FIRMS' MARKETING STRATEGIES AND CONSUMER RESPONSES IN PLATFORM-BASED E-COMMERCE MARKETS

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Limei

Li Mei

25 April 2016

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TABLE OF CONTENTS

SUMMARY

Enabled by information technologies, platform-based e-commerce marketplaces have tremendously changed the modern business landscape. The high accessibility and low entry barriers of such marketplaces have greatly facilitated the proliferation of online small businesses. However, the two-sided nature of these marketplaces forms a positive feedback loop between sellers and buyers, which usually renders the dominant markets overcrowded and hypercompetitive. Under such circumstances, effective marketing strategies or tactics become crucial for the sustenance of small business owners. Therefore, this dissertation aims for a better understanding of these online small business owners' marketing strategies, with particular emphasis on the aspects of product and promotion strategies (McCarthy 1960).

The first study (Chapter 2) highlights the value of appropriate product portfolio designs in achieving successful and cost-saving marketing effects. We investigate mobile app developers' app portfolio management strategies with a comprehensive dataset collected from the Apple App Store. Specifically, we evaluate the impacts of app portfolio on developers' app quality and popularity. For app quality, we examine the influence of mobile developers' app portfolio size and diversity. We measure a developer's app quality with the average user rating valence of its app portfolio. As developers may make portfolio diversification decisions endogenously based on their performance, we used dynamic propensity score matching to build a comparable developer sample. Missing app quality existed in the sample due to many developers did not have any apps being rated. We relied on Heckman selection model to address this censoring issue. The empirical results show a negative impact of

portfolio diversity on developers' app quality, which is moderated by portfolio size under certain circumstances. For app popularity, we assess the extent and direction of popularity spillover effects between developers' existing and new apps. Our empirical analysis with a simultaneous equations model shows that popular existing apps of a developer can promote the popularity of new apps both within and across categories. New apps, in turn, drive demand for a developer's existing apps in the same category. Our findings emphasize the importance of specialization for mobile developers, who are small in scale and deficient in resources.

The second study (Chapter 3) provides fresh perspectives on the promotion strategies through online targeted advertising for small business owners in platform-based e-commerce markets. Specifically, we focus on the differential impacts of online targeted advertising outlets and the content of the advertisement (ad) copy on the product demand of the emerging brands. We propose a two-level hierarchical model to model the impacts of the visits from four different targeted advertising outlets provided by Taobao, which is the largest e-commerce platform in China (iResearch 2012). A panel-level linear regression with first-order autoregressive disturbance structure has been used to evaluate the model with a proprietary dataset from an entrepreneurial e-commerce brand. The results show that the goal specificity of consumer search and the targetability of targeted advertisements have significant impacts on the product demand of visits from different advertising outlets. In addition, the price related information (i.e., price discount and free delivery messages) in the ad copy also exhibits different effects on product demand across advertising outlets.

These two studies deepen our understanding of online small business owners' marketing strategies and underscore the unique characteristics of these emerging business participants. As one of the earliest studies that take a close examination of these online small businesses, this dissertation also presents potential avenues for future research, which will be discussed in Chapter 4.

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1. INTRODUCTION

1.1 Background and Motivation

Benefiting from the advanced information technologies (ITs), platform-based e-commerce markets are playing an increasingly important role in our daily lives. They considerably reduce sellers' entry barriers, in the sense that shop rentals, shelf arrangements and storage are no longer the primary concerns for small business owners. Individuals also can launch their own businesses online with the least hassle (Freedman 2000). By catering to both sellers and buyers, platform-based e-commerce markets provide a concentrated venue where they can find the best matching partners. This two-sided nature of the platforms forms a positive feedback loop between sellers and buyers, which suggests that the participation on one side boosts the participation on the other (Armstrong 2006; Rochet et al. 2003). Such indirect network externality often reinforces the market power of the dominant platforms, resulting in extremely crowded and hypercompetitive marketplaces (Dubé et al. 2010).

According to the latest statistics of eBay (2015), there have been more than 112 million active users in the platform till 2015. As a platform-based market of information goods, the US Apple App Store has attracted 436,436 publishers to contribute apps (PocketGamer.Biz 2015). A considerably greater statistic comes from Taobao, the largest online and mobile commerce company in the world – the number of annual active sellers in Taobao has reached 8 million (AlibabaGroup 2014). The intensive competition in these online markets greatly threatens sellers' survival. Under such circumstances, effective marketing strategies or tactics are crucial for the survival of sellers.

1.2 Research Framework and Potential Contributions

McCarthy (1960) proposed a 4 Ps classification to describe the impactful marketing mix that firms need to address, namely product, price, promotion and place (shown in Figure 1-1). This classification is being widely used by marketers globally even today. For the small business owners in platform-based e-commerce markets, the Internet is the primary channel for them to distribute their products. Little variation exists in these sellers' choice of place, and this dissertation therefore would not discuss their place strategies. Nonetheless, the other 3 Ps are still critical for businesses in platform-based e-commerce markets. As a fundamental factor that influences trade between sellers and buyers, price is influential in almost all transactions. To respond the call from Yadav et al. (2014) that studies examining platform-based competition are strongly encouraged, this dissertation mainly focuses on platform-based sellers' marketing strategies regarding the aspects of product and promotion. The impacts of price will be accounted for as well.

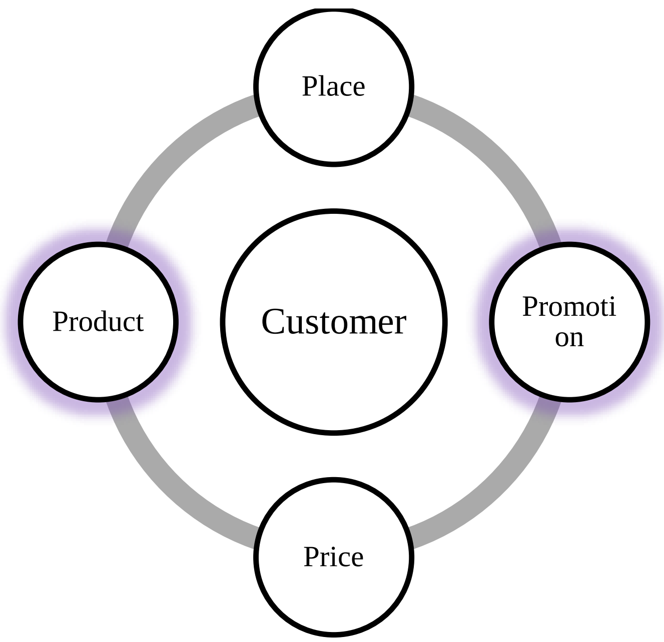

Figure 1-1 McCarthy's 4 Ps Classification of Marketing Mix

1.2.1 Product Strategies

A product represents the goods or services that firms produce to satisfy targeted customers' needs. Many decisions related to products need to be considered by firms, such as branding, warranty and product line management. A brand is an intangible asset owned by a firm to assist customers to distinguish its products from those of other firms (Wernerfelt 1988). Customers usually associate a well-established brand with high product quality. Building a good brand image helps firms to obtain price premiums over their competitors. Warranty is a form of quality insurance that firms provide to customers. It greatly influences profitability and hence firms should be cautious in making decisions on warranty provision. Product line management is also an important element of the product strategies of firms. It is difficult for one product to satisfy all customers' preferences. In order to win a larger market share, firms may consider diversifying their product portfolios to serve different customer segments. Decisions like packaging, features and accessories are all product related aspects that firms have to address, but we shall not elaborate on them in detail.

The advent of e-commerce has greatly reduced the cost of organizing and managing transactions (Houser et al. 2006). It provides small firms and even individuals with opportunities to launch an online business with minimal capital, resulting in the flourishing of "microbusinesses" (Freedman 2000). Some of these microbusinesses are individuals who run online businesses at home "with no inventory, overheads, or business acumen" (Halstead et al. 2003). While these microbusinesses are gradually producing substantial impacts in online markets, the academia's understanding of their characteristics and behavior is still scanty. It is unknown, for instance, whether the product strategies for traditional offline firms are applicable to the online small businesses, and how they can obtain competitive advantage given the limited resources they possess in the hypercompetitive online markets.

1.2.2 Promotion Strategies

Promotion refers to possible communication methods that marketers may utilize for providing product information to consumers (McCarthy et al. 1993). Typical promotion methods include advertising, sales promotion, external relations and others. Advertising is the most popular means for firms to increase potential consumers' awareness and interest in their brands or products. Besides traditional advertising channels such as television, magazines and radio, online advertising provides both large and small firms with ample opportunities to publicize themselves. Digital advertisements (ads) have many advantages over their counterparts in traditional media. The online environment allows advertisers to track the performance of each ad in real-time. The latest technologies enable publishers to display digital ads of a higher targetability, which increases customers' response probability dramatically. Moreover, the rapid development of the Internet has tremendously magnified the impacts of word-of-mouth transmission. The convenient access to the Internet considerably facilitates the information flow among people. Electronic word-of-mouth transmission has become a pivotal communication method for firms to promote their products.

Nevertheless, the proliferation of platform-based e-commerce markets has wrought many new challenges. The two-sided nature of the platform-based e-commerce markets implies that a flourishing customer side is generally related to a crowded seller side. Because of this, the reduced visibility of their products presents a serious problem for sellers. Consumer attention has become a scarce resource in the e-commerce markets. Given the limited resources possessed by the small business proprietors in platform-based markets, how to attract the right customers with the least investment is a question that merits careful examination.

1.2.3 Research Focus

We proposed two studies to address the aforementioned issues in this dissertation. The first study investigates third-party mobile developers' app portfolio management strategies in the Apple App Store. The Apple App Store is renowned to be an overcrowded e-commerce market. We are interested in how the category assortment of third-party developers' app portfolios influences their app production. We investigate app production from two aspects – app quality and app popularity. For app quality, we maintain that developers' app quality increases in the number of apps they have developed. In addition, fostering core competency in platform-based e-commerce markets is critical for mobile app developers' growth and an app portfolio engaging in as few categories as possible would greatly improve the app quality. Regarding app popularity, we contend that the impacts of brand in terms of a developer's name with regard to app popularity are more salient within a category than that across categories.

