervals and use the price interval as an alternative measure. In addition to price interval, I consider the relative price of the advertised products within the keyword search results as a predictor. The relative price of the product i within the keyword j's search is the standardized (adjusted by mean and variance) product price. The results are consistent with our main estimation results, and I keep the current predictor for better model fit.

Sponsored advertisements in all pages. For our main analysis, the sample consists only of advertisements on the first display pages, to rule out first-page biases (Agarwal et al. 2011) and incomparability issues. To determine if advertisements on later pages also are affected by price information, I run the proposed model with a sample containing all observations. The estimated results are consistent.

Latent instrumental variable. Another potential concern is the endogenous nature of the decision variables. Rutz et al. (2012) suggest latent instrumental variables might address potential endogeneity issues, so to verify the validity of our model identification, I adopt this approach (Ebbes et al. 2005) and reestimate the model. Testing for two–five latent categories, I determine that the model with two latent categories provides the best fit. The results are consistent with the main model.

TABLE 8

Study 1: Robustness Checks

	Panel A: Price Interval			**Panel B: Relative Price**	
Dependent Variable	**Click-through Rate**	**Conversion Rate**		**Click-through Rate**	**Conversion Rate**
Interval	**-.552(.095)**	**.341(.147)**	Relative Price	**-.055(.014)**	**.077(.028)**
Interval^2	**.471(.069)**	**-.325(.102)**	Relative Price^2	**.067(.004)**	**-.084(.028)**
Interval × Specificity	**.433(.078)**	**-.517(.098)**	Relative Price × Specificity	**.043(.005)**	-.032(.017)
Interval^2 × Specificity	**-.444(.062)**	**.443(.076)**	Relative Price^2 × Specificity	**-.043(.004)**	**.028(.009)**
Interval × Popularity	**-.390(.069)**	**.299(.092)**	Relative Price × Popularity	**-.024(.006)**	**.030(.015)**
Interval^2 × Popularity	**.351(.057)**	**-.303(.080)**	Relative Price^2 × Popularity	**.036(.004)**	-.027(.016)
DIC	2152363.921		DIC	1267104.717	

	Panel C: Sample with All Advertisements			**Panel D: Latent Instrumental Variable**	
Dependent Variable	**Click-through Rate**	**Conversion Rate**		**Click-through Rate**	**Conversion Rate**
Price Rank	**-1.379(.188)**	**1.064(.263)**	Price Rank	**-1.355(.079)**	**1.219(.207)**
Price Rank^2	**1.258(.175)**	**-.941(.188)**	Price Rank^2	**1.286(.067)**	**-1.184(.144)**
Price Rank × Specificity	**.659(.074)**	**-.901(.185)**	Price Rank × Specificity	**.953(.044)**	**-.819(.116)**
Price Rank^2 × Specificity	**-.669(.068)**	**.829(.172)**	Price Rank^2 × Specificity	**-.896(.044)**	**.767(.108)**
Price Rank × Popularity	**-.500(.079)**	**.370(.122)**	Price Rank × Popularity	**-.705(.064)**	**.450(.115)**
Price Rank^2 × Popularity	**.470(.072)**	**-.439(.111)**	Price Rank^2 × Popularity	**.593(.063)**	**-.503(.114)**
DIC	1578069.181		DIC	415976.997	

Note: 1. Specificity and Popularity are mean-centered; 2. Posterior means and posterior standard deviations (in parentheses) are reported, and estimates that are significant at 95% are bolded.

1.5.8 Summary and Discussion

I reveal asymmetric effects of price rank on click-through and conversion rates, such that consumers generally prefer extremely priced options for clicks, yet this extreme preference diminishes among consumers searching with more specific keywords and increases among those searching with more popular keywords. In contrast, the clicks of moderately priced options are more likely to convert into purchases, and the avoidance of extremes is especially notable for more popular keywords and weaker for more specific keywords. The post hoc analysis suggests that the price rank that optimizes advertising performance depends on the type of keywords searched; counterfactual analyses suggest that extreme prices provide the most clicks and conversions, but intermediate prices maximize the profitability of the sponsored advertisements, at least for niche general, popular general, and popular specific keywords.

1.6 Study Two: Evidences from an Experiment

The objectives of Study 2 are twofold. First, I seek to add confidence to the findings of Study 1 by addressing potential endogeneity concerns due to selection bias and omitted variables. Second, I use simulated clickstream data to investigate the underlying mechanisms.

1.6.1 Method

Participants and design. Three hundred ten respondents gathered from Amazon's Mechanical Turk (34.00 years on average, 34.84% women) were recruited and randomly assigned to either *search only* or *search and buy* experimental condition. In the *search only* condition, participants had to evaluate seven search advertisements and predict the price of a new product based on the information contained in those advertisements. In the *search and buy* condition, participants evaluated seven search advertisements and chose the product they would purchase. To guarantee their involvement, the participants read that their monetary rewards would be based on their task performance. The main dependent measures were click and conversion (purchase) behaviors (see Appendix D for details).

Procedure. The experimental webpage featured seven search advertisements that stemmed from a search for the keyword "cat stand." All seven advertisements were created to mimic actual search advertisements listed on Amazon.com. The seven advertised products featured prices ranging from $25.80 to $94.98, and the advertisements also provided basic information, such as a picture, review volume, and review ratings (see Appendix E for details). To avoid position effects, the sequence of the seven advertisements changed randomly for each participant. The review volume and ratings also were the same across the seven advertisements, to rule out potential review influences.

Participants could click any of the seven advertisements, which led them to a detailed product page. From this page, the participants in both conditions could choose to "return to the main page" or "buy this product" (only in buy condition). Clicking the "return" link put participants back on the original webpage displaying the seven search advertisements. There is no number limit of advertisements they can click. Clicking the "buy this product" button indicated a decision (completed search), so participants who clicked it left the website. Finally, participants completed questions measuring covariances and demographic questions.

1.6.2 Measurement and Model

Measures. The dependent variables are participants' clickstreams and purchase decisions. For participants in the search-and-buy condition, the clicks are captured by the subjects' clicking behaviors prior their final purchase, where the conversions are captured by the subjects' last click. For participants in the search-only condition, all the clicking behaviors are counted as clicks. For participants in the search-and-buy condition, the clicks are captured by the subjects' clicking behaviors prior their final purchase, where the conversions are captured by the subjects' last click. For participants in the search-only condition, all the clicking behaviors are counted as clicks.

To calculate the search phase, I relied on the sequence of clicks in the clickstream $Stream_{ij}$, or click sequence j divided by consumer i's total number of clicks N_i ($Stream_{ij} = \frac{j-1}{N_i - 1}$, $j = 1, \ldots, N_i$), ranging from 0 to 1. Therefore, $Stream_{ij} = 0$ if consumer i's jth click is the first one, and $Stream_{ij} = 1$ if it is the last click prior conversion, which marks a purchase decision in the buy condition and the end of the search in the search condition.

Model. I use a consumer utility function and multinomial choice model to estimate the clicks and conversions. Among the seven alternatives, participants choose the one with the highest utility, given their search orientations, search phase, and other covariances such as $Design_{ik}$ indicates consumer i's interest in the design of product k, measured as the designs of the advertised products as "not interested/extremely interested", and $PreClick_{ijk}$ indicates whether product k has been clicked by consumer i prior to the jth click. Among N_i clicks by consumer i, the probability that the jth click is on a product with price rank *k* (P_{ijk}), according to the latent consumer utility function U_{ijk}, is:

(17) $P_{ijk} = \frac{\exp(U_{ijk})}{\sum_q \exp(U_{ijq})}$, where q=1, 2,…., 7, and

(18) $U_{ijk} = \rho_{0k} + \rho_{1k} Stream_{ij} + \rho_2 Design_{ik} + \rho_3 PreClick_{ijk}$,

The conversion model with a similar framework is specified as

(19) $U_{ik} = \varphi_{0k} + \varphi_1 Design_{ik} + \varphi_2 PreClick_{ik}$,

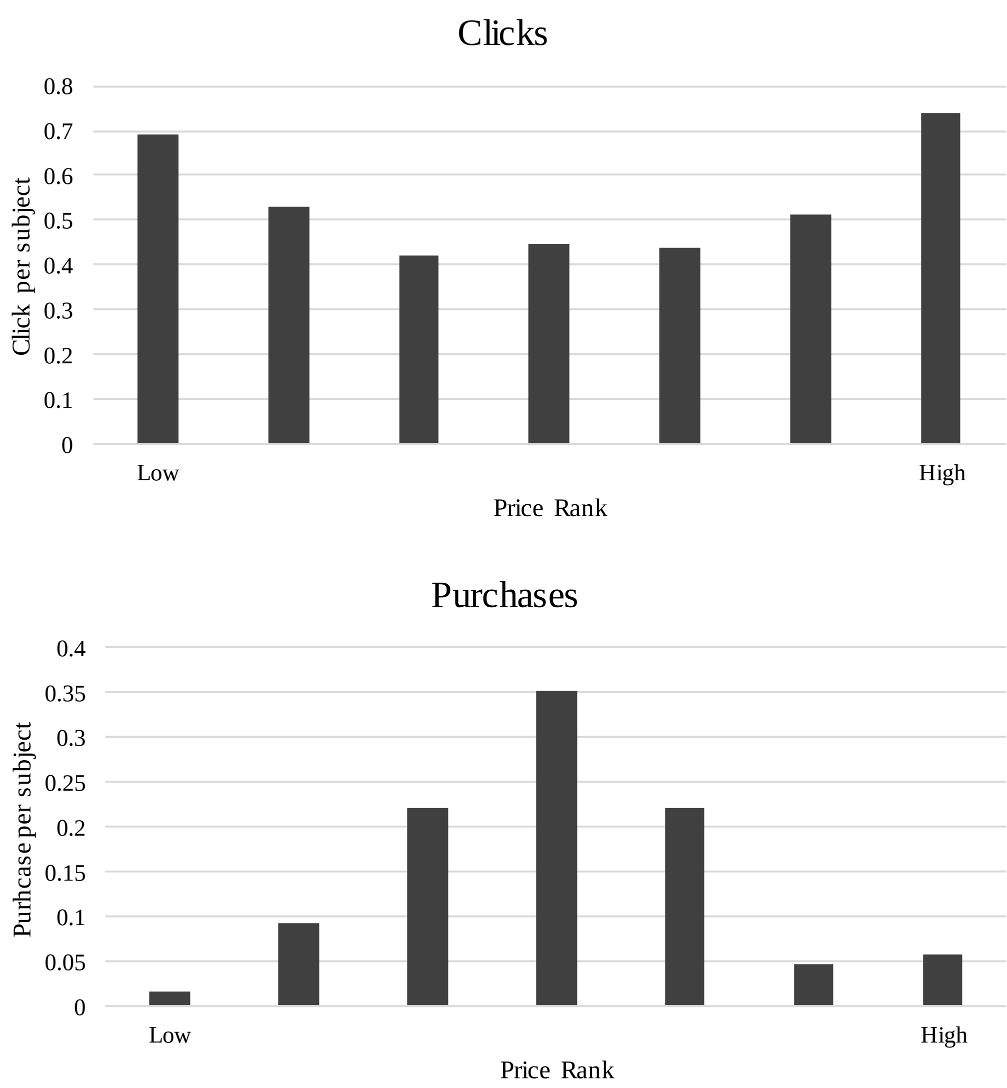
where $Stream_{ij}$ represents the phases of *j*th click along consumer *i*'s clickstream ranging from 0 to 1. Then ρ_{0k}, ρ_{1k} and φ_{0k} refer to the parameters specific to product *k*, such that ρ_{0k} captures the variations of probability that product *k* appears in the first click, $\rho_{0k} + \rho_{1k}$ captures the variations of probability that product *k* appears in the last click, and φ_{0k} captures the variations of probability that product *k* was finally purchased, all relative to the baseline.

1.6.3 Results

Figure 2 summarizes the average clicks and conversions per participants among the alternatives across price ranks. The multinomial choice model, estimated with maximum likelihood, produces the estimation results in Table 9, for which the second cheapest product (rank 2) serves as the reference. Extremely priced alternatives are more likely to be clicked at the beginning of the search process. Among participants in the search-and-buy condition (column 2, Table 9), products with extreme prices (ρ_{01} = 1.068, $p < .01$; ρ_{07} = 1.061, $p < .01$) receive more clicks than products with intermediate prices (ρ_{03} = -.740, $p < .05$; ρ_{04} = -1.635, $p < .01$; ρ_{05} = -1.117, $p < .01$). Similarly, participants in the search-only condition (column 4, Table 9) tend to click more on the extremes (ρ_{01} = 1.007,

$p < .01$; $\rho_{07} = .912$, $p < .01$) rather than moderate alternatives ($\rho_{03} = -.885$, $p < .10$; $\rho_{04} = -.848$, $p < .10$; $\rho_{05} = -.414$, $p > .10$).

FIGURE 2
Summary of Clicks and Conversions



Notes. The upper panel displays the average clicks per subject for all participants, and the lower panel displays the average purchases per subject for participants in the search-and-buy and buy-only conditions.

In contrast, participants' preferences toward products with extreme prices decrease when they approach the end of their clickstreams, such that *Stream* positively affects the click probability of moderately priced products for participants in search-and-buy (ρ_{14}=

1.540, $p < .05$; $\rho_{15} = 1.558$, $p < .01$) but not search-only condition ($\rho_{13} = .339$, $p > .10$; $\rho_{14} = .115$, $p > .10$; $\rho_{15} = -.147$, $p > .10$) conditions. In addition, *Stream* negatively affects the click probability for extremely priced products in both groups (search-and-buy $\rho_{11} = -.826$, $p < .10$; $\rho_{17} = -.980$, $p < .05$; search-only $\rho_{11} = -.925$, $p < .10$; $\rho_{17} = -.834$, $p < .10$).

The estimated results for conversion model (column 5, Table 9) suggests that participants prefer intermediately priced alternatives ($\varphi_{03} = .946$, $p < .01$; $\varphi_{04} = 1.260$, $p < .01$; $\varphi_{05} = .858$, $p < .01$) over extremely priced ones ($\varphi_{01} = -1.195$, $p < .05$; $\varphi_{06} = -.555$, $p > .10$; $\varphi_{07} = -.881$, $p < .05$).

Panel A and B of Figure 3 depict the dynamics in the click model. At the beginning of the clickstream, consumers concentrate on the extremes. As they progress, participants in the search-and-buy condition (Panel A) gradually shift their attention away from the extremes and they become more neutral at the end of the search phases. In contrast, participants in the search-only condition (Panel B) hold consistent preference toward products with extreme prices, although their extreme preferences weaken at the end of the search phases. Panel C of Figure 3 illustrate the estimated results for conversion model. For participants they show a strong preference toward products with intermediate price.

TABLE 9

Study 2: Estimated Results for Click-Throughs and Converions

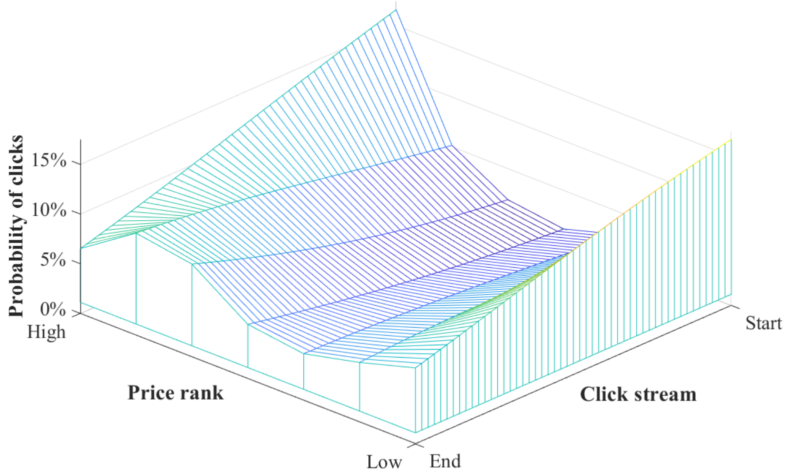
	Clicks				**Conversions**
	Search-and-buy		Search-only		
	(1) Main	(2) Full	(3) Main	(4) Full	(5)
Rank1 (ρ_{01})	.713(.167)***	1.068(.257)***	.567(.183)***	1.007(.304)***	-1.195(.509)**
Rank3 (ρ_{02})	-.425(.185)***	-.740(.351)**	-.666(.210)***	-.885(.436)*	.946(.278)***
Rank4 (ρ_{04})	-.564(.190)***	-1.635(.438)***	-.775(.216)***	-.848(.437)*	1.260(.269)***
Rank5 (ρ_{05})	-.202(.176)	-1.117(.369)***	-.505(.203)**	-.414(.388)	.858(.282)***
Rank6 (ρ_{06})	.196(.169)	-.109(.299)	.178(.185)	.390(.327)	-.555(.396)
Rank7 (ρ_{07})	.666(.166)***	1.061(.256)***	.517(.180)***	.912(.304)***	-.881(.447)**
Stream (ρ_{11})		-.826(.451)*		-.925(.475)*	
Stream (ρ_{13})		.494(.535)		.339(.604)	
Stream (ρ_{14})		1.540(.609)**		.115(.610)	
Stream (ρ_{15})		1.558(.532)***		-.147(.566)	
Stream (ρ_{16})		.644(.469)		-.395(.498)	
Stream (ρ_{17})		-.980(.458)**		-.834(.482)*	
Design (ρ_2)	.000(.027)	-.002(.028)	-.005(.031)	-.009(.031)	-.023(.045)
PreClick (ρ_3)	-1.837(.161)	-1.719(.161)***	-1.715(.180)***	-1.589(.181)***	-.596(.234)
R^2	.082	.114	.082	.079	.011
DIC	-922.829	-860.592	-713.183	-708.472	-315.391
Sample size	132		103		132