To validate our hypotheses, we collected a comprehensive dataset from the Apple App Store. We empirically estimated the impacts of portfolio size and category diversity on mobile developers' performance. The results suggest a negative influence of app portfolio category diversity on developers' app quality, which is moderated by the size of app portfolio under certain circumstances. These empirical results suggest a focused app portfolio is a favorable product portfolio design for mobile developers. Furthermore, we also find popularity spillovers between new and existing apps within the same category, but such a bidirectional spillover effect is not observed across categories. This further corroborates the importance of a concentrated app portfolio for mobile app developers to foster core competency in the extremely competitive mobile app market.

The second study investigates sellers' promotion strategies in platform-based e-commerce markets with emphasis on promotion through targeted advertising, which is most suitable for small business owners due to its effectiveness in targeting and converting potential customers to actual buyers. The performance-based pricing model of online targeted advertising also alleviates sellers' burden of investing large sums of marketing expenditure. However, there are many advertising outlets, where consumers are engaging in different tasks. How these different targeted advertising outlets impact consumers' product demand is still unknown. Furthermore, few prior studies have yet examined the design of ad copy for targeted advertising. Whether consumers in different targeted advertising outlets respond to the identical ad copy differently and how to increase the persuasive power of the ad copy are valuable questions for advertisers to explore. Therefore, we empirically address these questions in the second study.

To provide fresh perspectives on sellers' targeted advertising strategies in platform-based e-commerce markets, we examined the digital advertising campaigns of an e-commerce brand in Taobao, which is the largest e-commerce platform in China (iResearch 2012). Taobao provides targeted advertisement in four targeted advertising outlets, i.e., keyword search advertising, category search advertising, internal banner advertising and external banner advertising. We compared the impacts of the visits attracted by advertisements in these four outlets on product demand. The four outlets have been categorized into two groups according to consumers' information seeking state. Goal specificity and targetability are contingent factors that influence the performance of targeted advertisements in these two groups, respectively. Regarding the design of ad copy, no extant literature has systematically categorized the features of an ad copy. As an initial attempt, we evaluated the influence of the presence of price related information (i.e., price discount and free delivery) in the ad copy on consumers' responses to the targeted advertisements in different outlets.

A two-level hierarchical econometric model has been proposed to model the differential impacts of visits from the four targeted advertising outlets. The results based on a panel-level ordinary least square estimator with a first-order autoregressive disturbance structure suggest that the visits from category search advertising generate more product demand than those from keyword search advertising. Moreover, the visits from internal banners generate more product demand than those from external banners. In addition, the presence of discount messages in the ad copy increases the product demand of the visits from keyword search advertising, but reduces the product demand of the visits form category search advertising. Furthermore, the presence of free delivery messages in the ad copy only increases the product demand of the visits from external banner advertising.

1.2.4 Potential Contributions

This dissertation seeks a deeper understanding of the marketing mix in platform-based e-commerce markets. This market form is burgeoning with the rapid development of information technologies and benefits millions of small business owners tremendously. The behavior of both sellers and customers has been reshaped in such an environment. We choose two important aspects of the marketing mix, namely product and promotion, to examine online sellers' strategies. Our results show that the different market environment does present many new challenges for online sellers. Sellers need to adjust their marketing strategies to fit this new market form so as to achieve better performance. To sum up, this dissertation contributes to both academia and practice in the following ways.

First, the research subjects in this dissertation are all small-scale enterprises or individual business owners. Their prominent characteristic is the lack of sufficient resources and brand awareness. The extremely crowded online market environment requires them to utilize all possible resources effectively, including both their tangible and intangible assets. We highlight the importance of reasonably exploiting the intangible assets in their growth, such as making full use of brand image.

Second, despite the limited resources owned by small business owners in platform-based e-commerce markets, promotion strategies are necessary for them to distinguish themselves from the huge number of competitors in the markets. Effective advertising plans are of great value for them in maximizing the marketing impacts with minimum investment. This dissertation suggests that when conducting targeted advertising campaigns, potential consumers' information search behavior in different advertising outlets should be considered. Advertising outlets do not come with equal values. Advertisers should plan their advertising portfolios with consideration of both the costs and benefits of each advertising outlet.

Third, consumers' responses to the content in the ad copy vary across online advertising outlets due to the different information search modes of the consumers. For example, for advertising outlets where most consumers are in exploratory search, the presence of price discount messages in the ad copy increases the relevance of the advertisement. This emphasizes the necessity for advertisers to design the ad copy according to the ad display outlets.

Fourth, visitors from different advertising outlets react with different sensitivities to product prices. This finding provides clues for marketers to design differential price schemes for visitors from different sources. With the aid of modern information technologies, online business owners can offer personalized prices by considering each customer's willingness to pay, which helps profit maximization.

CHAPTER 2. STUDY I
– APP PORTFOLIO MANAGEMENT

2.1 Introduction

The introduction of mobile smart phones has radically altered the way people use communication and information technology devices. As a complementary product to these devices, mobile apps have gained much attention from both consumers and developers. The US Apple App Store alone has already attracted about 78 million consumers (comScore 2015) and more than 436,436 active developers[1] (PocketGamer.Biz 2015). Contrary to the purported lucrative sales in the mobile app industry, a majority of app developers earn meager revenues due to stiff competition in the app markets. A more serious issue is that most developers lack an effective plan to manage their app portfolios strategically.

A product portfolio refers to an assortment of products or services offered by a firm. Product portfolio management plays a critical role on a firm's sale revenues and production costs, and therefore, on the overall profitability of the firm (Cardozo et al. 1983; Eggers 2012). This is also true for mobile app developers. Although apps for a particular operating system are built in one specific programing language, the functionalities of the apps may greatly differ, requiring different sets of development capability and computational resources. Mobile app stores typically consist of many different app categories such as Books, Games and Navigation. Each category distinguishes itself from the others by its functionality and content. App developers have considerable flexibilities in choosing the number of apps to develop and the category of

1 Unless we specifically point out, a developer in this study refers to a publisher of mobile apps, either as an individual person or a software firm.

apps to specialize in or diversify to. However, due to the lack of a clear guidance on what constitutes a healthy path to success in the app markets, most developers rarely manage their app portfolios strategically. Often, they build apps they favor, with the assumption that mobile users will have an affinity for their apps, which usually is not the case (VisionMobile 2013).

In spite of the proliferation of studies on product portfolio management (e.g., Berry 1971; Shankar 2006; Tanriverdi et al. 2008), the extant research is hardly able to provide references for mobile app developers to effectively manage their app releases. There are systematic differences between the manufacturing sector, which has been heavily studied in the portfolio management literature, and the mobile app market that we study. First, unlike the traditional manufacturing sector where physical capital assets are important production factors (Gallivan et al. 2004), human capital plays a crucial role in the mobile app industry (Boh et al. 2007). Economies of scale have deep impacts on product portfolio management of the manufacturing industry. Compared with the physical assets, human capital is more malleable in reassignment and can be improved by learning. Nevertheless, how to harness this new production factor to achieve appropriate app portfolio management is still an open question. Second, due to the digital nature of mobile apps, marginal costs of reproduction are negligible and it would not cost too much to serve a large group of users, compared to the industries with physical products. App platforms have greatly reduced developers' entry barriers with app development toolkits. As a result, a large proportion of app developers today are now not professional software firms, but small-scale teams or individuals (Qiu et al. 2011). These developers may have different patterns in utilizing resources and tackling increasing competition. Traditional large IT companies usually serve multiple platforms and take advantage of the network externalities across platforms to secure their competitive positions in the market (Cottrell et al. 2004). Differing from them, most mobile app developers only serve one platform (Hyrynsalmi et al. 2016) and the product portfolio management of traditional IT companies hardly provides references to mobile developers. Third, app developers can easily market and sell their apps through effective online channels, thereby minimizing the distribution costs. With less need for a large capital investment and a highly efficient online distribution channel, the mobile app industry is characterized as a market with extremely intensive competition and short innovation cycles (Han et al. 2012). How mobile developers can leverage on these unique properties of this new industry to better manage their product line is an important yet underinvestigated area.

Despite the increased importance of the mobile app industry to digital economy, there is limited research in the literature that assesses the success factors in such a hypercompetitive environment. The question of how to manage app portfolios effectively remains largely unanswered. Though the study of Lee et al. (2014) suggests that broadening app portfolios to more app categories improves mobile developers' performance, this finding is confined to the top app developers and therefore may not provide references to a typical (or representative) app developer. How does app portfolio management affect the performance of a more general pool of app developers? With respect to app portfolios, we focus on two important metrics to assess the performance implications of app portfolio management – *app quality* and *app popularity*.

These two metrics assume more significance for performance because sale and download numbers of developers are not publicly available in the app markets (Han et al. 2012). In reference to app quality, we study how the size and the concentration of developers' app portfolios across different app categories influence the degree of app excellence. A more focused app portfolio helps developers accumulate experience in certain areas and foster core competencies. In contrast, a more diversified app portfolio distributes efforts across various categories although this approach enables developers to cater to users with different needs. In addition to size and assortment decisions on app quality, managing an app portfolio requires a clear understanding of how apps in a developer's portfolio influence the popularity of each other. Given the lack of information about the quality of a new app, consumers may infer the quality of a new app from the popularity of the developer's existing apps. Furthermore, the popularity of the new app may also affect the popularity of the developer's existing apps. Moreover, this possible bidirectional influence may be moderated by the category relatedness[2] between the existing apps and the new app. In summary, we seek to answer two critical questions about app portfolio management to provide prescriptive guidance to app developers. Specifically, we put forward the following research questions:

(1) How, and to what extent, do size and diversity of mobile app developers' app portfolios influence their app quality?

(2) How, and to what extent, do a developer's new app and existing apps, in either the same or different category, influence the popularity of each other?

2 Category relatedness refers to whether the existing apps are in the same category as the new app.

To answer these questions, we collected a comprehensive dataset from the Apple App Store. The data contains information about all mobile apps that were available for download in the store between January 2011 and March 2012. In order to examine the effects of category assortment on the quality of the apps produced, we measured monthly app portfolio size and portfolio diversity change for each developer. We used the average monthly user rating valence for each app to measure the quality of apps published by each developer. Developers may adjust their app portfolio according to their own performance, consequently introducing endogeneity to the analyses. To address this concern, we relied on the method (Xu et al. 2015) of dynamic propensity score matching (PSM) to construct a comparable developer sample, which contains developers with similar publishing and performance history but different portfolio diversification decisions. Furthermore, we observed some developers did not have any apps being rated in a month, resulting in a missing measurement of app quality. We employed Heckman selection model to deal with this censoring issue. Our analyses show that app portfolio diversity negatively influences developers' app quality. On average, one unit increase in category entropy, which measures app portfolio diversity, leads to a decrease of 0.111 in the average user rating of an app portfolio, which measures the quality of a developer's apps. This effect is further exacerbated by the increasing size of an app portfolio. We also conducted similar analyses on company and non-company developers separately. The results show slightly different impact patters of portfolio diversity on these two types of developers, but portfolio diversification in general is detrimental to mobile developers' app quality.

We next used a simultaneous equations system to evaluate how mobile app category assortment influences the popularity of a developer's existing apps and new apps. We measured the popularity of apps published by each developer with the average monthly user rating volume for each app. Our results suggest that there is a positive popularity spillover from existing apps to new apps both within and across categories, i.e., a one percent increase in the popularity of the existing apps in the same category and the popularity of the existing apps in different categories respectively translates into a 0.098 percent increase and a 0.094 percent increase in a new app's popularity. Interestingly, the popularity of a developer's new app greatly boosts the popularity of its existing apps in the same category. One percent increase in the popularity of a new app associates to 0.553 percent increase in the popularity of a developer's existing apps in the same category. The effect is more than five times larger than the popularity spillover in the reverse direction. No popularity spillover effect has been observed from a new app to the existing apps across categories. Therefore, there is a virtuous popularity reinforcement loop between the existing and new apps within a same category. Our results also imply that, apart from creating fresh revenue streams for developers, publishing new apps to existing categories also serve as a catalyst to induce consumers to explore and purchase developers' old apps in the same category.

This study presents several significant contributions. First, it expands the study of product portfolio management from traditional industries, where physical capital assets are important production factors, to a human capital intensive industry, namely the emerging mobile app industry. Second, we provide evidences for that specialization is critically important for mobile app developers, who are much smaller in scale, compared with the players in the traditional industries. Concentrating the limited resources on a few app categories helps them to foster core competency and make use of the popularity synergies between new and existing apps. Third, our findings indicate that app developers can carryover their reputation resulting from existing apps to new apps through the branding effect both within and across categories. In addition, the popularity of new apps substantially boosts the popularity of existing apps in the same category. Hence, there is a positive reinforcement loop between existing apps and new apps within category, thereby influencing the popularity of each other. Fourth, we provide practical suggestions for mobile app developers about how they can benefit from a well-planned app portfolio to succeed in highly competitive app markets.

2.2 Prior Literature

2.2.1 Product Portfolio Management

A product portfolio refers to the assortment of products or services offered by a firm and a well-managed product portfolio could generate positive short-term and long-term returns (Cardozo et al. 1983; Eggers 2012). The major incentive for firms to expand their product portfolio comes from two sources, i.e., supply side and demand side. On the demand side, consumers have long been recognized as possessing heterogeneous preferences (e.g., Berry et al. 1995; Hotelling 1929). Individuals also have discrepant tastes for the same product. Moreover, some consumers seek variety in their consumption. They gain greater utility from the consumption of different products (McAlister et al. 1982; Simonson 1990). These demand side effects incentivize firms to diversify their product portfolio. By producing multiple products, they could satisfy the needs of different consumer segments and better prepare for future demand uncertainties (Berry 1971). With a diversified product portfolio, firms may also be able to differentiate their products from their competitors, and obtain higher profits (Aribarg et al. 2008). In addition, a diversified product portfolio can help firms reduce risk and avoid market failure in particular industry sector (Amihud et al. 2007).

On the supply side, the decision of product portfolio expansion is tightly related to firms' cost structure. If economies of inter-product production exist, firms may choose to increase their product variety (Lancaster 1990). Economies of inter-product production could exist in various forms, such as spreading sunk costs (Bailey et al. 1982). If the resources required by existing products have not been fully occupied, and meanwhile the production of a new product can use these resources, firms may have enhanced incentive to add the new product to their portfolio, which probably can benefit them due to the demand side effects as stated earlier.

In spite of the various motivations for firms to diversify their product portfolio, the prior academic literature has not reached a consensus on the impacts of a diversified product portfolio. Many industrial organization studies (e.g., Gort 1962; Markham 1973) concluded that no significant effect of a diversified product portfolio on firms' performance. In contrast, strategic management studies (e.g.,Cottrell et al. 2004; Rumelt 1982) found positive impacts of portfolio diversification. One perspective that can reconcile these different findings is to consider the relatedness of diversification. Diversification can take place at different levels, such as product level and industry level. A diversified product portfolio at a lower level (e.g., product level) is more related compared with one at a higher level (e.g., industry level). Several studies (Jacquemin et al. 1979; Palepu 1985; Tanriverdi et al. 2008) found that diversification relatedness positively influence firms' performance, suggesting a moderately diversified product portfolio. The previous conflicting findings on the effects of a diversified portfolio are largely caused by the different level of diversification the researchers investigated.

A major research context of the aforementioned product portfolio management literature is the traditional manufacturing sector, which is mainly characterized by physical capital assets and produces physical goods. Only a few studies (Cottrell et al. 2004; Lee et al. 2010; Tanriverdi et al. 2008) examined the software industry, which intensively requires human capital resources and produces digital goods. The diversification studies in the context of software concluded that product diversification across market niches and platforms can improve firms' performance. However, these studies are based on fairly large software firms that possess sufficient resources to spread their product lines to different market niches and to multiple platforms. However, different from the developers or firms in the PC and server software industry, increasingly more app developers are micro entrepreneurs in the mobile app industry (VisionMobile 2013). These developers, compared with the traditional software firms, are much smaller in size and available resources and therefore may not have the same set of incentives to diversify their product portfolios. Consequently, research on product portfolio management in the context of mobile app market might be of greater importance for these emerging small-scale software developers. The current study aims to investigate how app portfolio diversification in the iOS platform influences mobile app developers' performance.

2.2.2 Mobile App Industry

Though Apple's first smartphone was unveiled in 2007, 2008 was the real epoch for the development of the Apple's mobile ecosystem. Apple launched the App Store in 2008, aiming to enhance the functionality of its mobile devices by leveraging on third-party developers' work (Apple 2008; Liu et al. 2014). This two-sided market initiative attracted overwhelming positive responses from both users and developers, and greatly motivated other mobile platforms to copy the success story (Wikipedia 2015). By opening the gates of the platforms, albeit at different degrees, mobile platform owners exploit third-party developers' innovation to improve user experience of their own products (Schlagwein et al. 2010). The mobile app markets enable third-party developers to interact with their potential users to understand their needs. The development environments and tool kits provided by the platform owners also ease the app development process considerably. This innovative business model of mobile app markets radically reduces mobile developers' entry barriers, attracting millions of developers working on various app platforms (VisionMobile 2014). Compared with the traditional software firms, these developers are much smaller in scale (Bergvall-Kåreborn et al. 2011; Qiu et al. 2011), since most of them are micro entrepreneurs. Possessing fewer resources than the traditional software companies, mobile app developers might pursue different product portfolio management strategies. However, the extant literature on product portfolio management in the mobile app industry is rare.

To the best of our knowledge, the study by Lee et al. (2014) is the only work that investigated mobile app developers' product portfolio strategies. Based on a dataset consisting of the apps that were ranked in the top-grossing 300 chart in the Apple App Store, they conducted econometric analyses. The results suggest that broadening an app portfolio to more categories positively influences app developers' performance. While the research questions in the current paper are similar to theirs, our findings are largely different. The current study finds that specialization in as few app categories as possible benefits mobile developers. We contend that the sample constructions are the key to explain this discrepancy. Their sample consists of developers who have at least one top-ranked app, but ours contains a larger cross-section of developers, including both large company developers and small-scale developers who may not have been successful enough to be ranked in the top charts. This helps rule out potential self-selection in that successful developers tend to publish apps in more app categories. Furthermore, they measure the app portfolio diversity with a simple count of the categories where developers have released apps in. We use a different yet more rigorous approach to quantify the app portfolio diversity with the entropy measure (Jacquemin et al. 1979) which is frequently utilized in strategic management studies and is more sensitive to small changes in the portfolio composition.

2.3 Theory and Hypotheses Development

The focus of this study is to investigate the impacts of category assortment of app portfolios on mobile app developers' performance. For app sales, the quality of an app is a critical metric to predict its success, since product quality directly influences consumers' willingness to pay (Bhargava et al. 2001; Dellarocas 2003). Hence, we discuss the influence of category assortment on the quality of apps produced by developers in the first part of our theory development.

The context of mobile app development relates to the software industry, as products are digital goods. The software industry, however, has long been recognized as human capital intensive unlike the industries in the manufacturing sector of the economy (Ang et al. 2002; Levina et al. 2007). Labor forces are soft assets of software firms and the capabilities of the human assets are influential in shaping firms' performance (Banker et al. 2008). As the mobile app industry is relatively new, most developers are still in the phase of learning the intricate dynamics of this industry. Therefore, a majority of experience gained by developers, whether on technical or managerial levels, is accumulated in the process of learning by doing (Argote et al. 2011; Boh et al. 2007; Mukhopadhyay et al. 2011; Singh et al. 2011). As such, the accumulation of development experience creates a valuable knowledge repository that can provide references and guidance for future app developments and releases.

Every mobile platform has its own software development kit (SDK). Developers need to familiarize themselves with the unique syntax, commands and libraries of the SDK to succeed in this new environment. To many developers, the main vehicle through which learning on development tasks, including framework design, code reuse and bug detection, takes place is publishing apps. This type of learning occurs regardless of the relatedness between the new and existing apps since the underlying architecture and process of app development are similar. An increasing number of apps provide developers with more opportunities to interact with potential customers and better understand demand dynamics in terms of their preferences and needs. Such accruing experiences increase developers' human capital, which in turn improves the quality of the apps they produce. A developer's app portfolio size, defined as the number of apps the developer currently has, reflects the developer's experience in app development. Consistent with the aforementioned arguments, we expect a positive impact of mobile app portfolio size on app quality. Hence, we posit that:

Hypothesis 1 (H1): The size of a developer's app portfolio is positively associated with the developer's app quality.