Notes. Rank 2 is used as baseline. Subjects of buy condition with at least 4 clicks are categorized in the search and buy group; Stage=0 for the first click; stage=1 for the last click (equals purchase for the buy task)

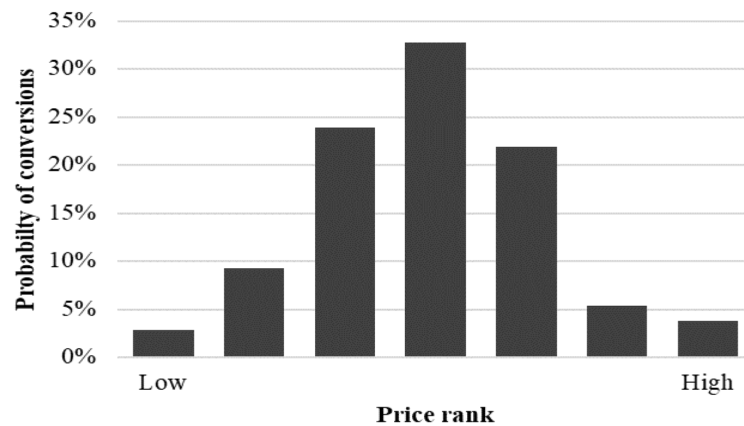
* p< .10, **p<.05, ***p<.01

FIGURE 3
Study 2: Estimated Results of Consumer Choices

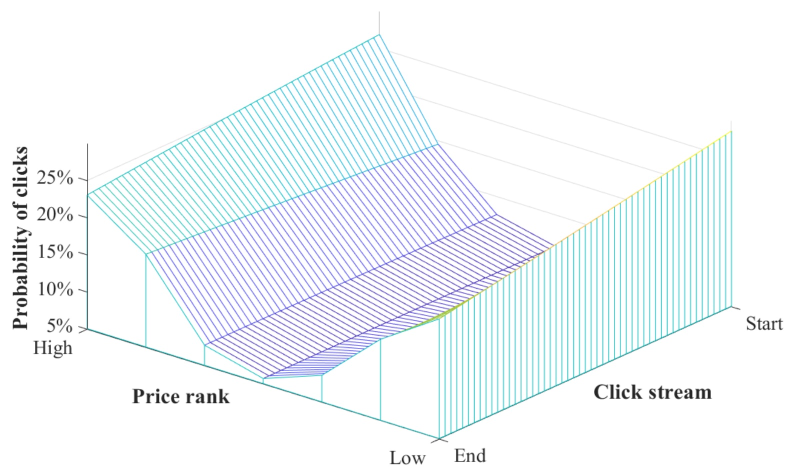
Panel A: Decision funnel for participants in search-and-buy condition



Panel C: Estimated results for conversions



Panel B: Decision funnel for participants in search-only condition



1.6.4 Summary and Discussion

The results of Study 2 add confidence to the empirical findings from Study 1, by verifying the mechanisms underlying within-consumer variations of click behaviors across different consumer groups. In particular, the results show that for *search-only* consumers, in early-stage search, they tend to click extremely priced options for developing anchors, and such pattern persists but weakens in late-stage search. This is consistent with our premise that anchoring is particularly relevant in early stage of the search process when consumers do not have enough information.

For *search and buy* consumers, when consumer preferences are ambiguous in early stage of the information search, preferences evolve through an anchoring-and-adjustment process (Carpenter and Nakamoto 1989; Hoch and Deighton 1989). In particular, early-stage consumers evaluate extremely priced alternatives to use as anchors. With this information gained from clicking on the extremes, consumers move toward the decision end of the purchase funnel, where they seek to evaluate a few plausible alternatives and make decisions. To do so, they find compromise options and limit their consideration set to a few moderately priced alternatives. Thus, as consumers move from the opening to the end of the purchase funnel, their focus shifts from extremely priced to moderately priced alternatives. The variations across decision phases cause consumers to display different preferences in terms of clicks and conversions.

1.7 General Discussion

Search advertising is a massive source of revenue for search engines and a vast advertising platform for online sellers. I consider how the advertised product price might determine the ways that consumers assess alternative options. Although advertising positions alone are critical for drawing consumers' attention, I also show that firms must set the prices of their products strategically, then select appropriate sponsored keywords according to their strategic goals. The price rank has a U-shaped effect on click-through rates and an inverted U-shaped effect on conversion rates. Furthermore, keyword specificity weakens the effect of price ranks, whereas keyword popularity enhances their effects, on both click-through rates and conversion rates. The analysis of clickstream data in Study 2 confirms that the click and conversion patterns from Study 1.

1.7.1 Theoretical Implications

To broaden extant understanding of search advertising, I introduce product price as a strong determinant of the effectiveness of sponsored keyword advertisements. In particular, I shed new light on the unique determinants of clicks and conversions (Agarwal et al. 2011; Ghose and Yang 2009; Rutz and Bucklin 2011). Clicks, as a means to search for generic information, tend to center on extremely priced options, particularly in the early stages of the purchase funnel. The extremely priced options, once clicked, serve as anchors for subsequent preferences and assessments of other alternatives. In contrast, conversion, as a form of deeper engagement, is more likely for moderately priced options that support feasible trade-off decisions in the late stages of purchase funnel.

These changes in consumer focus contribute to further variations. Over the course of a complete search–purchase process, consumers tend to click the extremes at first, then shift to intermediate values as they get close to a decision. Heterogeneity among consumers also contributes, such that search-oriented consumers might leave the purchase funnel after a few clicks on the extremes, because they have obtained the general information they needed. Purchase-oriented consumers, depending on their prior knowledge and needs, might enter the purchase funnel midway through and focus only on intermediate values, or else go through the purchase funnel from start to end but sequentially adjust their focus from extreme to intermediate values.

These findings contribute to pricing literature, which highlights the dynamics of two contrasting effects of pricing tactics, namely, the anchoring effect (Epley and Gilovich 2006; Krishna et al. 2006) and the compromise effect (Chernev 2004; Dhar et al. 2000; Kivetz et al. 2004b). I reconcile these two views by distinguishing their relevance for different stages along the purchase funnel. The anchoring effect of extreme priced options works better to explain clicks that seek exploratory information in early stages; the compromise effect offers a clearer explanation of conversions, which represent late stages closer to purchase decisions.

Keyword attributes, such as specificity and popularity, influence consumers' click and purchase decisions (Agarwal et al. 2011; Jerath et al. 2014; Narayanan and Kalyanam 2015); I extend prior insights to show that they also function as boundary conditions that shape the effect of price ranks on consumers' responses to sponsored keyword advertising. The attributes also signal different market segments. Specifically, the use of specific keywords implies that consumers have well-developed preferences and background knowledge; popular keywords instead imply a large segment, such as a mass market. The moderating effects of keyword specificity and popularity highlight how these two attributes can differentiate consumers' responses (i.e., clicks or conversions) to relative price information in sponsored advertisement lists. In turn, the need for anchors versus compromise differs across segments, as inferred from keyword attributes. Advertisements sponsoring more specific keywords are less likely to be affected by price comparisons, so the anchoring and compromise effects of the price rank diminish. In contrast, more popular keywords attract more competitors and more alternative options for a larger segment, with greater needs for both anchors and compromises. The empirical results highlight the distinct natures of these two moderators: Specific keywords indicate consumers who are more engaged and extreme-averse; popular keywords reflect competition in the choice set and increase consumers' need for market signals, such as those available from product prices.

1.7.2 Managerial Implications

Firms set budgets to sponsor a few keywords out of the millions available. Identifying the most effective set, given budget constraints, is challenging, especially considering the complicated nature of sponsored keyword advertising. Firms normally participate in keyword search advertising repeatedly and need to adjust their offers to improve their results. In interviews with sellers on online shopping websites, I find that they intentionally adjust their sponsored product prices (e.g., doorbuster price, premium price) to attract clicks or conversions. They closely track search advertising by their competitors and adjust their own strategies accordingly. In these efforts to improve their search advertising, sellers could integrate the results of our study to inform how they adjust prices of products presented in search results.

In particular, managers must acknowledge the nuanced effects of information displayed in sponsored advertisements, especially price information. I highlight discrepancies between clicks and conversions associated with price rank; more clicks driven by price rank do not necessarily lead to more conversions (i.e., sales). Instead, managers should develop differentiated strategies, depending on their objectives in terms of attracting either exploratory consumers and maximizing their exposures or consumers close to a purchase decision and maximizing advertising profitability. In the former case, managers should use an extreme price, so that the products achieve high or low positions in the price ranks. In the latter case though, managers should adopt a moderate pricing tactic to help consumers trade off between price and quality and identify products with the highest overall value.

Furthermore, managers should leverage keyword attributes as segmentation tools. By considering keyword specificity and popularity, they can strategically set the prices of their products, relative to those of competitors that also appear in the keyword search results. The results of our post hoc analysis across four combinations of keyword specificity and popularity (Table 5) offer specific suggestions: If firms target a consumer segment using popular and general keywords, they can increase the absolute number of clicks and conversions by gaining an extreme price position, especially at the low extreme. Alternatively, it is possible to improve the efficiency of search advertising, in terms of profitability, by adjusting the price to a moderate level. However, if firms target a consumer segment using niche and specific keywords, the price rank does not matter.

1.7.3 Limitations and Further Research

Although this study offers important insights on the role of price rank and the effects of its interaction with keyword attributes, some limitations also suggest research opportunities. First, I focus on price rank, yet sponsored keyword advertising contains diverse information, such as the seller's reputation, review comments, and temporary promotions. Both seller reputation and consumer comments are critical inputs that online consumers use in their purchase decisions (Chen and Xie 2008; Chevalier and Mayzlin 2006; Liu 2006). Research that incorporates these diverse aspects of online environments could deepen understanding of consumers' responses to sponsored keyword advertising.

Second, searches in online shopping websites also produce organic listings. Although I controlled for the effect of these organic listings by including their average price, further research might examine the influence of organic listings in more detail.

Third, further research should include more diverse keyword attributes, beyond specificity and popularity, to determine their segmentation potential, according to their ability to reflect consumers' knowledge, interests, or search goals. Investigating more diverse search keywords would be a promising path toward a greater understanding of consumers and their behaviors in online advertising environments.

ESSAY TWO: Dynamic Effects of Cross-Channel Price Integration: Evidences from a Quasi-Experiment

2.1 Abstract

Multi-channel sellers often face a decision of whether to coordinate product prices across channels. By leveraging a revised pricing policy implemented by an appliance retailer to its online and offline channels, the current research estimates the causal effects of price integration on the retailer's product sales as well as individual consumers' purchasing amount. This price variation event reveals varying effects on product sales across time, products, channels, and consumer segments. As an immediate consequence, price integration leads to a 14.70% decrease in sales of products without coordinated services across channels but a 14.68% increase in sales of products with coordinated services. The price integration effect is more positive in the long run, such that sales of products increase by 10.07% without coordinated services and 36.07% with coordinated services. Price integration is more likely to affect sales of products without coordinated services through online channels but products with coordinated services through offline channels. Finally, the consumer segmentation analysis suggests that the price integration is favorable to experience-sensitive consumers but is unfavorable to price-sensitive consumers. These findings provide unique insights on cross-channel pricing strategies and managerial implications for designing an effective strategy.

Keywords: cross-channel pricing, channel-specific pricing, price integration, perceived transaction value, service coordination, product sales, dynamic effects.

2.2 Introduction

Retailers often integrate channels to provide more consistent shopping experiences to consumers; by coordinating processes and technologies across all detached channels, it pursues "a consistent, yet unique and contextual brand experience across multiple customer-aware touchpoints" (Walker 2018). Retailers consider their cross-channel integration efforts a top priority (Staista 2017), though pricing strategies in these revised markets remain challenging (Grewal et al. 2010; Kireyev et al. 2017; Ratchford 2009; Wolk and Ebling 2010). Unlike a traditional, channel-specific pricing model—in which sellers price identical products differently across channels and focus on price competitiveness in each channel to meet the varying demands of consumers across channels (Liu et al. 2006; Ofek et al. 2011; Zettelmeyer 2000; Zhang 2009)—cross-channel price integration strategy purposefully makes the boundaries across channels more permeable. A channel-specific pricing strategy might perform well in multi-channel environments, which offer opportunities to exploit consumer surplus in each channel (Grewal et al. 1998; Khan and Jain 2005; Ratchford 2009; Robinson 1969). In contrast, a cross-channel price integration strategy implements consistent prices across channels to a uniform level, thereby offering integrity and a seamless shopping experience (Saghiri et al. 2017; Verhoef et al. 2015).

Such a price integration approach is getting popular that several retailers announced their uniform pricing strategy: Best Buy guarantees the same prices online and offline and offers QR-coded price tags so offline consumers can check the online prices (RetailGeek 2010); Zara guarantees that their online stores offer the full range of articles that the brand currently offers in its stores, with the same prices and the same commercial policy (Bailay 2017). On the contrary, Walmart experienced criticisms and online sales drop by intentionally disclosing the price discrepancies between online and offline stores (Anderson 2017; Hetu 2018). However, much less is known about the outcomes of this pricing strategy. In particular, this strategy, to some extent, contradicts price discrimination theory, which suggests charging prices that reflect consumers' willingness to pay, to maximize profits and exploit consumer surplus (Khan and Jain 2005; Robinson 1969). Charging channel-specific prices is a form of third-degree price discrimination that implies the firm is aware of differences in willingness to pay across but not within groups. Consistent prices across channels likely increase unexploited surplus, which means firms' profits are not maximized (Church and Ware 2000). This inconsistency between research and practice requires empirical evidence to resolve it.

First, a new price policy can have an immediate impact on sales, prompting both benefits and costs due to price changes in each channel, as well as confusion or inconvenience if consumers need to alter their shopping behaviors. In this sense, consumers need a "warm-up" period to become familiar with the new pricing strategy before they can fully evaluate and react to it (Venkatesh and Davis 2000). As they have opportunities to learn about the value of cross-channel price ingegration, the impact might vary over time. I therefore investigate the dynamic impact of cross-channel price integration. Second, price integration provides more consistent shopping experiences, which need to be combined with other relevant marketing activities to improve prouct value for consumers. In particular, coordinated service is one of the most important determinents for perceived value of omni-channel experiences (Huang et al. 2009; Lynch Jr and Ariely 2000). Accordingly, I investigate the presence of coordianted service as a boundary condition that determines the effects of cross-channel price integration on product sales. I pose two research questions:

1. What are the effects of a change from a channel-specific to a cross-channel integrated

pricing model on the retailer's sales performance over time?

2. How does the presence of a coordinated service in a product moderate the effect of the change of pricing models on the retailer's short- and long-term sales performance?

3. How the dynamic effects of cross-channel price integration vary across consumers?

I empirically investigate these research questions with a unique, quasi-experimental setting involving a leading household appliance retailer that shifted away from a channel-specific, mixed-pricing strategy to a uniform pricing strategy across channels.

With a coarsened exact matching (CEM) approach to address potential selection bias, I analyze 1,110,703 transactions involving 4,150 products over an 18-month period (December 2012–June 2014). These analyses suggest that price integration leads to a 14.70% immediate sales decrease for products without coordinated services but a 14.68% immediate sales increase for products with coordinated services. After a period (i.e., 6 months) of accommodation though, price integration improves sales for both types of products (without coordinated services, 10.07% future sales increase; with coordinated services, 36.07% future sales increase). Further, parametric and non-parametric (i.e., Generalized Synthetic Control methods) dynamic analyses suggest that all products, regardless of coordinated services, suffer from an immediate sales decreases, but the products with coordinated services recover from the immediate sales decreases much faster than the products without coordinated services. Finally, a consumer-level latent segment analysis investigates the dynamic effects of cross-channel price integration across consumers, that is, the changing shopping patterns of three consumer segments: the first segment favoring price integration from the beginning, the second segment negatively reacting to price integration, and the last segment holding a unfavorable attitude at first but turning favorable toward price integration over time.

With these findings, I make three main contributions. First, I reveal the dynamics of sales performance implications of cross-channel price integration. By considering price integration in a multi-channel retailing context composed of online and offline channels, this study offers novel insights about how consumers react to this strategy. Second, I empirically test and show the role of coordinated services in implementing cross-channel price integration. I maintain that coordinating services can enhance consumers' shopping experiences associated with price integration across channels and increase consumers' cost of searching and switching to other retailers. The results show coordinating services across online and offline channels improves product sales following price integration. Third, through the further analysis at the consumer level, this study enhances our understanding of characteristics of consumers exhibiting different purchasing behaviors to cross-channel price integration.

2.3 Theoretical Background

2.3.1 Perceived Transaction Value: Price vs. Experience

Consumers evaluate a transaction by comparing the perceived value of the product and the cost to obtain it (Zeithaml 1988). The perceived value a consumer receives from a product not only includes the value of the product, but also the value of shopping experience (Ghosh and MacLafferty 1987; Kerin et al. 1992). Multi-channel retailers usually implement either a channel-specific pricing strategy or a cross-channel price integration strategy. The two pricing strategies aim to increase retailers' competitiveness by either providing cost saving opportunities through flexible prices across channels or improving shopping experience through consistent prices across channels. In a channel-specific pricing strategy, sellers offer a reservation price for consumers in some channels and a lower price for consumers in other channels (Stahl 1989;

Varian 1980). By charging channel-specific prices, a retailer can compete with other retailers while maintaining profitability (Grewal et al. 2010; Huppertz et al. 1978; Khan and Jain 2005; Ratchford 2009). Reflecting consumers' willingness to pay and information asymmetry across channels, retailers have incentives to offer lower prices to attract consumers who are price sensitive and search more, but charge higher prices to exploit those who are less price sensitive and thus search less. This reflects a flexible Hi-Lo promotion oriented pricing strategy implemented across channels, which allows to differentiate prices depending on consumer characteristics in terms of price sensitivity (Hoch, Dreze, and Purk 1994). This pricing policy can also differentiate informed and uninformed consumers (Varian 1980). It has been highlighted that adopting a channel-specific pricing strategy tends to increase multi-channel retailers' overall profits (Besanko et al. 1998; Khan and Jain 2005; Montgomery 1997).