The diversity of a developer's app portfolio characterizes the extent of the developer's production concentration over app categories. Developing apps for multiple categories can bring about diversification to the app portfolio. A higher diversity indicates a less concentrated app portfolio. The Apple App Store has 23 major categories [3], ranging from spare time killers to productivity improvement tools. Each category distinguishes itself from the others by its functionality and content (Lee et al. 2014). From the developers' perspective, programing skills and other resources required by the development of apps in each category may vary. For example, apps in the Navigation category need strong support from the server end since frequent changes in maps should be updated frequently to the clients' devices via the server. In contrast, apps in the Games category may not need much server-end programming, but may require sophisticated designs in user interface and game play. In software design, a system is usually segmented into one or several tasks, each of which

3 The 23 categories include Books, Business, Catalogues, Education, Entertainment, Finance, Food & Drink, Games, Health & Fitness, Lifestyle, Magazines & Newspapers, Medical, Music, Navigation, News, Photo & Video, Productivity, Reference, Social Networking, Sports, Travel, Utilities and Weather.

corresponds with a module with well-defined input and output interface (Parnas 1972). The navigation apps and game apps in our example are usually implemented with different sets of modules, although developers may reuse modules for some common functions (Haefliger et al. 2008), such as camera access and data storage. Therefore, in line with the proposition that products in the same category have more features in common than those in different categories (Rosch et al. 1975), apps in the same category may share more common modules due to greater functional similarity in the services or contents they provide to consumers.

In the mobile app markets, most developers are typically small entrepreneurs or startups, who may lack financial assets or other valuable resources (Aggarwal et al. 2012; Qiu et al. 2011). Making full and efficient use of their production capacity is their primary goal. Apps from different categories usually provide users distinct functions, which may require programming skills for different functional modules. The development of an app in a new category requires developer's knowledge transferring from existing modules to new modules that fulfill the functionality of the new app (Haefliger et al. 2008). As the existing codes cannot be readily adapted to fit the new requirements, knowledge transfer between functional modules may incur large amount of cost (Brusoni 2005) Thus, developers with a diverse portfolio encounter more problems than developers who have a concentrated portfolio. The time that could have been used to obtain in-depth knowledge on existing modules has to be spread over the old and new modules constituting the diversified app portfolio. This effort distribution, in turn, drains their limited resources, leaving them little room to build core competencies and improve their app quality. Consequently, a diversified app portfolio may adversely impact developers' app quality. Moreover, if the developers meanwhile own a large app portfolio, they need to do substantial development work across different app categories, where production synergies can hardly be achieved. It is challenging to keep regular and quality maintenance for each of the apps that disperse in different categories. Under such circumstance, the adverse effect of app portfolio diversity on app quality will be further aggravated. Therefore, we hypothesize that:

Hypothesis 2a (H2a): The diversity of a developer's app portfolio is negatively associated with the developer's app quality.

Hypothesis 2b (H2b): The negative effect of the diversity of a developer's app portfolio on the developer's app quality exacerbates with the increasing size of the app portfolio.

The decision making process of consumers has long been a hot topic for researchers and marketers (e.g., Grewal et al. 2003; Häubl et al. 2000; Hoyer 1984). Faced with an overwhelming number of alternative choices available nowadays, consumers have to make decision with information from multiple sources (e.g., advertisement, salespersons and word of mouth). Alternative choices may come from different products under the same brand or products of different brands. Knowing how consumers evaluate an alternative is of great interests for brand owners to design new products as well as update exiting products. As new product strategies are an integral part of firms' product portfolio management, the second part of our theory formulation would focus on this aspect. The second part examines the impacts of app category assortment on the popularity of mobile developers' new and existing apps. Specifically, we are interested in assessing how the app popularity of existing apps impacts the popularity of a new app, and whether this popularity externality is mutual (i.e., from a new app to existing apps as well).

Consumers are often imperfectly informed about the quality and value of new products, especially for experience goods (Nelson 1970). Since mobile apps are experience goods, individuals' valuations of an app may vary substantially due to quality uncertainty and heterogeneity in preferences. In assessing experience goods, prospective consumers are predisposed to be influenced by evaluation of other products of the firm by the previous customers.(Liu 2006). One important aspect of customer evaluations entails product popularity. This is because the greater the popularity of a product, the higher level of acceptance among consumers (Bukowski et al. 1989; Coie et al. 1982; Newcomb et al. 1995). In the absence of other information, popularity of existing products can provide clues about the quality of a new product. Prospective customers can rely on these signals to form an opinion about the value of the new products. Similarly, customers can infer the quality and value of new app releases from the popularity of existing apps by the same developer.

The brand management literature (e.g., Montgomery et al. 1992; Wernerfelt 1988) contends that consumers' prior use experience or valuation of existing products influences their quality perception of a new product under the same brand. In mobile app stores, developers can release apps in various app categories. While apps from different categories are designed to satisfy consumers' different needs, apps in the same category provide common functionalities and therefore fulfill similar needs of users, such as entertainment in the Games category. Having a well-received app signals a developer's ability to develop high-quality apps. Since the apps in the same category share more common features, this quality inference is stronger for a new app within the same category, compared to one belonging to a different category. Specifically, high standings of a developer's existing apps that are in the same category as the new app conveys a message to consumers that the developer is capable of producing superior apps in that category. For apps across different categories, the transfer of quality perception may not be that salient due to the differences in app functionality and design. Thus, we hypothesize that:

Hypothesis 3a (H3a): The popularity of a developer's existing apps is positively associated with the popularity of its new app releases within the same category.

Hypothesis 3b (H3b): The popularity of a developer's existing apps is not associated with the popularity of its new app releases across different categories.

Besides the quality perception transfer from existing products to new products (Wernerfelt 1988), usage experience and reputation of new products, in turn, influence consumers' valuation of existing products (Erdem 1998). Mobile apps usually do not have brands but developer name is compulsory information in an app's profile, which gradually assumes the same function as a brand. A consumer's experience with an app may influence his/her evaluation of other apps by the same developer. Thus, the popularity of a developer's new app may influence the existing apps by the focal developer. This effect can materialize via two mechanisms. The first one is through the quality signaling effect of the new app. Existing studies that assess the impacts of piracy on the sales of albums found that music piracy, to a certain degree, boosted the music sales in legal distribution channels, since pirated music conveniently enabled consumers to sample the artists' music before making a purchase (Gopal et al. 2006; Hui et al. 2003; Sundararajan 2004). Similarly, once consumers have a positive experience with a new app, they may transfer this favorable evaluation to the existing apps – both in identical and different categories – by the same developer. In this case, the usage of the new app acts as a mode of sampling the developer's existing apps. Moreover, consumers' positive evaluation of the new app may also influence other consumers' quality perception about the developer due to the word-of-mouth effect (Chevalier et al. 2006; Godes et al. 2009).

The second mechanism for popularity spillover is through the new app's role as a discovery facilitator. A prominent feature of the major mobile app markets, including the Apple App Store, is the provision of various ranking charts (Carare 2012; Lee et al. 2014) to help consumers explore the app market and find relevant apps to purchase. Among these, charts specific to newly released apps showcase recently developed apps in each category. The incidence of being displayed in these charts greatly increases the visibility of not only the new app but also the developer, thereby making it easier for consumers to notice other apps by the same developer. Moreover, with the prevalent cross-advertising design[4] of mobile apps, developers also have opportunities to market their existing apps along with new app releases (Lee et al. 2014). The prominence of a new app increases the exposure of the existing

4 As the major app stores do not allow in-store advertisements, most developers embed links in their apps to advertise other apps in their portfolio.

apps, which are cross-advertised in the focal new app. Since developers are able to choose any app in their portfolio, either within the same category or from a different category, to cross-advertise, popular new apps can promote apps across different categories. Thus, through both quality signaling and discovery facilitator effects, a popular new app is able to redirect consumers' attention to other apps by the same developer regardless of their category relatedness. Hence, we hypothesize that:

Hypothesis 4a (H4a): The popularity of a developer's new app releases is positively associated with the popularity of its existing apps within the same category.

Hypothesis 4b (H4b): The popularity of a developer's new app releases is positively associated with the popularity of its existing apps across different categories.

2.4 Methodology and Results

2.4.1 Data Description

To empirically test our hypotheses, we obtained data on mobile apps in the Apple App Store from Mobilewalla (Datta et al. 2012). This dataset contains both time-invariant and time-varying information on all mobile apps that were released in the Apple App Store between January 2011 and March 2012. The time-invariant information of each app includes the name of the app, developer identity, release date, and category classification. We also have user review ratings of each app on a daily basis, which are time-varying.

2.4.2 The Impact of an App Portfolio on App Quality

2.4.2.1. Variable Definition and Model Specification

As our hypotheses relating to app development evaluate the impacts of app portfolio size and diversity on developers' app quality, the corresponding unit of analysis is at developer level. Prior research suggests that many developers publish only a few apps and they see developing and publishing apps on mobile platforms as fun only (Qiu et al. 2011). As a result, they may not see managing their app portfolios as a critical issue. This observation may confound the objective of our study, which is to provide insights for developers who view developing mobile apps as a business and seek to succeed in the app market. Therefore, we excluded developers who had only one app at the end of our observation period. We also excluded developers who entered the Apple App Store before 2011 since we did not have complete information about them[5].

Since our analyses aim to uncover the impacts of app portfolio size and diversity on developers' app quality, we believe the time granularity of one month is appropriate to capture the changes in developers' app portfolios. Hence, we clustered apps by developer and aggregated each developer's app release history to a monthly level. From the data, we can observe developers' monthly app portfolio compositions as well as the user rating information of each app.

As the valence of consumer reviews influences consumers' perception of product quality (Chevalier et al. 2006; Dellarocas et al. 2007; Duan et al. 2008), we use user rating valence (i.e., average rating score) to measure app quality. Other mobile app studies also used the same rating valence as a proxy

5 As a result, our sample contains information about developers who entered the Apple App Store in since 2011 and had 2 or more apps till March 2012. Our observation period covers a whole year and we are able to capture different segments of developers because the launch of the much anticipated iPhone 4 in late 2010 greatly invigorated the supply of mobile developers' output of apps in the market. Many small- to mid-sized developers joined the Apple App Store in 2011.

for app quality (Lee et al. 2014). In the Apple App Store, users who have installed an app are allowed to evaluate the app by assigning a score from 1 to 5, with an increment of 1. As there are multiple apps in a developer's app portfolio, we averaged the values of user rating valence across apps and used it as our dependent variable (DV). As there are a large proportion of apps in the store that do not receive any user ratings, some developers may not have all apps being rated in a particular month. To deal with the missing values of app rating valence, we imputed the missing rating valence of an app with the average rating valance of its developer's other apps in that developer-month, followed by the calculation of average rating valence over the developer's app portfolio. For developers who did not have any apps being rated in that developer-month, their average user rating valence is missing.