In contrast, a cross-channel price integration strategy aims to reduce price discrepancies across channels and establish a consistent shopping experience for consumers (Kauffman et al. 2009; Saghiri et al. 2017; Verhoef et al. 2015). In so doing, retailers sacrifice pricing flexibility; by charging uniform prices across channels, they lose margins from previously higher priced channels and sales from previously lower priced channels. Yet a cross-channel price integration strategy can increase retailers' competitiveness and consumers' transaction utility for two main reasons.

First, price integration reduces consumers' search effort, which should increase overall transaction value. When consumers encounter price discrepancies across channels, a natural response is to search for alternative options (Grewal et al. 1998; Lynch Jr and Ariely 2000). These searches impose extra, purchase-independent costs on consumers (Balasubramanian et al. 2005; Fassnacht and Unterhuber 2016) and intensify price competition among retailers (Lynch Jr and Ariely 2000). Integrated prices across channels provide a more consistent shopping experience, help mitigate consumers' concerns about suffering from price differences (Campbell 1999), and reduce incentives to search, either within or between retailers.

Second, consistent pricing across channels can evoke positive emotions to consumers, such as predictability, trustworthiness, and reliability (Bolton et al. 2003; Campbell 1999; Fassnacht and Unterhuber 2016; Xia et al. 2004). Integrating product prices across channels relieves consumers' concerns about experiencing price discrimination and enhances their trust in the retailers. Prior research has shown that changing prices can erode consumer confidence and make it difficult to communicate with consumers; for example, a consistent pricing policy such as EDLP has been noted as a way to maintain price consistency over time in a retail store (Ortmeyer, Quelch, and Salmon 1991). In a similar vein, cross-channel price integration can improve consumer confidence to the retailer by removing price variations among different channels of a retailer. As such, these two alternative pricing strategies in a multi-channel environment (i.e., channel-specific pricing and cross-channel price integration) have their own advantages.

2.3.2 Perceived Transaction Value: Consumer Preferences

Consumers perceive transaction value with various preferences. Zeithaml (1988) documents that consumers weigh "get" and "give" components of a product differently according to their preferences, whereby "get" components refer to benefits the consumers received from the transactions (e.g., quality, experiences, etc.) and "give" components refer to what consumers have to give up (e.g., price, search cost, etc.). Some consumers might consider "give" components as more important elements in evaluating transaction value, while others might consider "get" components as more salience in the value perception. For consumers with different preferences, cross-channel price integration can have different effects on their value perceptions. The strategic focuses (i.e., pricing flexibility and pricing consistency) of the two strategies cater to consumers with different preferences. Pricing flexibility via the channel-specific pricing strategy fits consumers preferring low prices and willing to search across channels; while the cross-channel price integration fits the consumers who prefer integrated channel and smooth channel switching experiences.

I postulate that implementing cross-channel price integration influences product sales as a result of the changing composition of consumers. Retailers implementing cross-channel price integration would lose the attractiveness toward price sensitive consumers but gradually gain attractiveness toward consumers who prefer a more integrated multi-channel shopping experience. Further, price integration is a part of a firm's marketing activities, which should be coordinated to maximize their impact on firm performance. I therefore propose that the effect of price integration can be magnified or reduced by complementary marketing activities. In particular, retailers often offer coordinated services across online and offline channels, such as allowing consumers searching the online store to arrange offline visit to get a consulting service at the nearest offline store, for products that may require additional information or customized service before consumers can make purchase decisions. For instance, when buying large house appliances such as washing machines and air conditioners, consumers would need to work with a specialty sales associate to customize details of product offerings and to see where and how it can be installed in their homes. I examine coordinated service as a factor that moderates the effect of price integration on the retailer's sales performance.

2.4 Hypotheses

2.4.1 Dynamic Effects of Price Integration

Changing prices has a straightforward, immediate impact on product sales, especially on the price sensitive consumers. Frist, price sensitive consumers will respond promptly to the change of pricing policy, becoming dominant in a short term. An integrated pricing strategy proposes a retailer to charge price somewhere between the highest and lowest channel-specific prices to maintain a certain margin rate (Kauffman et al. 2009), and the retailer cannot flexibly accommodate the varying price preferences of consumers in each channel. In particular, online retailers tend to generate intensive price competition, and retailers offering consistent prices across channels will have difficulty to match the competitive online price, due to the higher operational costs of their offline stores, compared with online stores. Thus, price sensitive consumers are likely to purchase less or leave the multi-channel retailer offering integrated prices.

Second, in a short term, it is difficult for consumers to realize the benefits of the new policy and adapt their behaviors. Consistent price is a key element for implementing channel integration in retailing, yet consumers may resist to a changed price policy, especially if the change forces them to alter their shopping behavior (Hoeffler 2003). Habits associated with an existing practice or behavior remain important barriers that create consumers' resistance to change (Ram and Sheth 1989), and the resistance to the new pricing strategy in turn might hurt the immediate sales performance of the retailer. As such, consistent price across channels would not be optimal in a short term. I therefore predict that,

H_1: Changing from channel-specific to integrated pricing has a negative effect on short-term product sales than does maintaining channel-specific pricing.

A consistent pricing strategy may become more beneficial in a delayed fashion. First, through a progressive process, the existing customers have opportunities to assess the benefits of the new pricing policy and adapt their purchasing behaviors. In contrast to the direct numeric implications brought by the price change, the benefits of consistent pricing are relevant to improving service quality and shopping experiences, which are less direct and more subjective (Bolton and Drew 1991; Mitra and Golder 2006). For the acceptance of new practices, perceived usefulness increases with consumers' familiarity (Davis et al. 1989; Venkatesh and Davis 2000). The market requires time to learn about the value of consistent shopping experiences associated with integrated prices across channels. Consumers also may need to verify the price integration, develop trust toward the retailer, and experience shopping under the new pricing policy. Over time, they gain more opportunities to realize the benefits of pricing consistency across channels. However, the need to engage in these learning activities delays their access to the benefits of the new price policy.

Second, the price integration policy can gain its attractiveness toward new consumers who prefer an integrated shopping experiences without the hurdle of price discrepancy across its online and offline channels. It takes time for the focal retailer to build its reputation of offering consistent prices. Reputation is an estimation of the consistency over time of an attribute (Herbig et al. 1994), the retailer would need progressive efforts to build and maintain the reputation of consistent pricing. Further, it also takes time to distribute the reputation of offering consistent pricing to the potential consumers. The potential consumers might be reached through information diffusion processes such as advertisements and word-of-mouth effects. The information diffusion is usually considered as a process with delays (Koenig 1985; Trusov et al. 2009). In the long run, there will be more chances to inform and convince potential customers regarding the benefits associated with consistent prices across channels. Therefore, price integration should have a positive effect on the long-term product sales. Formally,

H_2: Changing from channel-specific to integrated pricing has a more positive effect on long-term product sales than does maintaining channel-specific pricing.

2.4.2 Additional Value of Price Integration combined with Coordinated Service

In addition to the product itself, the services are considered as another crucial intrinsic cues for perceived quality (Zeithaml 1988), especially for products that require sales specialties. Coordinated service across channels, such as pre-purchase consulting for online consumers in offline stores, offered during the purchase of products can weaken the negative influence and enhance the positive influence of price integration. On the one hand, integrated prices provide a more consistent shopping experience when coordinated services are provided. While price-integrated products are vulnerable to price sensitive consumers, integrated prices combined with coordinated services can facilitate the process consumers realize the benefits of a more integrated shopping experiences across channels. Although coordinated services aim to encourage consumers to take full use of multi- channels (e.g., search online, face-to-face communication offline), the price discrepancy among channels motivate consumers to move toward the lower priced channel. Thus, offering consistent prices enable consumers to enjoy the coordinated product services without the concerns of being price discriminated. On the other hand, coordinated service can increase switching cost from one retailer to another (Porter 2008) and thus weaken the negative effects of losing pricing flexibility. The switching cost includes time and psychological efforts and the uncertainty to deal with a new sales associate (Dick and Basu 1994; Jones et al. 2002). This can discourage price-sensitive consumers from switching to other retailers. By adding experience elements to products, the coordinated service also makes product offerings less comparable with those of other retailers and relieves consumers' price sensitivities (Burnham et al. 2003; Lynch Jr and Ariely 2000). Thus, I predict the moderating effects of coordinated services for both short- and long-term sales effects of the change to integrated pricing.

H$_3$: The presence of service (a) reduces the negative effect of the change to integrated pricing on short-term product sales and (b) enhances the positive effect of the change to integrated pricing on long-term product sales.

2.5 Research Context

The research relies on a quasi-experiment, featuring a pricing policy change by a leading multi-channel home appliance and electronics retailer. Up until 2013, the retailer maintains more than 1600 brick-and-mortar stores across Asia and one online store and serves 167 million members. In 2013, the online store contributes 21% of the firm's total revenue, and the percentage gradually increase to around 40% in 2017. Across its brick-and-mortar and online stores, the retailer sells home appliances, computer, communication, consumer electronics, books, and general merchandise, spanning more than 3 million stock keeping units. Before 2013, the retailer has announced several omni-channel activities such as Buy-Online-Pickup-in-Store (BOPS) and coordinated services and sales guide. While the retailer allows products to adopt the channel-specific pricing strategy that it charged different prices between online and offline channels, and in mid-2013, it announced a new plan to integrate retail prices across channels. The focal retailer was among the first to implement the cross-channel price integration policy in mainland China. Through integrating product prices across channels, the retailer aims to enhance the omni-channel experiences by provide "a smoother shopping journey". Product manufacturers can choose to opt out from the new uniform pricing and stay with their existing pricing plan. Thus, the experimental group assignments are exogenous to the retailer. After integrating the product prices across channels, the participated products were guaranteed to have matched product prices, inventory and promotions across channels. After price integration, some 70% of the retailer's products were marked to represent the "same price" in both online and offline stores; the other 30% retained the existing pricing strategy. I assign products to the treatment group if their prices are integrated or the control group if not. For products affected by the new policy (i.e., treated group), the uniform prices, the values of which are usually between online and offline pre-policy prices, are set to maintain the pre-policy margin rate based on the sales predictions, and the uniform prices will be adjusted at the same pace if necessary. Products that participated in the program after the initial date (i.e., June 8) are excluded from our sample for analyses.

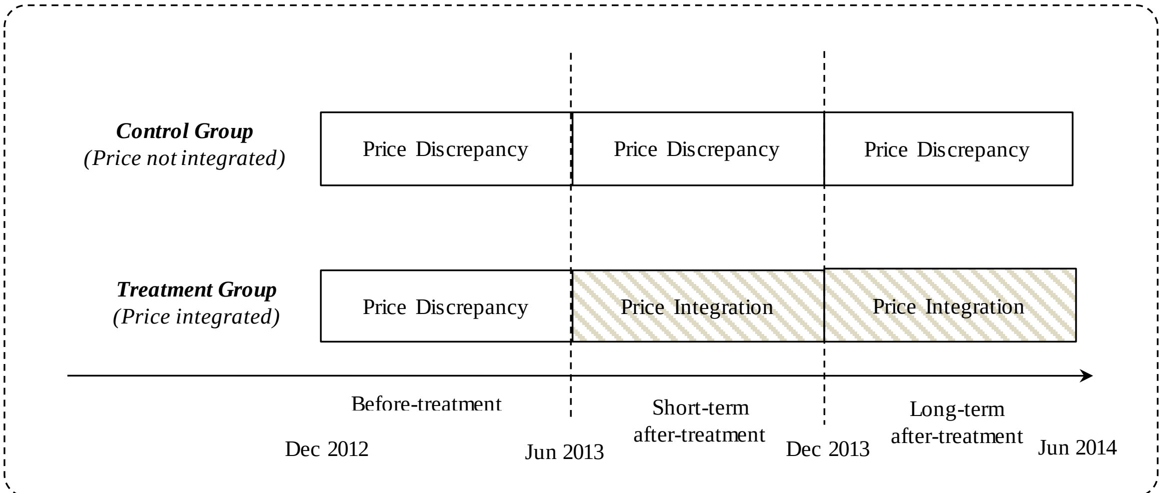
2.6 Product-Level Analysis: Effects of Cross-Channel Price Integration

2.6.1 Data

The data set comprises 1,110,703 transactions involving 4,150 products between December 2012 and July 2014, made by customers living in six cities in mainland China. The products are assigned to seven main categories: air conditioners (4.12%), refrigerators & washing machines (7.61%), kitchen & bath (6.10%), TV & home Theater (5.73%), digital appliance (10.75%), computers (19.81%), telecommunications (9.40%), and small appliances (36.48%). For each transaction, I gather the transaction time, online and offline retail prices, number of units sold, transaction channel, product information, and customer demographics. The 6-month period before the treatment (i.e., pricing policy change) provides the baseline condition, and the 12-

month period after the treatment provides the contrast between the sales of treated group and control group. Of the sampled products, 2,580 (62.17%) were affected by price integration and assigned to the treatment group. Figure 4 illustrates the empirical setting.

Figure 4
Quasi-Experiment Design



2.6.2 Measures

The unit of analysis is product. I aggregate the individual transactions into 15-day periods. For product i at period t, I calculate overall product sales (i.e., $Sales_{it}$). Then $Group_i$ is a dummy variable indicating whether product i is in the treatment group, and $Treat_t$ indicates if time t is after the treatment. The interaction term $Group_i \times Treat_t$ pinpoints the treatment condition. In addition, $Service_i$ indicates whether professional pre-purchase consulting (i.e., face-to-face expertise advice) can be arranged for online consumers in their nearby offline stores. Of the 4,150 products, 978 (23.57%) include coordinated services. The retailer indicated that services mainly apply to products such as air conditioners, refrigerators, washing machines, kitchen appliances, and bath appliances, whereas computers, cell phones, televisions, cameras, and telecommunication equipment rarely include service elements. Purchasing products associated with professional services requires consumers to work with the "specialty labor" from the retailer regarding any customized accommodation. A specialty sales associate will be assigned to assist the consumer throughout the purchase process. The specialty sales associates usually communicate with consumers face-to-face in the brick-and-mortar stores, and through an online chatting system in the online store. In contrast, purchasing a standard product without services is usually self-serviced, or with the help of a general sales associate.

I use two continuous variables to capture the difference of the product prices between online and offline channels prior to the pricing policy change, such that $Online\_High_i$ measures the price discrepancies if online price is higher than offline price, and $Offline\_High_i$ measures the price discrepancies if online price is higher than offline price. The patterns of price discrepancies hold for control group products before and after the treatment, so they provide an effective baseline for the between-group comparison.

Finally, I include several covariate variables in the analyses: $Popularity_i$ is the cumulative units of product i sold in 2012; $Competition_{it}$ refers to the number of alternative products within the sub-category; $Price_{it}$ equals the average transaction price of the product; and $Multi\_Ratio_{it}$ captures the percentage of sales contributed by consumers using both online and offline stores, determined according to their membership status. Table 10 summarizes the names, definitions, and measures of our key variables.

Table 10
Constructs, Definitions, and Operationalizations

Constructs	Definitions	Operationalizations
Product level analysis		
Group	Products which follow the consistent pricing after Jun 2013	Dummy variable $Group_i$ = 1, indicating product i follows the consistent pricing policy (Treatment Group)
Treat	The period after treatment	Dummy variable $Treat_t$ = 1, indicating time t is after the policy change (June 2013)
Sales	Product sales	Total number of units sold for product i in time t; $Sales_{it}$
Sales_Online	Product sales through online channel	Total number of units sold through online channel for product i in time t; $Sales\_Online_{it}$
Sales_Offline	Product sales through offline channel	Total number of units sold through offline channel for product i in time t; $Sales\_Offline_{it}$
Sales_Single	Product sales contributed by online-only customers	Total number of unit sold contributed by online-only customers for product i in time t; $Sales\_Single_{it}$
Sales_Omni	Product sales contributed by omni-channel customers	Total number of units sold contributed by omni-channel for product i in time t; $Sales\_Omni_{it}$
Online_high	Products having higher online retail price	Dummy variable $Online\_high_i$ = 1, indicating the number of days with higher online prices is larger for product i before treatment
Offline_high	Products having higher offline retail price	Dummy variable $Offline\_high_{it}$ = 1, indicating the number of days with higher offline prices is larger for product i before treatment
Service	Product associated with service	Dummy variable $Service_i$ = 1, indicating product i belongs to the product category need services
Price	Average Product Price	The average unit price of product i in time t; $Price_{it}$

Table 10 (Cont')

Popularity	The popularity of the product	Total number of product i sold in 2012; $Popularity_i$
Competition	The competition of the product faced	The number of alternative products sold within the sub-category where product i belongs; $Competition_i$
Multi_Ratio	The extent of omni-channel usage	The percentage of sales contributed by omni-channel customers over all sales
International	The origin of the firm	Dummy variable $International_i$ = 1, indicating product i belongs to a international firm
Public	The firm ownership status	Dummy variable $Public_i$ = 1, indicating product i belongs to an IPOed firm
Nproduct	The length of product line	The number of products belongs to the firm of product i
Consumer level analysis		
Sales	Consumer sales	Total number of units of product j (j=1 for price integrated product, j=0 otherwise) purchased by consumer i in time t; $Sales_{ijt}$
Age	Consumer age	The self-reported age of consumer i; Age_i
Membership	Consumer membership level	The consumer i's membership level at time t, ranging from 0 (lowest) to 4 (highest); $Membership_{it}$

2.6.3 Methods: Coarsened Exact Matching

In an ideal setting, with a randomized assignment, the difference between control and treatment groups would represent the treatment effect. In our research context, the manufacturers might self-select into the price integration choice. As with all observational studies, there is a possibility of selection bias, such that the treatment group might differ systematically from the corresponding control group. A common way to address this issue is to use matched sampling, which selects units from a large reservoir of potential controlled samples to produce a control group that is similar to a treated group with respect to the distribution of some observed covariates to reduce the possibility of a selection bias (Rosenbaum and Rubin 1985).

I use coarsened exact matching (hereafter CEM) to match treatment and control groups (Iacus et al. 2012). As a variation of exact matching, CEM relies on a coarsened range of covariates, which represents the joint distribution of all covariances, instead of matching on their exact values. Because CEM directly matches on the multivariate distributions of covariates, instead of on a single scale (e.g., propensity score), it does not rely on the functional form or discriminative ability of a first-stage propensity score model and integrates higher moments of the covariate distributions (Iacus et al. 2012).

I perform full-sample CEM with 27 variables, such as sales, revenues, and product characteristics (see Table 11 for details), and match the before-treatment aggregates of the control and treatment groups. I break the joint distribution of all 27 variables into 1184 strata and conduct within-strata matching. Through this matching process, I obtain a matched sample of 443,913 transactions with 2,547 products, as detailed in Table 11. To test the performance of CEM, I also performed the 1-to-1 Propensity Score Matching (hereafter PSM) with the same set of variables. The differences between the treatment and control groups suggest CEM outperforms PSM, thus I adopt the CEM to match experimental samples. The comparison between joint distributions of PSM-matched sample and CEM-matched samples also suggest CEM outperforms PSM. The CEM significantly improves the similarity between the joint distributions of the two groups, in contrast to PSM-matched sample and the before-matching sample (figures in Appendix F). I report the after-matching summary statistics in Table 12.

Table 11
Product-Level Analysis: Sample Matching Results

	Before matching			After matching					
				PSM			**CEM**		
	Treat	Control	Diff	Treat	Control	Diff	Treat	Control	Diff
Sales	60.11	159.84	-99.73	40.69	159.84	-119.15	46.22	69.01	22.79
Sales_online	32.58	63.71	-31.13	21.77	63.71	-41.94	25.78	37.54	11.76
Sales_offline	27.53	96.13	-68.60	18.92	96.13	-77.21	20.44	31.47	11.03
Sales_omni	43.07	100.90	-57.83	29.74	100.90	-71.16	32.67	49.33	16.66
Sales_online_omni	30.81	59.21	-28.39	20.99	59.21	-38.22	24.49	36.00	11.50
Sales_offline_omni	12.26	41.69	-29.43	8.75	41.69	-32.94	8.18	13.33	5.15
Sales_single	17.04	58.94	-41.91	10.95	58.94	-47.99	13.55	19.68	6.14
Sales_online_single	1.76	4.50	-2.74	0.78	4.50	-3.72	1.29	1.54	0.25
Sales_offline_single	15.27	54.44	-39.17	10.17	54.44	-44.27	12.26	18.14	5.88
Revenue	63363.81	348589.60	-285225.79	24398.79	348589.61	-324190.82	54317.90	78814.07	24496.17
Revenue_online	30246.54	106081.90	-75835.36	11226.18	106081.95	-94855.77	19286.90	25337.25	6050.35
Revenue_offline	33117.27	242507.70	-209390.43	13172.61	242507.66	-229335.05	35031.00	53476.82	18445.82
Online_ratio	0.55	0.42	0.13	0.57	0.42	0.15	0.54	0.54	0.00
Price	1112.94	2109.46	-996.52	829.57	2109.46	-1279.89	1030.12	1079.49	49.37
Service	0.15	0.37	-0.21	0.12	0.37	-0.25	0.14	0.14	0.00
Online_high	0.23	0.30	-0.07	0.17	0.30	-0.13	0.26	0.26	0.00
Offline_high	0.37	0.61	-0.24	0.18	0.61	-0.42	0.46	0.46	0.00
Popularity	590.59	560.35	30.24	724.58	560.35	164.24	368.53	376.15	7.62
Competition	1489.53	1565.19	-75.66	1532.64	1565.19	-32.55	1282.16	1298.64	16.48
Category1	0.03	0.07	-0.04	0.02	0.07	-0.05	0.02	0.02	0.00
Category2	0.03	0.15	-0.12	0.00	0.15	-0.15	0.04	0.04	0.00
Category3	0.05	0.07	-0.03	0.06	0.07	-0.02	0.02	0.02	0.00
Category4	0.13	0.08	0.05	0.18	0.08	0.11	0.08	0.08	0.00
Category5	0.26	0.09	0.17	0.40	0.09	0.31	0.18	0.18	0.00
Category6	0.10	0.08	0.02	0.12	0.08	0.04	0.05	0.05	0.00
Category7	0.35	0.38	-0.03	0.18	0.38	-0.20	0.55	0.55	0.00
Category8	0.05	0.07	-0.02	0.04	0.07	-0.04	0.06	0.06	0.00
Obs	2564	1586		1586	1586		1454	1093	

Table 12
Product-Level Analysis: Summary Statistics

Variables	Mean	Std.	Min	Max
Popularity	379.49	814.91	1.00	5458.25
Competition	1316.24	1789.32	7.00	9833.00
Service	0.21	0.41	0.00	1.00
Online_high	15.37	74.61	0.00	1413.74
Offline_high	58.41	154.70	0.00	1753.44
6-month period before treatment (per product)				
Sales	4.91	8.46	0.00	222.00
Online Sales	2.38	5.72	0.00	220.00
Offline Sales	2.53	5.63	0.00	135.00
Single Sales	1.64	3.72	0.00	100.00
Omni Sales	3.27	6.15	0.00	191.00
Price	1312.40	1660.64	1.00	10829.33
Omni_Ratio	0.46	0.42	0.00	1.00
6-month period after treatment (per product)				
Sales	4.46	10.81	0.00	520.00
Online Sales	2.87	7.99	0.00	353.00
Offline Sales	1.59	6.70	0.00	520.00
Single Sales	1.02	3.79	0.00	335.00
Omni Sales	3.44	8.29	0.00	404.00
Price	1228.90	1562.77	1.00	9490.00
Omni_Ratio	0.48	0.45	0.00	1.00
6-month period after 6 months of treatment (per product)				
Sales	5.16	12.32	0.00	594.00
Online Sales	2.85	8.18	0.00	448.00
Offline Sales	2.31	8.80	0.00	594.00
Single Sales	0.68	2.25	0.00	95.00
Omni Sales	4.48	11.02	0.00	554.00
Price	1225.77	1571.87	1.00	9490.00
Omni_Ratio	0.50	0.46	0.00	1.00

2.6.4 Model Specification

I anticipate three variations: between the before- and after-treatment periods, between treatment and control groups, and between products with coordinated services and products without coordinated services. I adopt a differences-in-differences-in-difference approach with a weighted random-effect negative binomial (RENB) framework (Hausman et al. 1984). The weighted RENB accounts for overdispersion and the correlation between before- and after-treatment periods. For product i in period t, I have

(20) $\mathrm{E}[Sale_{it} = y | \boldsymbol{X_{it}}, \mu_i, \varepsilon_{it}, w_i] = w_i \exp\{\boldsymbol{X_{it}\beta} + \mu_i + \varepsilon_{it}\}$,

where t = 0, 1, 2; μ_i is the random effect for product i that accounts for product-level heterogeneity; and w_i is the weights of product i generated through full-sample CEM. The term exp(μ_i) follows a gamma distribution with mean 1 and variance k, where k is the overdispersion parameter in the NB model. When there is no overdispersion (i.e., $k = 1$), RENB is equivalent to random-effect Poisson. Furthermore, ε_{it} is an idiosyncratic error term that captures all omitted variances specific to product i and time t. Thus,

(21) $\boldsymbol{X_{it}\beta} = \beta_0 + \beta_1 Time_t + \beta_2 Group_i + \beta_3 Service_i + \beta_4 Time_t \times Group_i + \beta_5 Time_t \times Service_i + \beta_6 Service_i \times Group_i + \beta_7 Time_t \times Group_i \times Service_i + \boldsymbol{\theta W_{it}} + \beta_8 Online\_High_{it} + \beta_9 Offline\_High_{it}$,

where $Sale_{it}$ is the number of units sold of product i during time t; $Time_t = 1$ if time t is in the after-policy period; $Group_i = 1$ if the product i belongs to the treatment group; $Service_i = 1$ if the product i requires additional services; the $Online\_High_i$ and $Offline\_High_i$ are two time-invariant variables describing the prices discrepancies between online and offline channels for product i before treatment; and $\boldsymbol{W_{it}}$ contains a vector of covariates for product i at time t, including the average price ($Price_{it}$), popularity of the product ($Popularity_i$), competition in the sub-category ($Competition_i$), percentage of transactions contributed by multi-channel customers ($Multi\_Ratio_{it}$), and seven dummy variables for the product categories.

The within-group comparison involves product sales before and after treatment; the between-group comparison pertains to the treatment and control groups and indicates that the effects are not due to time-variant unobserved factors. The difference-in-difference estimators β_4

and β_7 capture the treatment effects and the differences of treatment effects between products with services and without services, respectively.

2.6.5 Identification Assumption

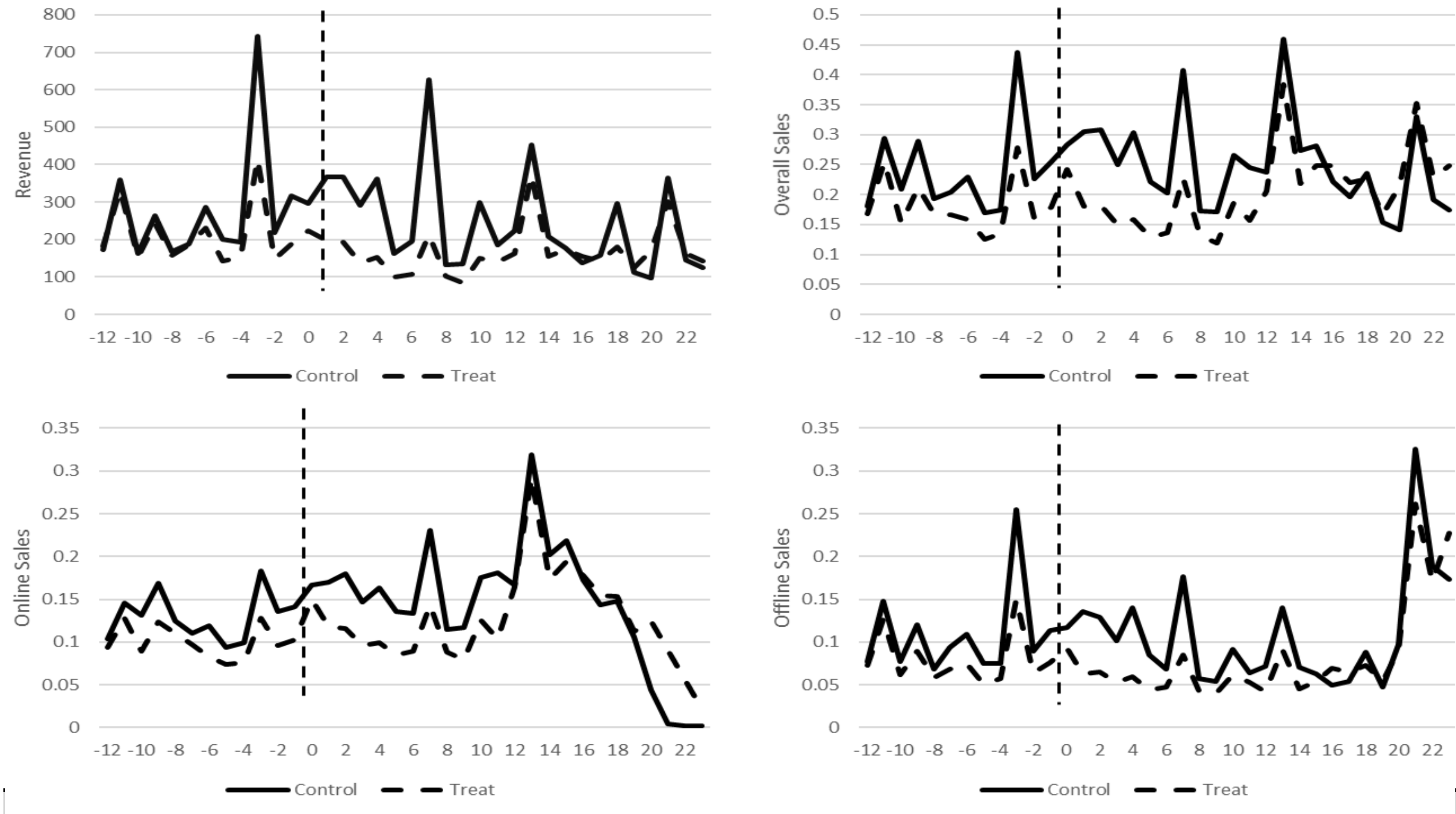
The identifying assumption of a differences-in-difference model is that the treatment group, had it not been treated, would have followed the same trajectory as the control group. The presence of differential time trends might cast doubt on the validity of this assumption. To verify that the matched samples follow the common trend assumption, I calculate group average in 15-day window overall sales for the control and treatment groups (Figure 5) and conduct a common trend analysis with the 15-day aggregates (Table 13). The two groups closely resemble each other in terms of sales, online sales, and offline sales in the 6-month period before the policy change (Period -11 to Period -1); significant trend differences appear only after the treatment (Period 0). This evidence suggests that our matching procedure reduces differences in trends, and the matched sample satisfies the common trend assumption in terms of our key dependent variables.

Table 13
Product-Level Analysis: Common Trend Analysis

Dependent	Sales	log(Revenue+1)	Sales_Online	Sales_Offline
Period -11	**.035(.065)**	**.072(.075)**	**-.048(.088)**	**.053(.111)**
Period -10	**-.073(.081)**	**-.019(.106)**	**-.099(.097)**	**-.078(.125)**
Period -9	**-.121(.083)**	**-.088(.082)**	**-.142(.135)**	**-.022(.109)**
Period -8	**-.141(.082)***	**-.115(.085)**	**-.113(.133)**	**-.135(.106)**
Period -7	**.024(.077)**	**.075(.083)**	**-.046(.121)**	**.039(.114)**
Period -6	**-.047(.081)**	**-.028(.081)**	**-.062(.106)**	**-.087(.112)**
Period -5	**-.044(.062)**	**-.078(.069)**	**-.193(.098)***	**-.167(.119)**
Period -4	**-.078(.064)**	**-.036(.069)**	**-.135(.112)**	**-.127(.118)**
Period -3	**.067(.063)**	**.079(.066)**	**-.014(.100)**	**.113(.122)**
Period -2	**-.038(.063)**	**-.071(.071)**	**-.075(.084)**	**-.136(.105)**
Period -1	**.009(.056)**	**.010(.063)**	**-.048(.083)**	**.025(.106)**
Period 1	.344(.080)***	.312(.085)***	.345(.100)***	.408(.133)***
Period 2	.125(.063)**	.058(.071)	.107(.093)	.120(.132)
Period 3	.136(.062)**	.021(.068)	.024(.102)	.234(.146)
Period 4	.206(.064)***	.147(.065)**	.117(.087)	.292(.121)**
Period 5	.034(.086)	-.020(.083)	.057(.087)	.023(.166)
Period 6	.037(.111)	.058(.091)	.058(.097)	-.018(.204)
Period 7	.203(.065)***	.121(.071)	.161(.083)*	.284(.133)**
Period 8	.044(.065)	.085(.074)	-.060(.089)	.235(.114)**
Period 9	.260(.063)***	.191(.070)**	.195(.088)**	.318(.154)**
Period 10	.240(.081)***	.215(.079)***	.159(.090)*	.259(.164)
Period 11	.200(.066)***	.157(.066)**	.085(.091)	.427(.116)***
Period 12	.183(.064)***	.191(.067)***	.050(.085)	.433(.118)***
Period 13	.457(.075)***	.492(.080)***	.424(.099)***	.380(.124)***
Period 14	.355(.068)***	.454(.078)***	.254(.086)***	.450(.121)***
Period 15	.333(.063)***	.367(.074)***	.243(.082)***	.441(.128)***
Period 16	.341(.067)***	.382(.071)***	.258(.097)**	.464(.129)***
Period 17	.510(.062)***	.477(.066)***	.381(.083)***	.876(.140)***
Period 18	.592(.082)***	.668(.114)***	.453(.100)***	.932(.145)***
Period 19	.471(.064)***	.517(.072)***	.391(.087)***	.667(.115)***
Period 20	.436(.065)***	.495(.072)***	.391(.090)***	.595(.129)***
Period 21	.752(.094)***	.839(.158)***	1.256(.109)***	.035(.143)
Period 22	.453(.065)***	.496(.084)***	3.067(.483)***	-.075(.116)
Period 23	.671(.079)***	.660(.088)***	3.402(.417)***	.246(.127)*
Period 24	.837(.101)***	.894(.128)***	2.996(.258)***	.619(.139)***

Notes: the common trend analysis is conducted based on 15-day aggregate, the last period before treatment (Period 0) is used as baseline group.
* p< 0.10, **p <0.05, ***p<0.01

Figure 5
Comparison between Treatment and Control Groups



2.6.6 Main Results

I investigate the influences of price integration on product sales by exploiting the variance before versus after the implementation of the cross-channel price integration. The estimated results are reported in column 1 and 2 of Table 14, pertaining to the coefficients of the interaction term between $Time_t$ and $Group_i$ and the three-way interaction, reveal a significant positive treatment effect ($\beta = .035$, $p < .05$) and a significant moderating effect of coordinated services ($\beta = .179$, $p < .01$). In other words, price integration increases sales of products without coordinated services by 3.56% and increases sales of products with coordinated services by 23.86%.