The key independent variables (IVs) related to our hypotheses are the size and diversity of an app portfolio. The size of an app portfolio is measured as the cumulative number of apps released by a developer till a given month. To measure the diversity of an app portfolio, we used entropy (as shown in Equations (1) and (2)), which is more sensitive to small changes than other alternative measurements and has been recommended in prior studies (Jacquemin et al. 1979). The Apple App Store allows an app to be classified under multiple categories. If an app belongs to more than one category, its production may need development skills for different functions. We used app-category combinations to measure a developer's effort distribution. We define each distinct pair of category and app in a developer's app portfolio as a combination. P_s captures the ratio of the number of combinations that belongs to category s to all the combinations in the developer's app portfolio. The entropy is the sum of ($-P_s * lnP_s$) over the non-empty categories.

$$CategoryEntropy = -\sum_{s \in Z} \left(P_s * lnP_s \right) \quad (1)$$

$$P_s = \sum_{j \in AP} 1(s \in C_j) \Big/ \sum_{j \in AP} count(C_j) \quad (2)$$

where Z is the predefined app category set in the Apple App Store, AP is the app portfolio the developer has. C_j *is the set of categories app j belongs to,* $count(C_j)$ *denotes the number of categories app j belongs to.* $\mathbf{1}(s \in C_j)$ *equals 1 if app j belongs to category s, and 0 otherwise.*

To illustrate the calculation of diversity, consider a developer who has two apps, namely App A and App B. Suppose that App A belongs to Category 1 and Category 2, while App B belongs to Category 2 only. We can show that 1/3 of this developer's work is related to Category 1, i.e., $P_{Category1} = 1/3$, and the other 2/3 is related to Category 2, i.e., $P_{Category2} = 2/3$. The entropy of this developer's app portfolio is thus $-(P_{Category1} * ln(P_{Category1}) + P_{Category2} * ln(P_{Category2})) = 0.64$.

Developers have huge freedom in determining their app portfolio. The portfolio diversification decision observed in our dataset might be a result of their intentional choices based on performance. In order to obtain unbiased estimation of the impacts of app portfolio diversity, we would like to create a sample with developers who had similar propensity to diversify app portfolio, but some diversified (treatment group) and some did not (control group). The diversification status of a developer is defined based on the number of app categories he/she involved in at the end of our observation period. If the developer engaged in more than 2 app categories[6], his/her divarication status is

[6] The Apple App Store allows an app to be categorized in up to two categories. If developers concentrate on the categories where they released their first app, the number of categories they are working in would not exceed two. In such a case, this can be considered as non-diversification, since they remain focused on their initial category scope.

1; otherwise, it is 0. We relied on the method (Xu et al. 2015) of dynamic propensity score matching (PSM) to construct such a sample. Differing form the procedure of static PSM, dynamic PSM makes use of time varying information of the treatment group and control group. That is, the propensity to diversify is calculated every month, allowing developers with a diversified app portfolio to be matched with different developers with a non-diversified app portfolio over time. We modeled developers' propensity to diversify app portfolio as a Probit process, which is shown in Equations (3) to (5). Equation (3) captures the factors that may influence a developer's propensity to diversify, including app portfolio size, whether the developer was a company, tenure of the developer, accumulated number of app user ratings the developer received, indicators of categories the developer worked in and a set of time dummies accounting for the time trends. Variable definitions and operationalization can be found in Table 2-1.

$$\begin{aligned} Diversification_{it}^{*} &= \Lambda \mathbf{Z}_{it} \\ &= \omega_1 APSize_{it} + \omega_2 Company_i + \omega_3 Tenure_{it} \\ &\quad + \omega_4 ln(AccRatingVolume_{it}) + \theta CategoryIndicators_{it} \\ &\quad + \gamma MonthDummies_t + \kappa YearDummy_t + \nu_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} &Diversification_{it} = 1 \text{ if } Diversification_{it}^{*} > 0, \\ &\text{and } Diversification_{it} = 0 \text{ otherwise} \end{aligned} \tag{4}$$

$$\begin{aligned} &Prob(Diversification_{it} = 1 \mid \mathbf{Z}_{it}) = \Phi(\Lambda \mathbf{Z}_{it}) \\ &Prob(Diversification_{it} = 0 \mid \mathbf{Z}_{it}) = 1 - \Phi(\Lambda \mathbf{Z}_{it}) \end{aligned} \tag{5}$$

where subscript i denotes developer and subscript t denotes month. $\mathbf{Z}_{i,t}$ *is a vector of covariates shown in Equation (3).*

Table 2-1 Variable Definitions and Operationalization

Variable	Definition and Operationalization
$Diversification_{it}$	=1, if developer *i* released apps in more than 2 categories at the end of our observation period; =0, otherwise.

OneAppRated$_{it}$	=1, if developer *i* has at least one app being rated in month *t*; =0, otherwise.
AvgRatingValence$_{it}$	Average user rating score of the apps in developer *i's* portfolio in month *t*, calculated using the rating scores on the last day of month *t*. For apps without any user ratings in developer *i's* portfolio, we imputed the value with the average rating score of other rated apps in developer *i's* portfolio. If all apps in developer *i's* portfolio do not have any user rating, this variable is coded as missing.
APSize$_{it}$	Total number of apps in developer *i's* portfolio in month *t*, calculated using developer *i*'s app portfolio on the last day of month *t*.
APDiversity$_{it}$	Category entropy of developer *i*'s portfolio in month *t*, calculated using Equation (1) and Equation (2).
AccAppSize$_{it}$	Accumulated size (in MB) of apps developed by developer *i* till month *t*.
AccRatingVolume$_{it}$	Accumulated number of app user ratings developer *i* had received till month *t*.
Company$_{i}$	Indicator for a company-based developer (=1, company developer; =0, individual developer). We classified developers based on the last word of their names (most company-based developers' names end with words such as "Ltd.", "Inc.", etc.) and their portfolio size, which is no less than 3 apps.
FreeRatio$_{it}$	Number of free apps divided by the total number of apps in developer *i's* portfolio in month *t*. Free apps are apps with zero average price in month *t*.
AvgPrice$_{it}$	Average price of all the apps in developer *i's* portfolio in month *t*. We first calculated the average price of each app in month *t*, and then computed the mean value of the average prices of apps in developer *i's* portfolio.
PromotionRatio$_{it}$	Number of apps that have been promoted divided by the total number of apps in developer *i*'s portfolio in month *t*. We first obtained the standard deviation of prices of each app in month *t*. Apps with non-zero price standard deviation were considered as having been promoted in month *t*.
AvgVersionNum$_{it}$	Average number of versions an app has in developer *i*'s portfolio in month *t*. We first counted the total number of versions that each app had on the last day of month *t*, then calculated the average number of versions for developer *i*'s apps.
Tenure$_{it}$	Number of months elapsed since developer *i* released the first app till month *t*.
iOSPromotionApps$_{t}$	Number of apps promoted in the Apple App Store in month *t* (in thousands). The operationalization of promoted apps is the same as that of *PromotionRatio*.
iOSAppNum$_{t}$	Total number of apps available in the Apple App Store in month *t*, excluding the new apps (in hundred thousands).
CategoryIndicators$_{it}$	A set of binary variables that indicate which categories developer *i* have released apps to in month *t*.
MonthDummies$_{t}$	A set of dummies capture which calendar month *t* is in.
YearDummy$_{t}$	Year dummy captures which calendar year *t* is in.

We have 16,157 mobile developers with a diversified app portfolio and 17,930 developers without at the end of our observation period. We estimated developers' propensity to have a diversified portfolio in each month based on the above models. Table 2-2 shows the results of propensity score estimation. To reduce bias and keep all developers in the treatment group, the algorithm of 1 nearest-neighbor with replacement has been used (Austin 2010; Stuart 2010). As a result, 16,157 developers in the treatment group were matched by 13,220 developers from the control group.

Table 2-2 Estimation of Propensity Score

VARIABLES	Diversification
APSize	0.040***
	(0.001)
Company	0.365***
	(0.006)
Tenure	0.030***
	(0.001)
ln(AccRatingVolume)	0.004***
	(0.001)
Category Indicators	YES
Month & Year Dummies	YES
Pseudo-R^2	0.170
Observations	306,220

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The matched sample still has observations with missing average rating valence. Previous literature (Anderson 1998) suggests that users with extreme (either bad or good) user experience are more willing to rate a product. As users are self-selected to rate an app, we should account for the impacts of missing app rating valence. Heckman selection model thus is being employed to address the issue (Heckman 1976; Heckman 1979). The selection process is shown in Equations (6) – (8). We contend that developer *i*'s portfolio composition influences the rating status of their app portfolio. Developers who produce more apps or engage in more app categories (i.e., *APSize* and

APDiversity) have higher probability to own rated apps due to more exposure to customers. Developers who have written more codes may produce better apps that are able to attract consumer attention. Furthermore, company developers may have more marketing resources to induce user engagement. We also control for the price level and free ratio of a developer's portfolio. Additionally, users may differ from one category to another in terms of their willingness to rate. Therefore, we have incorporated category indicators in Heckman first-stage selection equation. After modeling the selection of app ratings, we specify an econometric model to capture the factors that affect developer *i*'s app quality, which is shown in Equation (9). Variable definitions and operationalizations are presented in Table 2-1. $\boldsymbol{\alpha}$'s and $\boldsymbol{\beta}$'s are the model coefficients. $v_{it,}$ and ε_{it} are residual errors with standard assumptions. The changes in app portfolios may take time to affect developers' app quality. Hence, all IVs are lagged by one month.