To understand the evolution of the impacts of price integration, I divided the post-treatment observations into two 6-month sub-samples, and reestimate the model with the baseline condition. The estimation results for the first post-treatment periods reflect the immediate impacts, while the second post-treatment periods reflect the impacts after a period of accommodation. The estimated results of the immediate impacts are reported in column 3 and 4 of Table 14, pertaining to the coefficients of the interaction term between $Time_t$ and $Group_i$ and the three-way interaction, reveal a significant negative treatment effect ($\beta = -.163$, $p < .01$) and a significant moderating effect of coordinated services ($\beta = .353$, $p < .01$). That is, price integration decreases sales of products without coordinated services by 15.04% and increases sales of products with coordinated services by 20.93% in the short term. That is, price integration has immediate negative impacts on sales of products without coordinated services but positive impacts on sales of products with coordinated services, in support of H1 and H3.

The estimated results using the second post-treatment sub-sample are reported in column 5 and 6 of Table 14, indicating that price integration has insignificant positive effects on sales of products, both without ($\beta = .204$, $p < .01$) and with coordinated services ($\beta = .077$, $p > .10$). I thus find that price integration increases the long-term sales of products with and without coordinated services by 22.63%. Thus, the price integration increases long-term performances of products without coordinated services and products with coordinated services, in support for H2 and H4.

Table 14
Product-Level Analysis: Estimation Results

	Overall sample		First 6-month period		Second 6-month period	
	(1)	(2)	(1)	(2)	(3)	(4)
Dependent	Sales	Sales	Sales	Sales	Sales	Sales
Constant	-1.545(.043)***	-1.563(.044)***	-1.361(.049)***	-1.364(.050)***	-1.474(.051)***	-1.491(.052)***
Treat	-.309(.031)***	-.259(.032)***	-.058(.030)*	-.011(.030)	-.394(.032)***	-.331(.032)***
Group	-.188(.037)***	-.197(.038)***	-.091(.043)**	-.102(.044)**	-.187(.045)***	-.197(.046)***
Service	-.233(.048)***	-.137(.055)**	-.225(.057)***	-.190(.063)***	-.288(.058)***	-.183(.065)***
Treat×Group	**.062(.015)*** **	**.035(.016)** **	**-.111(.017)*** **	**-.163(.018)*** **	**.218(.017)*** **	**.204(.019)*** **
Treat×Service		-.362(.030)***		-.340(.034)***		-.427(.037)***
Group×Service		.128(.043)***		.049(.047)		.147(.047)***
Treat×Group×Service		**.179(.041)*** **		**.353(.047)*** **		**.077(.049)**
Popularity	-.013(.017)	-.009(.017)	-.005(.020)	-.002(.020)	-.027(.020)	-.022(.020)
Competition	-.087(.017)***	-.088(.017)***	-.105(.020)***	-.108(.020)***	-.094(.020)***	-.092(.020)***
Price	-.063(.014)***	-.056(.014)***	-.031(.016)**	-.026(.016)	-.042(.016)**	-.032(.016)**
Omni-channel ratio	2.182(.011)***	2.185(.011)***	1.992(.012)***	1.993(.012)***	2.193(.013)***	2.201(.013)***
Online_High	.003(.003)	.004(.003)	.001(.003)	.001(.003)	.012(.003)***	.012(.003)***
Offline_High	.013(.002)***	.014(.002)***	.010(.003)***	.010(.003)	.019(.003)***	.020(.003)***
IMR	.010(.009)	.014(.010)	.013(.011)	.013(.011)	.003(.012)	.006(.012)
Likelihood	-188464.338	-126731.940	-126811.008	-126745.062	-127606.012	-127472.250
BIC	377545.588	377345.315	254084.892	253959.809	255674.945	255440.353
Obs	91692	91692	61128	61128	61128	61128

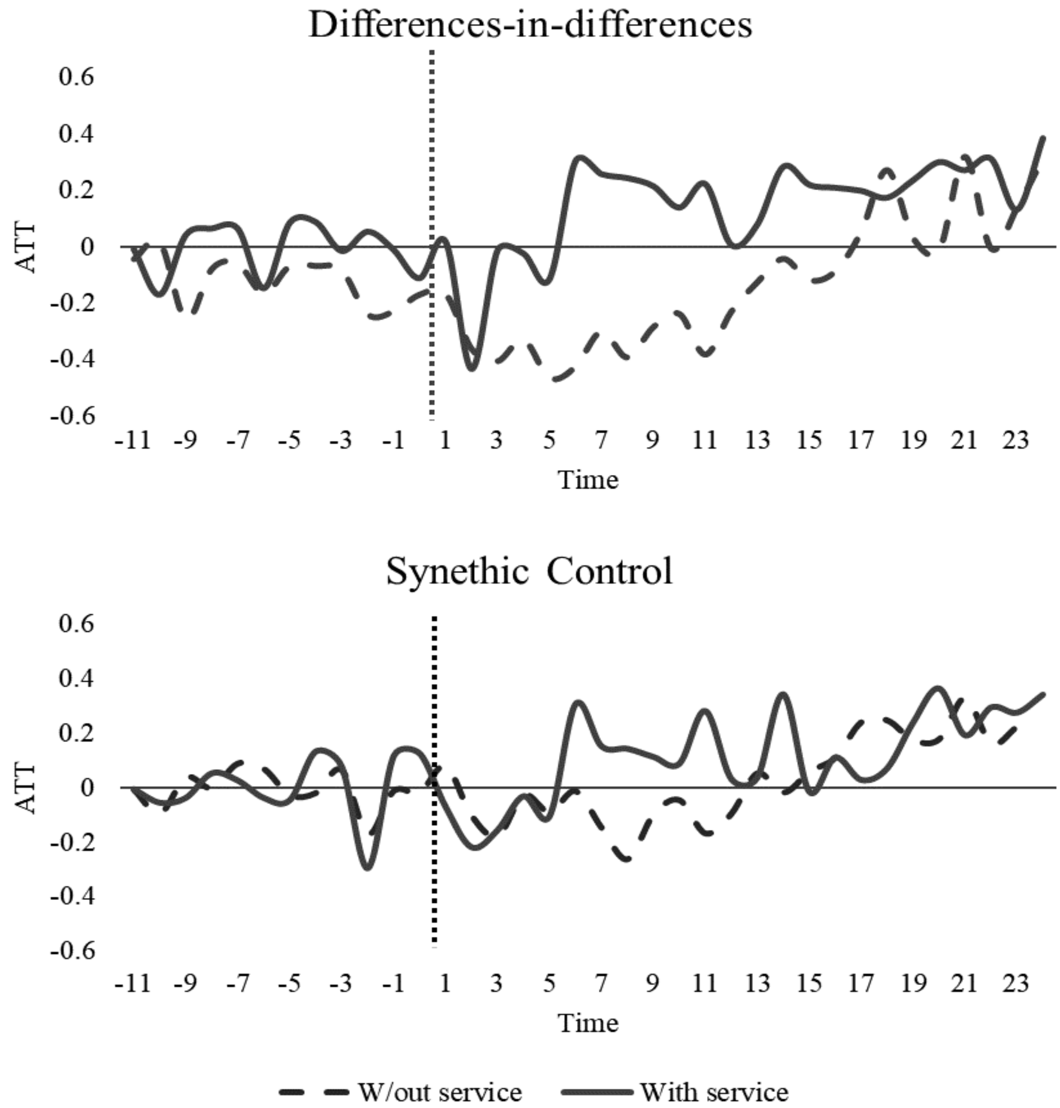
Notes. Parameters of interests are bold, and standard error in parentheses in table 5 and 6
*** p<0.01, ** p<0.05, * p<0.10

2.6.7 Dynamics of Price Integration

The main analysis suggests that the impacts of price integration on product sales evolve over time, especially for the product without coordinated services. To further understand the dynamics, I conduct an additional analysis investigating the dynamic impacts of price integration. I replace the variable $Time_t$ with 35 dummy variables indicating each 15-day periods and re-estimate the main results model.

The Panel A of Figure 6 plots the estimated coefficients of $Group_i$ over time. The plot suggests that both products with coordinated services and without coordinated services suffer from a short period of sales decrease after the policy change. However, products with coordinated services recover from the sales decrease a lot faster than the products without coordinated services. In other words, it is easier for consumers to learn the advantages of the consistent pricing when they are shopping products with coordinated services than products without coordinated services.

Figure 6
The Comparison of Dynamic Effects between DiD and SC



2.6.8 Robustness Checks

Fixed-effect negative binomial**.** I also try different model specifications. Instead of RENB, I re-run the analysis with a fixed-effect negative binomial, with fixed means and standard deviations. The results in Panel A of Table 15 again are consistent with our main results. I retain the REBN model because of its lower log-likelihoods.

K2K CEM matched sample. I also try different matching criterion. Instead of full sample CEM matching, I re-run the analysis with the k2k CEM matching. The k2k CEM matched sample include 818 products in control group and 818 products in the treated group. The results are reported in Panel B of Table 15, which is consistent with our main results.

Zero-inflated negative binomial. Another concern that might affect the validity of estimation is the zero's in our dependent variables. To verify that our estimation results are not sensitive to the zero's, I re-run the analysis with zero-inflated negative binomial model where I use all the covariances to predict the zero's in a logit framework. The results are reported in the Panel C of Table 15, which is consistent with our main results.

Negative binomial with clustering standard errors. In the main analysis, I adopt the random-effect negative binomial model to account for the potential autocorrelation among within-panel observations. Another alternative way to address the within-panel autocorrelation is using clustering Standard Errors (Bertrand et al. 2004). To test the validity of our results, I re-estimate the model using standard errors clustered at the brand-level. The results are reported in Panel D of Table 15, which is consistent with the results of random-effect model.

Table 15
Product-Level Analysis: Robustness Checks

	Panel A: Fixed-Effect Negative Binomial			**Panel B: K2K CEM Matched Sample**			**Panel C: Zero-Inflated Negative Binomial**		
Dependent	**Overall**	**First half**	**Second half**	**Overall**	**First half**	**Second half**	**Overall**	**First half**	**Second half**
	(1)	(2)	(3)	(4)	(5)	(6)	(4)	(5)	(6)
	Sales	Sales	Sales	Sales	Sales	Sales	Sales	Sales	Sales
Constant	.637(.029)***	-1.261(.055)***	-1.326(.058)***	.678(.037)***	-.982(.055)***	-1.140(.057)***	-.423(.035)***	-.478(.042)***	-.397(.044)***
Treat	-.466(.034)***	-.183(.032)***	-.523(.035)***	-.505(.041)***	-.220(.039)***	-.488(.041)***	-.153(.006)***	-.061(.008)***	-.222(.007)***
Group	-.195(.041)***	-.057(.048)	-.190(.051)***	-.235(.041)***	-.156(.047)***	-.205(.049)***	-.186(.023)***	-.100(.029)***	-.184(.029)***
Service	-.229(.059)***	-.305(.068)***	-.321(.071)***	-.255(.060)***	-.244(.068)***	-.270(.072)***	-1.179(.030)***	-.989(.038)***	-1.183(.040)***
Treat×Group	**.033(.016)****	**-.169(.018)*****	**.202(.019)*****	**.030(.020)**	**-.074(.023)*****	**.119(.024)*****	**.035(.009)*****	**-.166(.011)*****	**.212(.010)*****
Treat×Service	-.358(.031)***	-.331(.035)***	-.425(.038)***	-.316(.030)***	-.178(.033)***	-.489(.036)***	-.342(.012)***	-.317(.016)***	-.400(.015)***
Group×Service	.182(.045)***	.091(.051)*	.230(.051)***	.047(.047)	-.046(.051)	.060(.052)	.125(.027)***	.064(.031)**	.135(.032)***
Treat×Group×Service	**.179(.041)*****	**.354(.047)*****	**.082(.049)**	**.051(.044)**	**.154(.051)*****	**-.027(.053)**	**.154(.020)*****	**.331(.025)*****	**.039(.023)**
Popularity	-.016(.019)	-.028(.022)	-.027(.023)	-.021(.020)	-.044(.023)*	-.007(.024)	-.002(.013)	.001(.016)	-.015(.016)
Competition	-.113(.019)***	-.155(.024)***	-.131(.023)***	-.061(.024)**	-.045(.028)	-.081(.028)***	-.075(.012)***	-.110(.015)***	-.077(.017)***
Price	-.074(.015)***	-.046(.018)**	-.066(.018)***	.053(.016)***	.065(.019)***	.080(.019)***	-.068(.009)***	-.047(.012)***	-.048(.012)***
Omni_ratio	2.185(.011)***	2.001(.012)***	2.198(.013)***	2.006(.012)***	1.822(.015)***	2.081(.016)***	2.181(.006)***	1.986(.008)***	2.193(.009)***
Online_High	-.002(.003)	-.014(.004)***	-.010(.004)**	-.007(.003)**	-.008(.004)**	-.004(.004)	-.004(.002)**	.001(.002)	.011(.002)***
Offline_High	.013(.003)***	.001(.003)	.024(.003)***	.005(.003)	.003(.004)	.011(.004)**	.014(.002)***	-.010(.002)***	-.019(.002)***
IMR	.014(.010)***	.011(.012)	.004(.013)	.005(.010)	.007(.011)	-.003(.012)	.012(.006)**	.012(.007)*	.003(.008)
Likelihood	-173147.768	-112628.640	-113190.382	-126878.320	-87125.474	-84391.505	-189412.267	-127370.573	-128301.012
BIC	346924.236	225731.158	226854.608	254382.711	174727.231	169258.795	378938.667	254851.229	256712.107
Obs	91692	61128	61128	58896	39264	39264	91692	61128	61128

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

2.6.9 Non-parametric Approach: Generalized Synthetic Control

For DiD estimation, the identification of causal effect relies on the matched samples of Coarsened Exact Match based on 27 observed variables and the Heckman correction function. However, the validity of the exogenous variables in Heckman correction function and excluding the relevant unobserved variables might decreases the validity of parametric estimation results. To address these concerns, I adopt Generalized Synthetic Control (GSC) method (Xu 2017) to further examine the validity of the parametric estimation results. The proposed GSC model takes the following form:

(22) $Sales_{it} = \delta_{it}D_{it} + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{\lambda}'_{it}\boldsymbol{f}_{\boldsymbol{t}} + \alpha_i + \eta_t + \varepsilon_{it},$

where the treatment indicator D_{it} equals 1 if product *i* has been affected by the price integration at time *t*, and equals 0 otherwise; δ_{it} is the homogenous treatment effect of product *i* at time *t*; $\boldsymbol{x_{it}}$ is the vector containing time-variant covariances (i.e., $Price_{it}$ and $Omni\_ratio_{it}$); $\boldsymbol{f_t}$= (f_{1t}, $f_{2t}, \ldots, f_{rt}$) is a vector of unobserved common factors for time *t*; $\boldsymbol{\lambda_{it}}$= ($\lambda_{it1}, \lambda_{it2}, \ldots, \lambda_{itr}$) is the vector of unobserved factor loadings for product *i* at time *t*; α_i is the product i's specific fixed effect; η_t is the fixed effect for time t; and ε_{it} is the normal idiosyncratic terms for product *i* at time *t*. The seemingly unrestricted unobserved factors and the product specific factor loadings could cover a wide range of unobserved heterogeneities. The average treatment effect on treated (ATT) at time *t* is captured by the average of homogenous treatment effects, i.e. $Att_t = \sum_i^N \delta_{it} / N$.

Identification. The key identification assumption for causal inference is that the error terms is independent with the treatment assignment, observed covariances, unobserved factors and factor loadings, i.e., $\varepsilon_{it} \perp D_{it}, X_{it}, \lambda_i, f_t$. The addictive time and product fixed effects, and the unobserved factors would largely capture the confounders that affects the independence of the error terms. The time and product fixed effects could capture common trend of time and the time-invariant product unobserved heterogeneity, whereas the unobserved manufacturer-time specific confounders could be captured by the unobserved factors. As I discussed earlier, the endogeneity concern of the DiD model is most likely derived from the nonrandom treatment assignments, i.e., manufacturers' strategic decisions on whether to participant the price integration policy. The unobserved confounders could be decomposed into a common trend (i.e., the focal retailer initiating the idea of price integration) and the heterogenous impacts across products (i.e., manufacturers determine whether to participant based on their time-invariant heterogeneity). Thus, including the interactions between time-specific unobserved factors and product-specific factor loadings could alleviate the influences of the unobserved confounders.

Estimation and Results. The GSC model is fitted with the unmatched full sample, including 1,110,703 transactions of 4,150 products. The number of unobserved factors is selected by cross validation. I tried 1 to 5 unobserved factors and found that models with 2 unobserved factors display the best model fit. The estimation results are reported in Table 16 and the estimated unobserved factors are reported in the Web Appendix G.

The column 1-3 of Table 16 reports the estimation results for the full sample, indicating a positive effect of price integration on product sales (ATT=.164, $p<.01$). Similar to the results of DiD model, I found that the impacts of price integration tend to be positive along the timeline, as the treatment effects in the first half of the post-treatment period is insignificant (ATT= .000, $p>.10$) and treatment effects become positive in the second half of the post-treatment period (ATT= .302, $p<.01$). Column 4-6 of Table 16 suggests that products with services suffer from sales decreases in the first half (ATT= -.109, $p<.05$) and enjoy sales increases in the second half (ATT= .276, $p< .01$). In contrast, products with services would enjoy an insignificant sales increase in the first half (ATT= .093, $p>.10$) and a significant sales increase in the second half

(ATT= .306, p<.05). The estimation results of GSC are largely consistent with the results of the DiD model with the matched sample.

The panel B of Figure 3 plots the dynamics of ATT. In contrast to the DiD estimation, the estimations of GSC are smaller in terms of impact size, especially for products without services. While the general trend of the treatment dynamics is largely consistent for both products with services and products without services.

Table 16
Product-Level Analysis: Results for Generalized Synethic Control

All products			
	(1)	(2)	(3)
	Overall	First half	Second half
ATT	.164(.017)***	.000(.054)	.302(.019)***
Omni-channel ratio	1.000(.016)***	.944(.015)	1.025(.016)***
Price	.247(.050)***	-.330(.063)***	-.085(.045)*
BIC	-.471	-.191	-.292
Obs	149400	99600	99600
Product w/out services			
	(4)	(5)	(6)
	Overall	First half	Second half
ATT	.036(.075)	-.109(.054)**	.276(.070)***
Omni-channel ratio	.985(.016)	.964(.019)***	.991(.019)***
Price	.055(.065)	.237(.126)*	.263(.080)***
BIC	-.631	-.398	-.481
Obs	114192	76128	76128
Product with services			
	(7)	(8)	(9)
	Overall	First half	Second half
ATT	.126(.112)	.093(.095)	.306(.116)**
Omni-channel ratio	.076(.019)***	.688(.023)***	.734(.021)***
Price	-.367(.078)***	-.420(.095)***	-.256(.066)***
BIC	-.576	-.248	-.452
Obs	35208	23472	23472

Notes. Estimation is based on 2 latent factors selected by cross-validation
*** p<0.01, ** p<0.05, * p<0.10

2.7 Consumer-Level Analysis: Consumer Segmentation and Dynamics

In previous section, the product-level analysis suggests that the impacts of cross-channel price integration on product sales turns from negative to positive over time. Theoretically, our framework posits that the effects of price integration are attributed to the interactions between the two strategic focuses — pricing flexibility (i.e., better prices) and pricing consistency (i.e., better experiences), by either attracting or repelling consumers with certain preferences (e.g., ”give” focus vs. “get” focus)(Zeithaml 1988). The attractiveness of a pricing policy to individual consumers with varying preferences cannot be investigated at the product-level analysis. I therefore further conduct the consumer-level analysis to investigate the dynamic effects of cross-channel price integration on the consumers’ product purchasing.

2.7.1 Research Context and Data

The unit of analysis is individual consumers of the focal retailer used in the product-level analysis. The data set of this consumer-level analysis comprises individual transactions of the sampled consumers between December 2012 and July 2014. To avoid the influences of outliers, consumers with order amounts below 1% and above 99% quantile are excluded. I end up with 1,190,225 transactions of 63,526 consumers. Within the 18-month period, the average number of purchases per consumer is 18.73 (min 3 and max 195), with 75.27% products being affected by the policy change, and the average spending is 37,776.03 local currency (min 105 and max 712,788). Among the sampled consumers, 19,866 (31.78%) are those who completed their first transaction after the policy change during our data window.

2.7.2 Measures

I aggregate the individual transactions of products affected by the price integration (i.e., treated group) and products not affected by the price integration (i.e., control group) separately into 3-month periods for each consumer. For consumer *i* at time *t*, $Sales_{i1t}$ is the number of purchased products affected by the price integration, and $Sales_{i0t}$ is the number purchased products not affected by the price integration. For each consumer, there are 12 quarterly aggregated observations within the 18-month periods. The price integration occurred on the first day of the third quarter. The bottom part of Table 1 explains the definition and operationalization of the three key variables for the consumer-level analysis.

2.7.3 Model Specification

A latent class model with a zero-inflated Poisson framework is adopted to analyze the individual-level data. Conditional on a finite mixture of *K* consumer segments, the conditional likelihood function of consumer *i*'s observations on sales $\boldsymbol{y}_i$ is given as:

(23) $f(\boldsymbol{y}_i|\boldsymbol{X}_i,\boldsymbol{\beta},\boldsymbol{\Sigma},\boldsymbol{\lambda}_i) = \sum_{k=1}^{K}\lambda_{ik}\prod_{t=1}^{T_i}\prod_{j=1}^{2}f(y_{ijt}|\boldsymbol{X}_{it},\boldsymbol{\beta}_k,\sigma_k)$,

where y_{ijt} is the number of products affected by price integration (j=1) or number of products not affected by price integration (j=0) purchased by consumer *i* at time *t*, i.e., $Sales_{ijt}$; *K* is the number of latent consumer segments; T_i is the number of observations of consumer *i*;

$\boldsymbol{X}_i = (\boldsymbol{X}_{i1},\boldsymbol{X}_{i2} \dots \boldsymbol{X}_{T_i})$ is the vector of covariates of consumer *i* of T_i periods; $\boldsymbol{\beta} = (\boldsymbol{\beta}_1,\boldsymbol{\beta}_2 \dots \boldsymbol{\beta}_K)$ is the vector of coefficients contains the coefficients of all *K* segments; $\boldsymbol{\Sigma} = (\sigma_1,\sigma_2 \dots \sigma_K)$ is the vector of standard deviations for all *K* classes. $\boldsymbol{\lambda}_i = (\lambda_{i1},\lambda_{i2} \dots \lambda_{iK-1})$ is the vector of the *K*-1 independent probability of consumer *i* belongs to group *k* (k=1,2…,K-1), defined as:

(24) $\lambda_{ik} = \frac{\prod_{t=1}^{T_i}\prod_{j=1}^{2}\exp(u_{ijtk}-u_{ijt1})}{\sum_{q=2}^{K}\prod_{t=1}^{T_i}\prod_{j=1}^{2}\exp(u_{ijtq}-u_{ijt1})}$, and $\sum_{k=1}^{K}\lambda_{ik} = 1$.

Given the individual probability λ_{ik}, the mixing proportions of latent segments in the population could be calculated as $\lambda_k = \sum_{i=1}^{N}\lambda_{ik}/\mathrm{N}$, where N is the total number of consumers.

The dependent variable y_{ijt} is assumed to follow a zero-inflated Poisson distribution:

(25) $f(y_{ijt}|\boldsymbol{X}_{it}, \boldsymbol{\beta}_k, \sigma_k) = [q_{ijtk} + (1 - q_{ijtk})R(0)]^{I_{ijt}} \times [(1 - q_{ijtk})R(y_{ijt})]^{1-I_{ijt}}$,

where q_{itk} is the norm link function $q_{ijtk} \sim N(\tau_k \exp(u_{ijtk}), \nu_{ijtk})$, I_{ijt} is the indicator that equals 1 if $y_{ijt} = 0$, and $R(y_{ijt})$ is defined as:

(26) $R(y_{ijt}) = e^{-u_{ijtk}} u_{ijtk}{}^{y_{ijt}}/y_{ijt}!$, and

(27) $u_{ijtk} = \exp(\beta_{0k} + \beta_{1k} Group_{ijt} + \beta_{2k} Group_{ijt} \times Quarter3_t + \beta_{3k} Group_{ijt} \times Quarter4_t + \beta_{4k} Group_{ijt} \times Quarter5_t + \beta_{5k} Group_{ijt} \times Quarter6_t + \beta_{6-11} \boldsymbol{Quarter}_t + \beta_{12} Age_i + \beta_{13} Membership_{it} + \varepsilon_{ijtk})$

where θ is the inverse of overdispersion parameter; $Group_{ijt}$ is a dummy indicator indicating if consumer *i*'s *j*th aggregate is the number of products affected by price integration purchased at time *t*; $\boldsymbol{Quarter}_t$ = ($Quarter2_t$, $Quarter3_t$, $Quarter4_t$, $Quarter5_t$, $Quarter6_t$) is the vector of 6 quarter dummy variables of time *t*. The policy change (i.e., price integration) occurred on the first day of the third quarter, thus including $Quarter3_t$ to $Quarter6_t$ are equivalent to including the treatment indicator. Age_i is the consumer *i*'s registered age, $Membership_{it}$ is the membership level (from 0 to 4) of consumer *i* at time *t*, and $\varepsilon_{ijtk} \sim N(0, \sigma_k)$ is the idiosyncratic normal error term.

2.7.4 Results

The model is estimated with the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. Models with 2 to 9 latent classes are tested and the model with 6 latent classes displays the best model fit (i.e., lowest BIC). Table 17 reports the estimation results of the latent class zero-inflated Poisson model.

The results suggest that the sampled consumers could be categorized into three categories: *lovers*, *haters* and *adapters*. Specifically, the first category of consumers, *lovers* (i.e., segment 1 and 2), are the consumers whose sales are mostly positively affected by the price integration. Specifically, the price integration policy has a strong and positive effects on the sales of consumers in the segment 1 (β_{21}= 1.017, $p<.01$; β_{31}= 1.128, $p<.01$; β_{41}= 1.207, $p<.01$; β_{51}= 1.297, $p<.01$) and segment 2 (β_{22}= .302, $p<.01$; β_{32}= .599, $p<.01$; β_{42}= .880, $p<.01$; β_{52}= .950, $p<.01$). The second category of consumers, *haters* (i.e., segment 3 and 4), are the consumers whose sales are strongly negatively affected by the price integration, and time doesn't weaken the negative effects. Specifically, the price integration has a negative effect on the sales of consumers in segment 3 (β_{23}= -.836, $p<.01$; β_{33}= -.936, $p<.01$; β_{43}= -.696, $p<.01$; β_{53}= -.654, $p<.01$) and segment 4 (β_{24}= -.012, $p>.10$; β_{34}= -.611, $p<.01$; β_{44}= -.746, $p<.01$; β_{54}= -.741, $p<.01$). The last category of consumers, *adaptors* (i.e., segment 5 and 6), are the consumers whose sales are negatively affected by the price integration at the beginning, and the negative impacts gradually becomes positive along the timeline. In specific, the effects of price integration turn from negative to positive for consumers in segment 5 (β_{25}= -.499, $p<.01$; β_{35}= -.250, $p<.01$; β_{45}= .065, $p<.01$; β_{55}=.150, $p<.01$) and segment 6 (β_{26}= -.133, $p<.01$; β_{36}= .187, $p<.01$; β_{46}= .595, $p<.01$; β_{56}= .609, $p<.01$). In other words, time has a positive moderating effect on the impacts of price integration on the sales for these consumers.

Table 17

Consumer-Level Analysis: Estimation Results for Latent Class Model

	Lovers		Haters		Adapters	
	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6
Constant	1.805(.005)***	-.935(.006)***	-.887(.006)***	-.527(.008)***	.313(.005)***	-.078(.005)***
Group	-.699(.044)***	.991(.007)***	1.783(.006)***	1.864(.009)***	.097(.007)***	1.176(.005)***
Group*Quarter3	1.017(.044)***	.302(.008)***	-.836(.009)***	-.012(.008)	-.499(.013)***	-.133(.008)***
Group*Quarter4	1.128(.044)***	.599(.008)***	-.936(.009)***	-.611(.010)***	-.250(.011)***	.187(.007)***
Group*Quarter5	1.207(.044)***	.880(.008)***	-.696(.008)***	-.746(.011)***	.065(.009)***	.595(.007)***
Group*Quarter6	1.297(.044)***	.950(.008)***	-.654(.008)***	-.741(.010)***	.150(.008)***	.609(.006)***
Prob(λ)	.190***	.152***	.259***	.016***	.304***	.079***

Notes. Other covariances are not reported for parsinomy

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

Table 18

Consumer Characteristics Across Latent Segments

	Lovers		Haters		Adapters	
	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5	Segment 6
Online ratio	.248	.302	.442	.359	.312	.301
Cheaper channel ratio	.306	.337	.552	.441	.337	.318
Membership status	2.004	1.849	1.854	1.893	1.900	1.917
Return consumer ratio	.540	.321	.266	.283	.311	.371

2.7.5 Post Hoc Analysis: Consumer Characteristics across Segments

To further uncover the impacts of price integration across consumer segments, consumer characteristics are calculated. The selected consumer characteristics include the ratio of online purchases in pre-treatment period, ratio of orders from the lower-priced channel in the pre-treatment period (i.e., price sensitivity), the average membership level (i.e., life time value) and the ratio of consumers who made no purchase in the 6-month pre-treatment period (i.e., returning consumers). Table 18 summarizes consumer characteristics in each latent segment. For the *lovers*, it is worth noting that this category has relatively more returning consumers (54.0% and 32.1%). Among the remaining non-returning consumers, they have a relatively lower ratio of online shopping (24.8% and 30.2%). In contrast, consumers in the category of *haters* shop more frequently in online channel (44.2% and 35.9%), more likely to select the lower-priced channel (55.2% and 44.1%) and are relatively lower in membership level (1.854 and 1.893). In summary, the consumers who are shopping online frequently and price sensitive are more likely to be driven away by the price integration policy, whereas consumers who are less price sensitive and high in consumer life time values are more likely to accept the policy.

The results of our consumer-level analysis shed lights on the interactive nature of the underlying mechanisms. In particular, the results suggest the existence of three groups of consumers: the group of price sensitive consumers and online shoppers leave after the price increase caused by the price integration policy; the group of offline shoppers and returning customers are more likely to be attracted by the price integration regardless of price change; while the rest consumers tend to leave after the price increase and then gradually attracted by benefits of pricing consistency.

2.8 General Discussion

2.8.1 Theoretical Implications

This research offers the first empirical test of the effects of implementing a cross-channel price integration on the product sales in the context of multi-channel retailers. Three key findings emerge from these analyses.

First, cross-channel price integration immediately lowers the sales of products regardless of coordinated services. After a period of accommodation, price integration increases sales of products without services in a slower pace and increases the sales of products with coordinated services in a much faster pace. Further, our consumer segmentation analysis further reveals that implementing price integration eventually attract consumers with preferences for consistent experiences but repel customers with preferences for better prices.

Second, this research contributes to emerging multi-channel literature by investigating the effects of cross-channel price integration on product sales. Prior research mostly focuses on channel integration (Gallino and Moreno 2014; Gao and Su 2016) or consumer experiences (Bell et al. 2017; Cao and Li 2015; Saghiri et al. 2017), with a general assumption that multi-channel consumers would not encounter inconsistencies related to price discrepancies. This research sheds new light on the unique influences of price integration. In particular, it highlights the dynamic effects of two prevalent pricing strategies, along with the two contrasting mechanisms (i.e., pricing constraint and pricing consistency).

Third, the research also contributes to pricing literature, by highlighting the contrasting characteristics of channel-specific versus cross-channel price integration models. Prior multi-channel pricing literature emphasizes the costs and benefits of a channel-specific pricing strategy (Cavallo 2017; Kireyev et al. 2017; Vogel and Paul 2015; Yan and Pei 2011) and consumers' perceptions of price discrimination (Bolton et al. 2003; Cuellar and Brunamonti 2014; Fassnacht and Unterhuber 2016; Wu et al. 2012; Xia et al. 2004). I extend these insights by addressing two pricing strategies in a multi-channel context. Consistent with prior literature, I show that a channel-specific pricing model works better in the short run, because the inability to price the products according to the channel-specific context has an immediate effect on product sales; while in the long run, cross-channel price integration is preferable, because customers have a more consistent, seamless shopping experience the cross-channel price integration supports, which would outweigh the incentives looking for lower price alternatives. In other words, channel-specific pricing model features the price-orientated model that attracts consumers through competitive prices, and cross-channel price integration emphasizes the service-oriented model that attracts consumers by improving their shopping experiences.

2.8.1 Managerial Implications

Pricing strategies are critical, with ramifications for retailers' performance, market competition, and consumer relationships. Retailers need to synergize their marketing mix across all available channels, but doing so might decrease price competitiveness and limit their pricing flexibility (Grewal et al. 2010; Kireyev et al. 2017). Our research establishes that it takes time for consumers to grow accustomed to cross-channel price integration, so price integration might hurt firms in the short run, due to their loss of pricing flexibility. In a sense, firms that focus on long-term benefits should integrate product prices across channels, but if they aim to maintain competitiveness through providing a more flexible pricing policy, firms should stick to a channel-specific pricing strategy.

In addition, firms should consider the boundary conditions that determine the effectiveness of price integration, such as product type (with vs. without coordinated services), and target consumer segments (experience- vs. price focused consumers). Price integration improves a consistent shopping experience, which is more important for products with high search costs, such as those involving services and experience-based offerings. Minimizing costly search efforts for these products by applying a cross-channel price integration can increase the retailer's competitiveness. Furthermore, price integration provides a more consistent shopping environment without cross-channel price discrepancies, yet it is beneficial only if the target segments have a stronger preference toward better experiences than better prices.

2.8.2 Limitations and Further Research Directions

Some limitations of this study suggest some worthwhile research opportunities. First, I focus on channel integration by one retailer, though manufacturers' cross-channel integration decisions also might affect consumers' choices of retailer. Some manufacturers adopt a channel integration strategy that incorporates all touchpoints, including retailers. For example, Apple products list the same retail prices, across all retailers and Apple stores. Such manufacturer-level integrated multi-channel pricing might reduce consumers' incentives for between-seller searches or competition. Research that focuses on manufacturers' cross-channel pricing strategy could deepen understanding of consumers' responses.

Second, beyond the influences on product sales, it would be helpful to investigate the effects on margins. As posited in prior literature, a key advantage of channel-specific pricing is that sellers can increase their margin rates among less price sensitive customers (Cuellar and Brunamonti 2014; Kireyev et al. 2017). In contrast, sellers that integrate cross-channel prices lose pricing flexibility, which might reduce their profitability. I indirectly infer the impacts on profits, according to overall revenue; data limitations prevent us from addressing margin outcomes directly. Therefore, continued research should identify the profitability implications when retailers implement a cross-channel price integration strategy.