$$\begin{aligned} OneAppRated^{*}_{i,t} &= \Lambda\mathbf{X}_{i,t} \\ &= \alpha_1 APSize_{i,t-1} + \alpha_2 APDiversity_{i,t-1} \\ &\quad +\alpha_3 APSize_{i,t-1} * APDiversity_{i,t-1} \\ &\quad +\alpha_4 ln(AccAppSize_{i,t-1}) + \alpha_5 Company_i + \alpha_6 FreeRatio_{i,t\text{-}1} \\ &\quad +\alpha_7 AvgPrice_{i,t\text{-}1} + \theta CategoryIndicators_{i,t-1} + \nu_{i,t} \end{aligned} \tag{6}$$

$$OneAppRated_{i,t} = 1 \text{ if } OneAppRated^{*}_{i,t} > 0, \text{ and } OneAppRated_{i,t} = 0 \text{ otherwise} \tag{7}$$

$$\begin{aligned} &Prob(OneAppRated_{i,t} = 1 \mid \mathbf{X}_{i,t}) = \Phi(\Lambda\mathbf{X}_{i,t}) \\ &Prob(OneAppRated_{i,t} = 0 \mid \mathbf{X}_{i,t}) = 1 - \Phi(\Lambda\mathbf{X}_{i,t}) \end{aligned} \tag{8}$$

$$\begin{aligned} AvgRatingValence_{i,t} &= \beta_1 APSize_{i,t\text{-}1} + \beta_2 APDiversity_{i,t\text{-}1} + \beta_3 APDiversity_{i,t\text{-}1} * APSize_{i,t\text{-}1} \\ &\quad +\beta_4 Company_i + \beta_5 FreeRatio_{i,t\text{-}1} + \beta_6 AvgPrice_{i,t\text{-}1} \\ &\quad +\beta_7 PromotionRatio_{i,t\text{-}1} + \beta_8 AvgVersionNum_{i,t\text{-}1} + \beta_9 Tenure_{i,t\text{-}1} \\ &\quad +\beta_{10} iOSPromotionApps_{t\text{-}1} + \beta_{11} iOSAppNum_{t\text{-}1} \\ &\quad +\gamma MonthDummies_t + \lambda YearDummy_t + \varepsilon_{i,t} \end{aligned} \tag{9}$$

where subscript i denotes developer and subscript t denotes month. $\boldsymbol{X}_{i,t}$ *is a vector of Heckman first-stage model covariates shown in Equation (6).*

To measure the moderating effect of portfolio size on diversity, we incorporated an interaction term between app portfolio diversity and portfolio size to the model. Moreover, we accounted for other factors that might influence developers' app quality. These control variables are categorized into two groups: *developer-level heterogeneities* (e.g., developer's tenure, average price of developer's apps) and *platform-level competition factors* (e.g., numbers of existing apps and apps being promoted on the platform). In addition, we include month and year dummies to capture the time trends.

Table 2-3 Descriptive Statistics (obs. = 65,146)

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
AvgRatingValence	3.74	0.93	1.00	5.00
APSize	5.73	9.23	1.00	279.00
APDiversity	0.97	0.42	0.00	2.66
AccAppSize	98.93	397.25	0.10	15911.70
Company	0.31	0.46	0.00	1.00
FreeRatio	0.57	0.39	0.00	1.00
AvgPrice	1.20	5.19	0.00	324.99
PromotionRatio	0.03	0.13	0.00	1.00
AvgVersionNum	1.93	1.51	0.50	30.00
Tenure	6.50	3.41	1.00	14.00
iOSPromotionApps (in 1k)	4.87	5.20	0.05	36.83
iOSAppNum (in 100k)	5.42	0.78	3.29	6.38

2.4.2.2 Results and Discussion

The descriptive statistics of all variables in the Heckman second-stage regression equation, namely Equation (9), are shown in Table 2-3. The correlation matrix in Table 2-4 shows that there is one highly correlated variable pair, namely *Tenure* and *iOSAppNum*. If the estimated coefficients of these two variables later are significant, the high correlation only decreases estimator efficiency and will not cause the multicollinearity problem (Wooldridge 2012). Thus, we choose to keep the two variables for now. We employ Heckman selection model to estimate the impacts of the IVs of our research interests and the results are shown under Model (1) in Table 2-5.

The coefficient of *APSize* is not significant in Model (1), and thus does not support H1. The coefficient of *APDiversity* is negative and significantly different from zero, which suggests that app portfolio diversity negatively affects app quality, thus supporting H2a. The interaction term between *APDiversity* and *APSize* is significantly negative. It implies that developers who produce many apps in different categories have worse app quality. Hence, H2b is supported.

Table 2-4 Correlation Matrix

Variable	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***
1. AvgRatingValence	1.00										
2. APSize	-0.12	1.00									
3. APDiversity	-0.10	0.27	1.00								
4. Company	0.00	0.07	0.01	1.00							
5. FreeRatio	0.01	-0.16	-0.09	-0.01	1.00						
6. AvgPrice	0.01	0.02	0.00	0.00	-0.22	1.00					
7. PromotionRatio	0.05	-0.04	-0.04	0.01	-0.18	0.02	1.00				
8. AvgVersionNum	0.06	-0.15	-0.13	-0.02	0.07	0.00	0.13	1.00			
9. Tenure	-0.12	0.16	0.21	0.00	0.02	0.01	-0.09	-0.12	1.00		
10.iOSPromotionApps	-0.01	-0.04	-0.05	0.00	0.01	0.00	0.13	0.10	-0.17	1.00	
11. iOSAppNum	0.03	0.12	0.18	-0.02	0.00	0.00	-0.09	-0.23	0.60	-0.29	1.00

Table 2-5 Estimation Results (Imputed Valance)

	(1) *TotalApps>=2*		(2) *TotalApps>=3*		(3) *TotalApps>=4*	
VARIABLES	Main	Selection	Main	Selection	Main	Selection
APSize	-0.002	0.002	-0.000	0.004	0.001	0.003
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
APDiversity	-0.111***	0.014	-0.093***	0.118***	-0.122***	0.101***
	(0.025)	(0.025)	(0.029)	(0.029)	(0.033)	(0.034)
*APDiversity*APSize*	-0.004*	0.009***	-0.005**	0.006**	-0.004**	0.007**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
FreeRatio	-0.017	0.119***	0.020	0.167***	0.060	0.217***
	(0.026)	(0.022)	(0.032)	(0.028)	(0.039)	(0.033)
AvgPrice	0.001	-0.005**	0.001	-0.005*	0.001	-0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
PromotionRatio	0.226***		0.315***		0.369***	

	(0.043)		(0.053)		(0.067)	
AvgVersionNum	0.035***		0.050***		0.051***	
	(0.006)		(0.008)		(0.011)	
Tenure	-0.054***		-0.047***		-0.039***	
	(0.003)		(0.004)		(0.004)	
iOSPromotionApps	-0.001		-0.001		-0.002	
	(0.002)		(0.002)		(0.003)	
iOSAppNum	0.241***		0.213***		0.195***	
	(0.019)		(0.024)		(0.028)	
ln(AccAppSize)		0.165***		0.177***		0.175***
		(0.006)		(0.008)		(0.009)
Company	0.031	0.124***	0.068***	0.161***	0.071***	0.137***
	(0.021)	(0.019)	(0.023)	(0.021)	(0.027)	(0.025)
Constant	2.757***	-1.121***	2.750***	-1.253***	2.764***	-1.256***
	(0.121)	(0.037)	(0.147)	(0.044)	(0.172)	(0.052)
Category Indicators	NO	YES	NO	YES	NO	YES
Month & Year Dummies	YES	YES	YES	YES	YES	YES
Rho	0.104***		0.103***		0.119***	
	(0.034)		(0.039)		(0.043)	
Log-likelihood	-193989		-136578		-100298	
Censored Obs.	116,661		76,483		51,771	
Uncensored Obs.	65,146		47,359		35,764	
Number of Developers	28,452		16,841		11,351	

Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

A significantly positive coefficient has been observed for *PromotionRatio*, which suggests that developers with more apps on promotion produce apps of higher quality. This result might be driven by our DV operationalization that we used to measure app quality. Users' expectation of app quality may reduce with the price cut and thus they likely rate promoted apps higher. The coefficient of *AvgVersionNum* is significantly positive, indicating that developers who update apps more frequently have better app quality. The negative coefficient of *Tenure* indicates that new developers in the mobile platform produce better apps compared to developers with longer tenures. This might be caused by many dormant developers in the app store, who became less active when their app performance was below their expectation. Moreover, *iOSAppNum*, which measures the competition intensity in the Apple App Store, is positively associated with developers' app quality. Possibly, as the number of competitor apps grew on the platform, mobile developers invested more resources and efforts to improve app quality, resulting in the positive coefficient we observe. The two highly correlated variables *Tenure* and *iOSAppNum* are both significant and therefore multicollinearity is not an issue for this model.

The selection equation investigates which developers are more likely to have rated apps. The results shown in the *Select* Column under Model (1) suggest that developers who produce more apps and at the same time engage in more app categories have higher probability to have rated apps. Developers who have richer development experience, measured by the size of apps produced, are more likely to gain user ratings. Similarly, developers with more free apps, developers pricing apps cheaper and company developers have higher probability to have rated apps.

Next, we modify the thresholds of the total number of apps that a developer has to test the sensitivity of the results to sample constructions. We keep developers who produced three or more apps and conduct the same analysis on them as what we have done on developers who produced two or more apps. The results are shown under Model (2) in Table 2-5. We also apply the same analysis to developers who produced four or more apps, as shown under Model (3) in Table 2-5. The key variables of our research interests in Model (2) and Model (3), namely *APSize, APDiversity* and their interaction term, have the same coefficient signs as those in Model (1). This demonstrates that our results are not sensitive to the choice of the thresholds of total apps owned by a developer. The coefficients of the remaining variables in Model (2) and Model (3) are generally similar to those in Model (1). One place to notice is that Model (2) and Model (3) both suggest that company developers have higher app quality.

Table 2-6 Separated Sample Estimation (Imputed Valance)

	(1) *TotalApps>=2*				(2) *TotalApps>=3*				(3) *TotalApps>=4*			
	Company		Non-Company		Company		Non-Company		Company		Non-Company	
VARIABLES	Main	Selection	Main	Selection	Main	Selection	Main	Selection	Main	Selection	Main	Selection
APSize	0.002	-0.004	-0.006	0.005	0.002	-0.004	-0.002	0.010	0.001	-0.007	-0.000	0.009
	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.005)	(0.007)	(0.004)	(0.006)
APDiversity	-0.052	0.084*	-0.137***	-0.011	-0.052	0.084*	-0.122***	0.135***	-0.114**	0.020	-0.127***	0.140***
	(0.044)	(0.047)	(0.029)	(0.029)	(0.044)	(0.047)	(0.039)	(0.037)	(0.051)	(0.057)	(0.043)	(0.043)
*APDiversity*APSize*	-0.007**	0.014***	-0.002	0.007*	-0.007**	0.014***	-0.003	0.003	-0.005	0.017***	-0.004	0.003
	(0.003)	(0.005)	(0.002)	(0.004)	(0.003)	(0.005)	(0.002)	(0.004)	(0.003)	(0.005)	(0.002)	(0.004)
FreeRatio	-0.100**	0.074*	0.017	0.132***	-0.100**	0.074*	0.116***	0.227***	-0.038	0.100*	0.141***	0.288***
	(0.046)	(0.043)	(0.032)	(0.025)	(0.046)	(0.043)	(0.045)	(0.035)	(0.057)	(0.053)	(0.053)	(0.042)
AvgPrice	0.005**	-0.007**	-0.000	-0.005*	0.005**	-0.007**	-0.001	-0.004	0.009**	-0.008*	-0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
PromotionRatio	0.366***		0.165***		0.366***		0.255***		0.375***		0.354***	
	(0.066)		(0.053)		(0.066)		(0.080)		(0.086)		(0.102)	
AvgVersionNum	0.051***		0.030***		0.051***		0.049***		0.049***		0.054***	
	(0.011)		(0.007)		(0.011)		(0.011)		(0.014)		(0.017)	
Tenure	-0.049***		-0.056***		-0.049***		-0.045***		-0.040***		-0.038***	
	(0.005)		(0.004)		(0.005)		(0.005)		(0.006)		(0.006)	
iOSPromotionApps	-0.004		0.001		-0.004		0.001		-0.005		0.001	
	(0.003)		(0.002)		(0.003)		(0.003)		(0.004)		(0.004)	
iOSAppNum	0.215***		0.251***		0.215***		0.212***		0.203***		0.188***	
	(0.032)		(0.024)		(0.032)		(0.034)		(0.039)		(0.039)	
ln(AccAppSize)		0.180***		0.161***		0.180***		0.173***		0.185***		0.169***
		(0.013)		(0.007)		(0.013)		(0.010)		(0.015)		(0.012)
Constant	2.848***	-1.091***	2.753***	-1.088***	2.848***	-1.091***	2.734***	-1.254***	2.848***	-1.079***	2.760***	-1.274***
	(0.193)	(0.070)	(0.152)	(0.043)	(0.193)	(0.070)	(0.213)	(0.056)	(0.234)	(0.084)	(0.243)	(0.065)
Category Indicators	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Month & Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Rho	0.142***		0.073		0.142***		0.066		0.152**		0.087	
	(0.055)		(0.046)		(0.055)		(0.057)		(0.064)		(0.060)	
Log-likelihood	-55065		-138614		-55065		-81225		-39090		-61006	
Censored Obs.	28,121		88,540		28,121		48,362		18,532		33,239	
Uncensored obs.	20,226		44,920		20,226		27,133		14,704		21,060	
Developers	6,522		21,930		6,522		10,319		4,270		7,081	

Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Analyses in Model (2) and Model (3) show that the quality of apps produced by company developers and non-company developers is significantly different. To better understand the underlying mechanisms, we conduct the same analyses on company developers and non-company developers separately. The results are shown in Table 2-6. As company developers at least have three apps in their app portfolio, the results of Models (1) and (3) are the same. Comparing the results in Table 2-5 and Table 2-6, we can find that the effects of *APDiversity* and the interaction term are largely driven by company and non-company developers respectively. The interaction term between *APSize* and *APDiversity* brings negative impacts to company developers, implying that the negative impact of portfolio diversity on developers' app quality increases in portfolio size. However, the negative impact is not moderated by portfolio size any more for company developers who have four or more apps in their final app portfolio. The change perhaps can be attributed to the removal of company developers with two or three apps from the sample. For these removed developers, the maximum impact of one unit increase in their portfolio diversity is a decrease of 0.021 units (i.e., -0.007 * 3) in their app quality. Comparatively, the marginal effect of portfolio diversity on company developers with four or more apps in their final portfolio is much larger, which is a decrease of 0.114 units in their app quality. This comparison suggests that portfolio diversity has a lesser negative impact on company developers with a smaller app portfolio. In contrast, portfolio diversity has a relatively stable negative impact (i.e., -0.137, -0.122 and -0.127) on non-company developers regardless of their final app portfolio size. The marginal negative effect of portfolio diversity on non-company developers is larger than that on company developers in all the three models. Therefore, an app portfolio with higher diversity incurs more harm to non-company developers than to company developers.

To test the robustness of the results, we operationalized the DV app quality as average rating valence weighted by rating volume, which gives apps with more user ratings in a developer's app portfolio higher weights. Same analyses have been done on this new DV. The results are shown in Table 2-7 and Table 2-8. The directions of the variable coefficients of our research interests are similar to those in Table 2-5 and Table 2-6, recommending a specialized app portfolio for both company and non-company developers.

Table 2-7 Estimation Results (Weighted Valance)

	(1) *TotalApps>=2*		(2) *TotalApps>=3*		(3) *TotalApps>=4*	
VARIABLES	Main	Selection	Main	Selection	Main	Selection
APSize	-0.004	0.002	-0.001	0.004	-0.001	0.003
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
APDiversity	-0.116***	0.014	-0.098***	0.118***	-0.127***	0.101***
	(0.025)	(0.025)	(0.030)	(0.029)	(0.033)	(0.034)
*APDiversity*APSize*	-0.003	0.009***	-0.004*	0.007**	-0.003*	0.007**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
FreeRatio	-0.017	0.119***	0.018	0.167***	0.056	0.217***
	(0.026)	(0.022)	(0.033)	(0.028)	(0.039)	(0.033)
AvgPrice	0.001	-0.005**	0.001	-0.005*	0.001	-0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
PromotionRatio	0.222***		0.309***		0.357***	
	(0.044)		(0.054)		(0.070)	
AvgVersionNum	0.035***		0.049***		0.053***	
	(0.006)		(0.008)		(0.011)	
Tenure	-0.055***		-0.048***		-0.040***	
	(0.003)		(0.004)		(0.004)	
iOSPromotionApps	-0.001		-0.002		-0.002	
	(0.002)		(0.002)		(0.003)	
iOSAppNum	0.243***		0.215***		0.199***	
	(0.019)		(0.024)		(0.028)	
ln(AccAppSize)		0.165***		0.177***		0.175***
		(0.006)		(0.008)		(0.009)
Company	0.025	0.125***	0.065***	0.161***	0.070**	0.137***
	(0.021)	(0.019)	(0.024)	(0.021)	(0.028)	(0.025)
Constant	2.751***	-1.121***	2.742***	-1.253***	2.746***	-1.257***
	(0.122)	(0.037)	(0.150)	(0.044)	(0.175)	(0.052)
Category Indicators	NO	YES	NO	YES	NO	YES
Month & Year Dummies	YES	YES	YES	YES	YES	YES
Rho	0.104***		0.106***		0.117***	
	(0.035)		(0.040)		(0.044)	
Log-likelihood	-194473		-136989		-100633	
Censored Obs.	116,661		76,483		51,771	

Uncensored Obs.	65,146	47,359	35,764
Developers	28,452	16,841	11,351

Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2-8 Separated Sample Estimation (Weighted Valance)

	(1) *TotalApps>=2*				(2) *TotalApps>=3*				(3) *TotalApps>=4*			
	Company		Non-Company		Company		Non-Company		Company		Non-Company	
VARIABLES	Main	Selection	Main	Selection	Main	Selection	Main	Selection	Main	Selection	Main	Selection
APSize	0.002	-0.004	-0.009**	0.005	0.002	-0.004	-0.004	0.010	0.001	-0.007	-0.002	0.009
	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.005)	(0.007)	(0.004)	(0.006)
APDiversity	-0.060	0.084*	-0.141***	-0.011	-0.060	0.084*	-0.126***	0.135***	-0.124**	0.021	-0.129***	0.140***
	(0.045)	(0.047)	(0.029)	(0.029)	(0.045)	(0.047)	(0.039)	(0.037)	(0.051)	(0.057)	(0.044)	(0.043)
*APDiversity*APSize*	-0.007**	0.014***	-0.001	0.007*	-0.007**	0.014***	-0.002	0.003	-0.005	0.017***	-0.002	0.003
	(0.003)	(0.005)	(0.002)	(0.004)	(0.003)	(0.005)	(0.002)	(0.004)	(0.003)	(0.005)	(0.002)	(0.004)
FreeRatio	-0.102**	0.074*	0.017	0.132***	-0.102**	0.074*	0.113**	0.227***	-0.042	0.100*	0.135**	0.288***
	(0.046)	(0.043)	(0.032)	(0.025)	(0.046)	(0.043)	(0.045)	(0.035)	(0.057)	(0.053)	(0.053)	(0.042)
AvgPrice	0.005**	-0.007**	-0.000	-0.005*	0.005**	-0.007**	-0.001	-0.004	0.009**	-0.008*	-0.001	-0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
PromotionRatio	0.363***		0.161***		0.363***		0.247***		0.357***		0.348***	
	(0.069)		(0.054)		(0.069)		(0.081)		(0.091)		(0.105)	
AvgVersionNum	0.053***		0.029***		0.053***		0.046***		0.055***		0.053***	
	(0.012)		(0.007)		(0.012)		(0.012)		(0.015)		(0.017)	
Tenure	-0.050***		-0.056***		-0.050***		-0.046***		-0.041***		-0.040***	
	(0.005)		(0.004)		(0.005)		(0.005)		(0.006)		(0.006)	
iOSPromotionApps	-0.005		0.001		-0.005		0.001		-0.005		0.001	
	(0.003)		(0.002)		(0.003)		(0.003)		(0.004)		(0.004)	
iOSAppNum	0.215***		0.253***		0.215***		0.216***		0.204***		0.194***	
	(0.032)		(0.024)		(0.032)		(0.034)		(0.039)		(0.039)	
ln(AccAppSize)		0.180***		0.161***		0.180***		0.173***		0.185***		0.169***
		(0.013)		(0.007)		(0.013)		(0.010)		(0.015)		(0.012)
Constant	2.843***	-1.091***	2.747***	-1.088***	2.843***	-1.091***	2.728***	-1.255***	2.838***	-1.079***	2.745***	-1.275***
	(0.198)	(0.070)	(0.153)	(0.043)	(0.198)	(0.070)	(0.216)	(0.056)	(0.241)	(0.084)	(0.247)	(0.065)
Category Indicators	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Month & Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Rho	0.143**		0.069		0.143**		0.066		0.152**		0.079	
	(0.057)		(0.046)		(0.057)		(0.059)		(0.066)		(0.062)	
Log-likelihood	-55321		-138851		-55321		-81390		-39284		-61156	
Censored Obs.	28,121		88,540		28,121		48,362		18,532		33,239	
Unensored Obs.	20,226		44,920		20,226		27,133		14,704		21,060	
Developers	6,522		21,930		6,522		10,319		4,270		7,081	