Third, I take a holistic perspective; further research might consider specific influences on consumers' perceptions and migration behaviors. Investigating the consumer's shopping journey in a cross-channel price integration context represents a promising path toward a greater understanding of consumers and their behaviors in this multi-channel settings.

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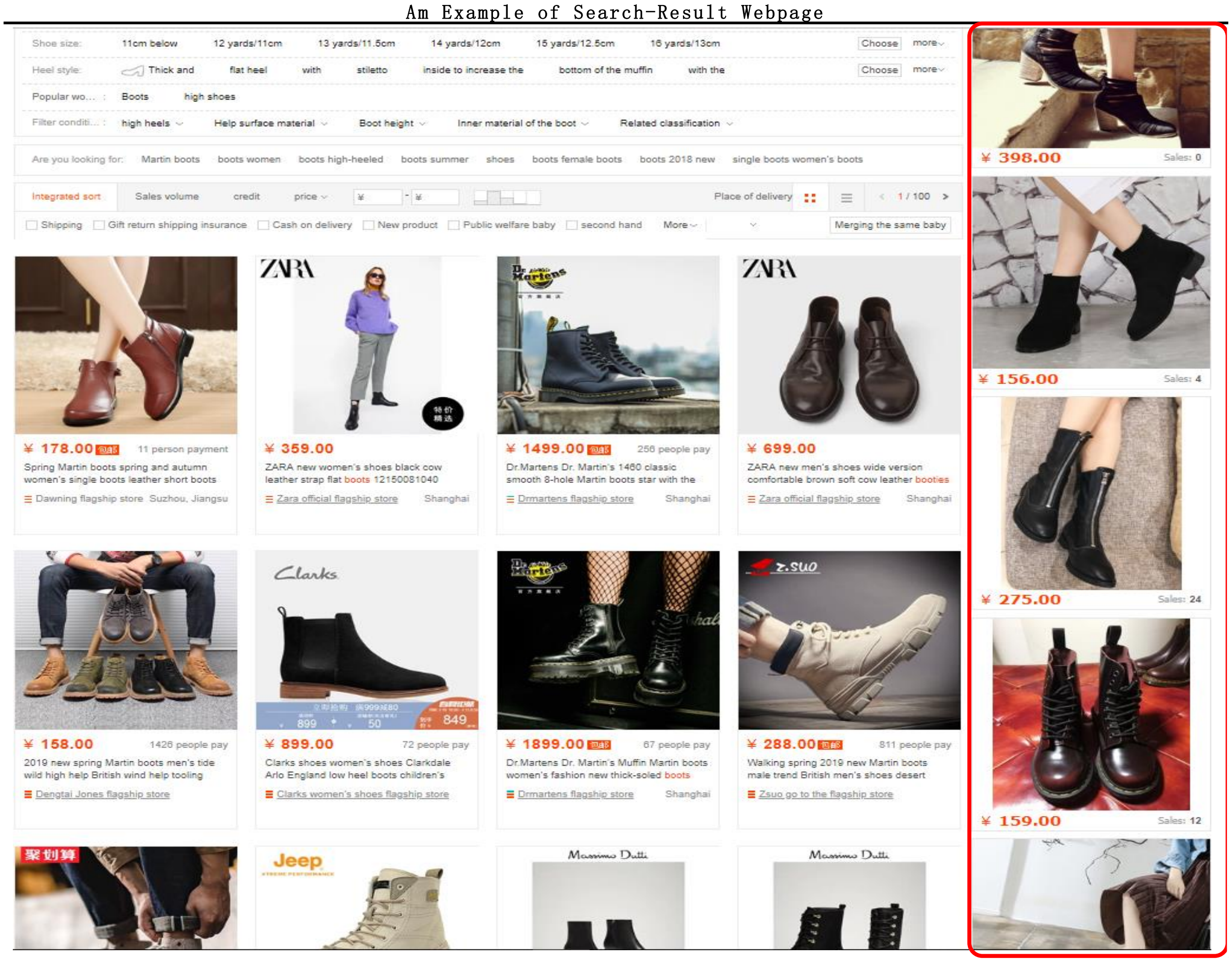
APPENDIX A: Example of Sponsored Advertisements list (Essay 1)

Figure A1
Am Example of Search-Result Webpage



Notes. Sponsored advertisements are vertically listed (within the red rectangle) in the separate column with organic results.

APPENDIX B: The MCMC Algorithm (Essay 1)

We ran the MCMC chain for 80,000 iterations and used the every 40th of the last 40,000 iterations to compute the mean and standard deviation of the posterior distribution of the model parameters, in the application presented in the paper. We report below the MCMC algorithm for the simultaneous model of click-through rate, conversion rate, and price rank.

As specific, we define

$a_1' = [\alpha_{3-5}], a_2' = [\beta_{3-6}], a_3' = [\psi_{0-7}], a_4' = [\varphi_{0-6}]$

$b_{i1}' = [\alpha_{0i}, \alpha_{1i}, \alpha_{2i}], b_{i2}' = [\beta_{0i}, \beta_{1i}, \beta_{2i}]$

$x_{r,ijt1} = x_{r,ijt2} = [1, Pricerank_{ijt}, Pricerank_{ijt}^2]$

$x_{ijt1} = [Specificity_i, Popularity_i, DisplayRank_{ijt}]$

$x_{ijt2} = [Specificity_i, Popularity_i, DisplayRank_{ijt}, Review_{ijt}]$

$x_{ijt3} = [1, Pricerank_{ijt-1}, p_{ijt-1}, q_{ijt-1}, Displayrank_{ijt}, Review_{ijt}, Specificity_i,$
$Popularity_i]$

$x_{ijt4} = [1, Displayrank_{ijt-1}, p_{ijt-1}, q_{ijt-1}, Review_{ijt}, Specificity_i, Popularity_i]$

Step 1. Draw u_{ijt}^p and u_{ijt}^q

The likelihood function of the number of clicks n_{ij} and number of purchases m_{ij} is

$l(u_{ijt}^p, u_{ijt}^q | n_{ijt}, m_{ijt}) \propto [p_{ijt} q_{ijt}]^{m_{ijt}} [p_{ijt}(1 - q_{ijt})]^{n_{ijt} - m_{ijt}} (1 - p_{ijt})^{N_{ijt} - n_{ijt}}$,

where $p_{ijt} = \frac{\exp(u_{ijt}^p)}{1+\exp(u_{ijt}^p)}$ and $q_{ijt} = \frac{\exp(u_{ijt}^q)}{1+\exp(u_{ijt}^q)}$

$u_{ijt}^p = m_{ijt}^p + \eta_{ijt}, u_{ijt}^q = m_{ijt}^q + \varepsilon_{ijt}$

$m_{ijt}^p = x_{r,ijt1} b_{i1} + x_{ijt1} a_1 + \delta_t^{click} + \theta_j^{click}$

$m_{ijt}^q = x_{r,ijt2} b_{i2} + x_{ijt2} a_2 + \delta_t^{conv} + \theta_j^{conv}$

$c_{ijt1} = x_{ijt3} a_3 + \delta_t^{price} + \theta_j^{price}$

$c_{ijt2} = x_{ijt4} a_4 + \delta_t^{price} + \theta_j^{price}$

$$D = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix} - \begin{bmatrix} \Omega_{13} & \Omega_{14} \\ \Omega_{23} & \Omega_{24} \end{bmatrix} \begin{bmatrix} \Omega_{33} & \Omega_{34} \\ \Omega_{43} & \Omega_{44} \end{bmatrix}^{-1} \begin{bmatrix} \Omega_{31} & \Omega_{32} \\ \Omega_{41} & \Omega_{42} \end{bmatrix}$$

$$E_{ijt} = \begin{bmatrix} \Omega_{13} & \Omega_{14} \\ \Omega_{23} & \Omega_{24} \end{bmatrix} \begin{bmatrix} \Omega_{33} & \Omega_{34} \\ \Omega_{43} & \Omega_{44} \end{bmatrix}^{-1} [c_{ijt1}, c_{ijt2}]$$

We use Metropolis-Hastings algorithm with a random walk chain to generate draws of $u_{ijt} = (u^p_{ijt}, u^q_{ijt})$. Let $u^{(k)}_{ijt}$ denote the previous draw; then $u^{(k+1)}_{ijt}$ the next draw is given by

$$u^{(k+1)}_{ijt} = u^{(k)}_{ijt} + \Delta,$$

with the accepting probability given by

$$\min\{\frac{\exp[-\frac{1}{2}\left(u^{(k+1)}_{ijt} - m_{ijt} - E_{ijt}\right)' D^{-1}\left(u^{(k+1)}_{ijt} - m_{ijt} - E_{ijt}\right)] l(u^{(k+1)}_{ijt})}{\exp[-\frac{1}{2}\left(u^{(k)}_{ijt} - m_{ijt} - E_{ijt}\right)' D^{-1}\left(u^{(k)}_{ijt} - m_{ijt} - E_{ijt}\right)] l(u^{(k)}_{ijt})}, 1\}$$

$\triangle$ is a draw from the density MVN ($u^{(k)}_{ijt}$, $0.5D$).

Step 2. Draw $a = [a_1', a_2', a_3', a_4']$

$$x_{ijt} = \begin{bmatrix} x'_{ijt1} & 0 & 0 & 0 \\ 0 & x'_{ijt2} & 0 & 0 \\ 0 & 0 & x'_{ijt3} & 0 \\ 0 & 0 & 0 & x'_{ijt4} \end{bmatrix}$$

$$y_{ijt1} = u^p_{ijt} - \left(b_{i1} x'_{r,ijt1} + \delta^{click}_t + \theta^{click}_j\right)$$

$$y_{ijt2} = u^p_{ijt} - \left(b_{i2} x'_{r,ijt2} + \delta^{conv}_t + \theta^{conv}_j\right)$$

$$y_{ijt3} = Pricerank_{ijt} - \left(\delta^{price}_t + \theta^{price}_j\right)$$

$$y_{ijt4} = Displayrank_{ijt} - \left(\delta^{rank}_t + \theta^{rank}_j\right)$$

$$a_0 = 0_{21\times 1}, \Sigma_0 = 100I$$

$$B = [X'\Omega^{-1}X + \Sigma_0^{-1}]^{-1}, A = B[X'\Omega^{-1}Y + \Sigma_0^{-1}a_0]$$

Then $a \sim \text{MVN}(A, B)$

Step 3. Draw Ω.

$$y_{ijt1} = u^p_{ijt} - \left(x_{r,ijt1} b_{i1} + x_{ijt1} a_1 + \delta^{click}_t + \theta^{click}_j\right)$$

$$y_{ijt2} = u^p_{ijt} - \left(x_{r,ijt2} b_{i2} + x_{ijt2} a_2 + \delta^{conv}_t + \theta^{conv}_j\right)$$

$$y_{ijt3} = Pricerank_{ijt} - \left(x_{ijt3} a_3 + \delta^{price}_t + \theta^{price}_j\right)$$

$$y_{ijt4} = Displayrank_{ijt} - \left(x_{ijt4} a_4 + \delta^{rank}_t + \theta^{rank}_j\right)$$

$$Q_0 = 10I, q_0 = 10, N = \text{no. of obs}$$

Then $\Omega \sim \text{IW}(\sum_i \sum_j \sum_t y_{ijt}' y_{ijt} + Q_0, N + q_0)$

Step 4. Draw $b_i = [b_{i1}', b_{i2}']$

$$y_{ijt1} = u_{ijt}^{p} - \left(a_1 x_{ijt1} + \delta_t^{click} + \theta_j^{click}\right)$$

$$y_{ijt2} = u_{ijt}^{p} - \left(a_2 x_{ijt2} + \delta_t^{conv} + \theta_j^{conv}\right)$$

$$x_{ijt} = \begin{bmatrix} x_{ijt1}' & 0 \\ 0 & x_{ijt2}' \end{bmatrix}, \Sigma = \begin{bmatrix} \Sigma^{\alpha} & 0 \\ 0 & \Sigma^{\beta} \end{bmatrix}$$

$$x_{ijt1} = x_{ijt2} = [1, PriceRank_{ijt}, PriceRank_{ijt}^2]$$

$$\bar{b}_{i1} = \bar{\alpha}_0, \bar{b}_{i2} = \bar{\alpha}_1 + a_{11} Specificity_i + a_{12} Popularity_i,$$

$$\bar{b}_{i3} = \bar{\alpha}_2 + a_{21} Specificity_i + a_{22} Popularity_i,$$

$$\bar{b}_{i4} = \bar{\beta}_0, \bar{b}_{i5} = \bar{\beta}_1 + \beta_{11} Specificity_i + \beta_{12} Popularity_i,$$

$$\bar{b}_{i6} = \bar{\beta}_2 + \beta_{21} Specificity_i + \beta_{22} Popularity_i,$$

$$B_i = [x_i' \mathrm{D}^{-1} x_i + \Sigma^{-1}]^{-1}, A_i = B_i [x_i' \mathrm{D}^{-1} y_i + \Sigma^{-1} \bar{b}_i]$$

Then, $b_i \sim$ MVN (A_i, B_i)

Step 5. Draw $\delta_t = [\delta_t^{click}, \delta_t^{conv}, \delta_t^{price}, \delta_t^{rank}]$

The likelihood function is

$$l(\delta_t | \cdot) \propto \prod_i \prod_j \prod_t [p_{ijt} q_{ijt}]^{m_{ijt}} \left[p_{ijt}\left(1 - q_{ijt}\right)\right]^{n_{ijt} - m_{ijt}} \left(1 - p_{ijt}\right)^{N_{ijt} - n_{ijt}} \exp[-\tfrac{1}{2}\left(Y_{ijt} - C_{ijt}\right)' D^{-1} \left(Y_{ijt} - C_{ijt}\right)]$$,

where $p_{ijt} = \frac{\exp(u_{ijt}^{p})}{1+\exp(u_{ijt}^{p})}$ and $q_{ijt} = \frac{\exp(u_{ijt}^{q})}{1+\exp(u_{ijt}^{q})}$

$$u_{ijt}^{p} = x_{r,ijt1} b_{i1} + x_{ijt1} a_1 + \delta_t^{click} + \theta_j^{click} + \eta_{ijt}$$

$$u_{ijt}^{q} = x_{r,ijt2} b_{i2} + x_{ijt2} a_2 + \delta_t^{conv} + \theta_j^{conv} + \varepsilon_{ijt}$$

$$c_{ijt1} = x_{ijt3} a_3 + \delta_t^{price} + \theta_j^{price}$$

$$c_{ijt2} = x_{ijt4} a_4 + \delta_t^{rank} + \theta_j^{rank} + \omega \gamma_{ijt}$$

$$\mathrm{C}_{ijt} = [\mathrm{c}_{ijt1}, \mathrm{c}_{ijt2}]$$

$$\mathrm{Y}_{ijt} = [\mathrm{y}_{ijt3}, \mathrm{y}_{ijt4}]$$

$$D = \begin{bmatrix} \Omega_{33} & \Omega_{34} \\ \Omega_{43} & \Omega_{44} \end{bmatrix} - \begin{bmatrix} \Omega_{31} & \Omega_{32} \\ \Omega_{41} & \Omega_{42} \end{bmatrix} \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{bmatrix}^{-1} \begin{bmatrix} \Omega_{31} & \Omega_{41} \\ \Omega_{32} & \Omega_{42} \end{bmatrix}$$

We use Metropolis-Hastings algorithm with a random walk chain to generate draws of $\delta_t = (\delta_t^{click}, \delta_t^{conv}, \delta_t^{price}, \delta_t^{rank})$. Let $\delta_t^{(k)}$ denote the previous draw; then $\delta_t^{(k+1)}$ the next draw is given by

$$\delta_t^{(k+1)} = \delta_t^{(k)} + \Delta$$

with the accepting probability given by

$$\min\{\frac{\exp[-\frac{1}{2}\left(\delta_t^{(k+1)} - \bar{\delta}\right)'\Sigma^{\delta^{-1}}\left(\delta_t^{(k+1)} - \bar{\delta}\right)]l(\delta_t^{(k+1)})}{\exp[-\frac{1}{2}\left(\delta_t^{(k)} - \bar{\delta}\right)'\Sigma^{\delta^{-1}}\left(\delta_t^{(k)} - \bar{\delta}\right)]l(\delta_t^{(k)})}, 1\}$$

Δ is a draw from the density MVN $(\bar{\delta}, 0.5\Sigma^{\delta})$.

Step 6. Draw $\theta_j = [\theta_j^{click}, \theta_j^{conv}, \theta_j^{price}, \theta_j^{rank}]$, similar to step 5.

Step 7. Draw $\Sigma^{\alpha}, \Sigma^{\beta}, \Sigma^{\delta}$ and Σ^{θ}.

Let $Q_0 = 10I, q_0 = 10, N = \text{no. of keywords},$

then $\Sigma^{\alpha} \sim \text{IW}(\Sigma_i\left(b_{1i} - \bar{b}_1\right)'\left(b_{1i} - \bar{b}_1\right) + Q_0, N + q_0);$

Let $Q_0 = 10I, q_0 = 10, N = \text{no. of keywords},$

then $\Sigma^{\beta} \sim \text{IW}(\Sigma_i\left(b_{2i} - \bar{b}_2\right)'\left(b_{2i} - \bar{b}_2\right) + Q_0, N + q_0);$

Let $Q_0 = 10I, q_0 = 10, N = \text{no. of t's},$

then $\Sigma^{\delta} \sim \text{IW}(\Sigma_t\left(\delta_t - \bar{\delta}\right)'\left(\delta_t - \bar{\delta}\right) + Q_0, N + q_0);$

Let $Q_0 = 10I, q_0 = 10, N = \text{no. of sellers},$

then $\Sigma^{\theta} \sim \text{IW}(\Sigma_j\left(\theta_j - \bar{\theta}\right)'\left(\theta_j - \bar{\theta}\right) + Q_0, N + q_0).$

Step 8. Draw $f_1 = [\bar{\alpha}_0, \bar{\alpha}_1, \bar{\alpha}_2, a_{11}, a_{12}, a_{21}, a_{22}]$

$$x_i = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & Specificity_i & Popularity_i & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & Specificity_i & Popularity_i \end{bmatrix}$$

$a_0 = 0_{7\times 1}, \Sigma_0 = 100I,$

$B = [X'\Sigma^{\alpha^{-1}}X + \Sigma_0^{-1}]^{-1}, A = B[X'\Sigma^{\alpha^{-1}}b_1 + \Sigma_0^{-1}a_0]$

Then $f_1 \sim$ MVN (A, B)

Step 9. Draw ω

$B = [\gamma' D^{-1}\gamma + \Sigma_0^{-1}]^{-1}$, $A = B[\gamma' D^{-1} c_{ijt2} + \Sigma_0^{-1}\omega_0]$

where $c_{ijt2} = Displayrank_{ijt} - x_{ijt3}a_3 - \delta_t^{rank} - \theta_j^{rank}$, $\Sigma_0^{-1} = 100I$, $\omega_0 = 0$ and

$$D = \Omega_{44} - [\Omega_{41} \quad \Omega_{42} \quad \Omega_{43}] \begin{bmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} \end{bmatrix}^{-1} \begin{bmatrix} \Omega_{14} \\ \Omega_{24} \\ \Omega_{34} \end{bmatrix}$$

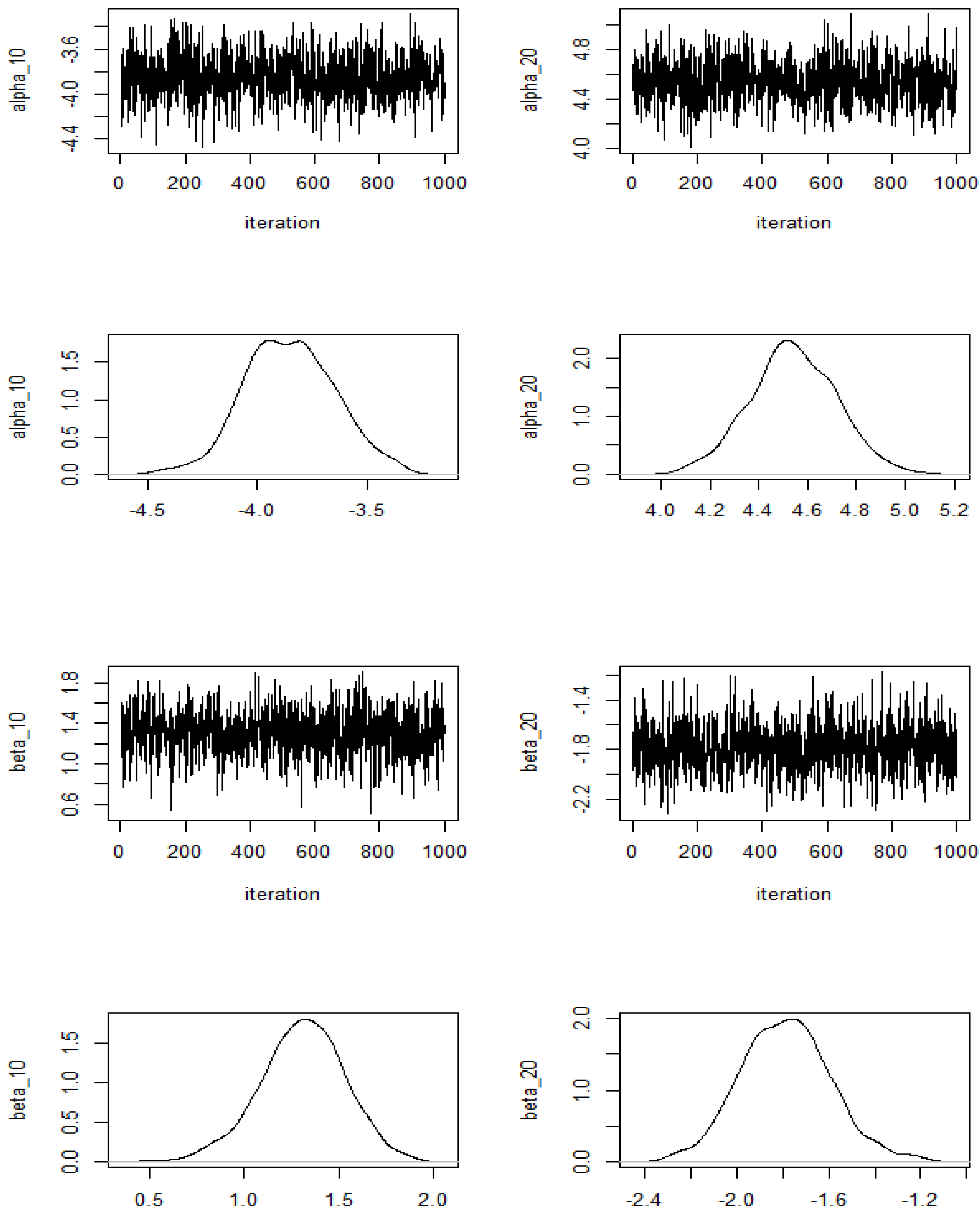
Then, $\omega \sim$ MVN (A, B)

Step 10. Draw $f_2 = [\bar{\beta}_0, \bar{\beta}_1, \bar{\beta}_2, \beta_{11}, \beta_{12}, \beta_{21}, \beta_{22}]$, similar to step 8.

Step 11. Draw $\bar{\delta} = [\bar{\delta}^{click}, \bar{\delta}^{conv}, \bar{\delta}^{price}, \bar{\delta}^{rank}]$, similar to step 8.

Step 12. Draw $\bar{\theta} = [\bar{\theta}^{click}, \bar{\theta}^{conv}, \bar{\theta}^{price}, \bar{\theta}^{rank}]$, similar to step 8.

APPENDIX C: MCMC Diagnosis (Essay 1)



APPENDIX D: Task Descriptions for Participants Used in Study 2 (Essay 1)

Search and buy:

Assume you recently adopted a cute kitty and would like to buy a cat stand. After searching the keyword "Cat Stand" on one of your favorite online shopping websites, 7 advertisements pop out.

Among all the 7 advertisements, you are able to click the advertisements linking to the detailed product page. After clicking on one advertisement, you will be led to the detailed page of the product you clicked. You could choose to 1) buy the product, or 2) return to the main page.

Your task is to evaluate the product information and select the worthiest deal to buy.

Search-only:

Assume you recently adopted a cute kitty and would like to buy a cat stand. After searching the keyword "Cat Stand" on one of your favorite online shopping websites, 7 advertisements pop out.

Among all the 7 advertisements, you are able to click the advertisements linking to the detailed product page. After clicking on one advertisement, you will be led to the detailed page of the product you clicked. You could choose to 1) proceed to the next step, or 2) return to the main page.

Your task is to collect as much information as possible, and estimate the price of a relating new product.

APPENDIX E: Example Webpages Used in Study 2 (Essay 1)

FIGURE E1
Example Search Advertisements

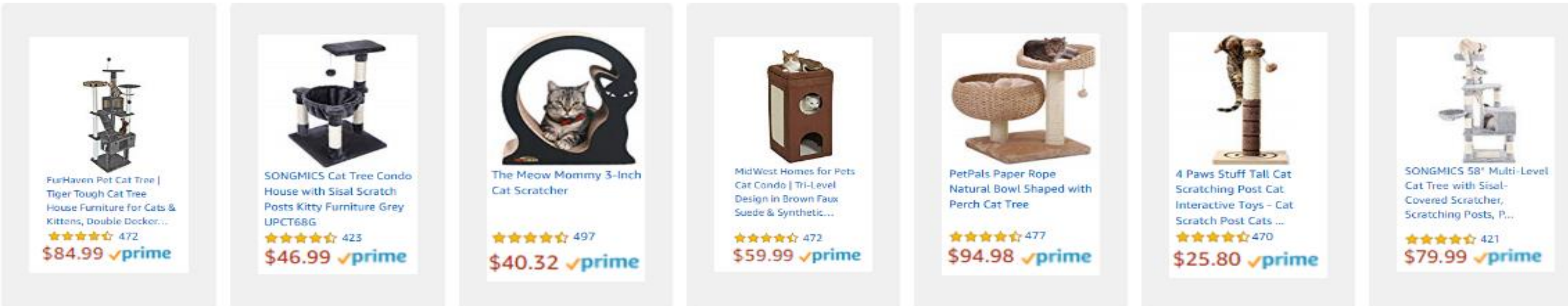


Figure E2
Example After-Click Product Page

PetCheer Cat Face Ultimate Scratcher Lounge Bed with Catnip

by PetCheer

497 customer reviews

Amazon's Choice for "scratch post"

Price: $40.32 ✓prime

Pay ~~$40.32~~ $0.00 after using available American Express Membership Rewards points.

FREE Delivery by **Friday**
if you order within 23 hrs 49 mins, or

Get it **Thursday** if you order within 21 hrs 4 mins and choose paid One-Day Shipping at checkout Details

Ships from and sold by Amazon.com. Gift-wrap available.

Style: **Round**

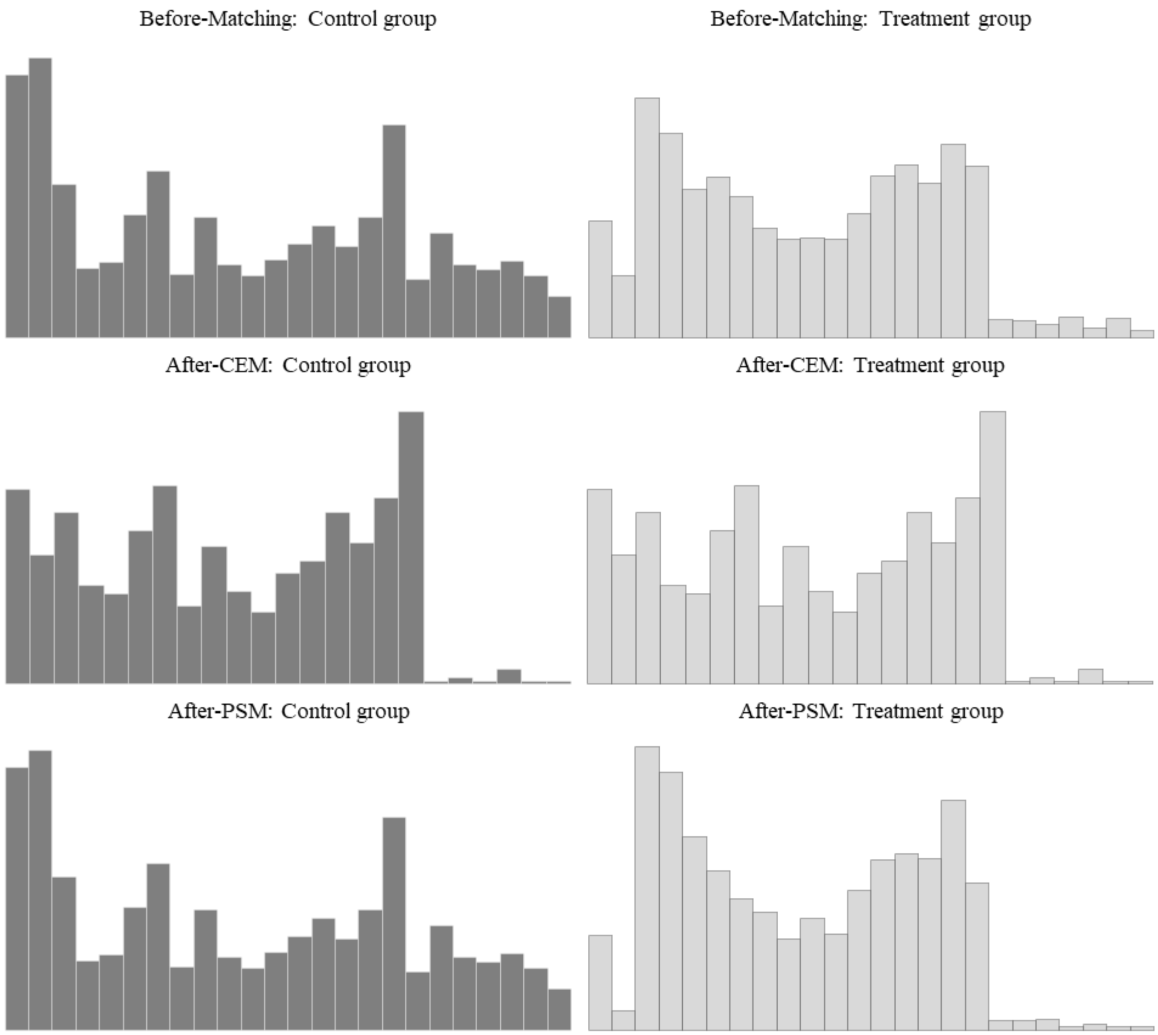
- Created with premium Pressed cardboard, the scratcher is dense and durable
- Cat love scratch it and curl up inside and sleep in it
- Manufactured with quality standards.100% recyclable materials. Heavy duty corrugated cardboard construction
- Reversible for two different configurations and double the longevity
- Recommended to save your furniture as cats prefer the feel of cardboard

Return to main page

Buy this product

APPENDIX F: Joint Distributions of Matched Samples (Essay 2)

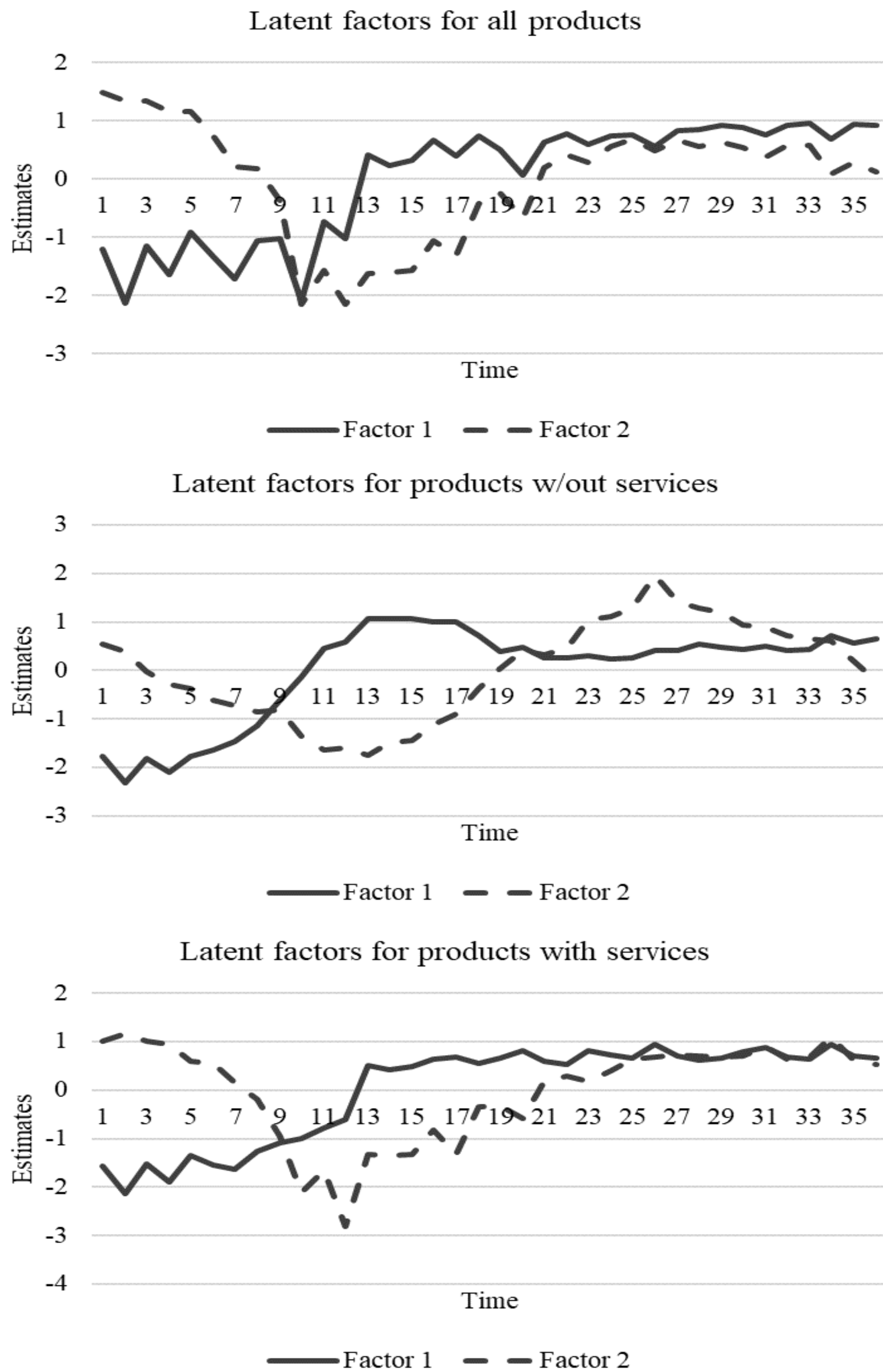
Figure F1
Joint Distributions of Covariances between the Matched Groups



Notes. The figures display the joint distribution of the 27 variables that were used in sample matching, and the joint distributions are divided into 1184 stratas.

APPENDIX G: Unobserved Factors for GSC (Essay 2)

Figure G1
Estimated Unobserved factors



Notes. Factors selected based on leave-one-out-cross-validation.