Clustered standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

2.4.3 The Impact of an App Portfolio on App Popularity

2.4.3.1 Variable Definitions and Model Specification

In this section, we seek to uncover the effect of category assortment of developers' portfolios on app popularity. Basically, we evaluate how the popularity of existing mobile apps impacts the popularity of a new app by the same developer, and whether the new app also influences the popularity of existing apps. To examine the popularity spillover effects between existing apps and a new app, we categorized each developer's existing apps into two groups. One group contains apps that are in the same category as the focal new app, and the other group contains apps that belong to different categories. Since the popularity of the new and existing apps may concurrently influence each other, a simultaneous equations system, consisting of Equations (10), (11) and (12), is proposed to evaluate the effects.

$$\begin{aligned} ln(RatingVol_{it}) = {} & \alpha_i + \beta_1 ln(SameCatRatingVol_{it}) + \beta_2 ln(DifCatRatingVol_{it}) \\ & + \beta_3 ln(SameCatNewRatingVol_{it}) + \beta_4 ln(DifCatNewRatingVol_{it}) \\ & + \beta_5 ln(SameCatApps_{it}) + \beta_6 ln(DifCatApps_{it}) \\ & + \beta_7 ln(SameCatNewApps_{it}) + \beta_8 ln(DifCatNewApps_{it}) + \beta_9 Free_{it} \\ & + \beta_{10} Price_{it} + \beta_{11} RatingVal_{it} + \beta_{12} MissingRatingVal_{it} \\ & + \beta_{13} Promotion_{it} + \beta_{14} ln(NewAppsInCat_{it}) + WeekDummies + \varepsilon_{it} \end{aligned} \tag{10}$$

$$\begin{aligned} ln(SameCatRatingVol_{it}) = {} & \kappa_i + \theta_1 ln(RatingVol_{it}) + \theta_2 SameCatFreePerc_{it} \\ & + \theta_3 SameCatPrice_{it} + \theta_4 SameCatSize_{it} \\ & + \theta_5 SameCatRatingVal_{it} \\ & + \theta_6 MissingSameCatRatingVal_{it} \\ & + WeekDummies + \nu_{it} \end{aligned} \tag{11}$$

$$\begin{aligned} ln(DifCatRatingVol_{it}) = {} & \eta_i + \varphi_1 ln(RatingVol_{it}) + \varphi_2 DifCatFreePerc_{it} \\ & + \varphi_3 DifCatPrice_{it} + \varphi_4 DifCatSize_{it} \\ & + \varphi_5 DifCatRatingVal_{it} \\ & + \varphi_6 MissingDifCatRatingVal_{it} \\ & + WeekDummies + \mu_{it} \end{aligned} \tag{12}$$

where i denotes the new app and t denotes the number of weeks after the release of app i. α_i, κ_i *and* η_i *capture the time-invariant unobserved heterogeneities of the new app, the existing apps in the same category as the new app, and the* *existing apps in different categories, respectively.* β_1, β_2, θ_1 and φ_1 *are the parameters of our interest.*

As the volume of consumer reviews, namely the number of reviews received by a product, reflects the popularity of the product (Forman et al. 2008), we use the volume of user ratings of an app to measure its popularity. Lee et al. (2014) also used this measure to capture the latent app popularity. The popularity of a new app is measured by *RatingVol* , which records the volume of user ratings for a developer's new app. *SameCatRatingVol* measures the average rating volume of the developer's existing apps in the same category as the new app. Similarly, *DifCatRatingVol* captures the average rating volume of the developer's existing apps that are in different categories. Equation (10) models the popularity spillover from the existing apps, both within the same and across different categories, to the new app, whereas Equations (11) and (12) assess the impacts of the new app's popularity on the popularity of existing apps, again within the same and across different categories. In our simultaneous equations system, we control for the quality of the new app as well as that of existing apps by accounting for apps' rating valence. As some apps did not have any app rating, indicators for missing app ratings have been incorporated into the econometric models to account for the variation. Hence, popularity spillover between the new app and existing apps can be interpreted as quality-adjusted spillover of popularity. Apart from controlling for quality, we control for a number of other relevant factors that might play a role in these relationships. Each equation contains a set of control variables. The three sets of control variables have overlaps but are not exactly the same, ensuring the identifiability of the simultaneous equations system (Wooldridge 2002a; Wooldridge 2002b). We provide definitions and descriptive statistics of the relevant variables in Table 2-9 and Table 2-10, respectively. Volumes of user ratings and app numbers have been log-transformed due to high skewness, which can be observed in Table 2-10. Therefore, the coefficient estimates of these variables can be interpreted as elasticities.

Table 2-9 Variable Definition and Operationalization

Variable	**Definition**
$RatingVol_{it}$	Total number of user ratings for new app *i* till week *t*.
$SameCatRatingVol_{it}$	Average number of user ratings till week *t* for existing apps by the developer who developed the new app *i*, and that are in the same category as the new app *i*.
$DifCatRatingVol_{it}$	Average number of user ratings till week *t* for existing apps by the developer who developed the new app *i*, and that are in different categories from that of the new app *i*.
$SameCatNewRatingVol_{it}$	Average number of user ratings till week *t* for other new apps by the developer who developed the new app *i*, and that are in the same category as the new app *i*.
$DifCatNewRatingVol_{it}$	Average number of user ratings till week *t* for other new apps by the developer who developed the new app *i*, and that are in different categories from that of the new app *i*.
$SameCatApps_{it}$	Cumulative number of existing apps till week *t*, that are released by the developer who developed the new app *i*, and which are in the same category as the new app *i*.
$DifCatApps_{it}$	Cumulative number of existing apps till week *t*, that are released by the developer who developed the new app *i*, and which are in different categories from that of the new app *i*.
$SameCatNewApps_{it}$	Total number of other new apps in week *t* released by the developer who developed the new app *i*, and which are in the same category as the new app *i*.
$DifCatNewApps_{it}$	Total number of other new apps in week *t* released by the developer who developed the new app *i*, and which are in different categories from that of the new app *i*.
$Free_{it}$	= 1 if new app *i* is free; = 0 otherwise.
$Price_{it}$	Price of new app *i* in week *t*.
$RatingVal_{it}$	Average user rating score of the new app *i* at the end of week *t*. If app *i* did not have any user rating, this variable is coded as 0.
$MissingRatingVal_{it}$	=1, if app *i* did not have any user rating at the end of week *t;* =0, otherwise.
$Promotion_{it}$	= 1 if new app *i* was on promotion in week *t*, = 0 otherwise. New app *i* is considered as being promoted if its price standard deviation in week *t* is non-zero.
$NewAppsInCat_{it}$	Total number of new apps that were released by all developers in week *t* that are in the same category as new app *i*.

SameCatFreePerc$_{it}$	Percentage of free existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in the same category as the new app *i*.
DifCatFreePerc$_{it}$	Percentage of free existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in different categories from that of the new app *i*.
SameCatPrice$_{it}$	Average price of existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in the same category as the new app *i*.
DifCatPrice$_{it}$	Average price of existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in different categories from that of the new app *i*.
SameCatSize$_{it}$	Average size (in MB) of existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in the same category as the new app *i*.
DifCatSize$_{it}$	Average size (in MB) of existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in different categories from that of the new app *i*.
SameCatRatingVal$_{it}$	Average user rating valence of existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in the same category as the new app *i*. For existing apps without any user rating, we imputed their rating valences with the average user rating valence of the developer's other rated apps in the same category as the new app *i*. The calculation of average rating valence was after the imputation if any. If the developer's existing apps in the same category as the new app *i* were all non-rated, this variable is coded as 0.
MissingSameCatRatingVal$_{it}$	=1, if the developer's existing apps in the same category as the focal new app *i* in week *t* are all non-rated; =0, otherwise.
DifCatRatingVal$_{it}$	Average user rating valence of existing apps in week *t* in the portfolio of the developer who released the new app *i*, and that are in different categories from that of the new app *i*. For existing apps without any user rating, we imputed their rating valences with the average user rating valence of the developer's other rated apps in different categories from that of the new app *i*. The calculation of average rating valence was after the imputation if any. If the developer's existing apps in different categories from that of the new app *i* were all non-rated, this variable is coded as 0.
MissingDifCatRatingVal$_{it}$	=1, if the developer's existing apps in different categories from that of the new app *i* in week *t* are all non-rated; =0, otherwise.
WeekDummies$_{t}$	A set of week dummies to capture time trends.

Table 2-10 Descriptive Statistics (obs. = 38,154)

Variable	Mean	Std. Dev.	Min	Max
RatingVol	85.25	1967.86	0.00	111085
SameCatRatingVol	228.46	1596.03	0.00	69609
DifCatRatingVol	36.46	643.47	0.00	32612

SameCatNewRatingVol	9.11	305.27	0.00	20212.70
DifCatNewRatingVol	0.14	5.55	0.00	777.50
SameCatApps	20.49	53.95	0.00	653.00
DifCatApps	14.60	56.85	0.00	706.00
SameCatNewApps	0.98	4.05	0.00	67.00
DifCatNewApps	0.78	4.85	0.00	80.00
Free	0.49	0.50	0.00	1.00
Price	1.80	9.70	0.00	499.99
Promotion	0.01	0.09	0.00	1.00
RatingVal	1.00	1.72	0.00	5.00
MissingRatingVal	0.73	0.44	0.00	1.00
NewAppsInCat	875.83	469.93	12.00	2850.00
SameCatFreePerc	0.40	0.41	0.00	1.00
SameCatPrice	2.36	13.36	0.00	466.66
SameCatSize	16.85	58.67	0.00	1413.12
SameCatRatingVal	1.33	2.06	0.00	5.00
MissingSameCatRatingVal	0.70	0.46	0.00	1.00
DifCatFreePerc	0.23	0.37	0.00	1.00
DifCatPrice	0.70	1.82	0.00	44.24
DifCatSize	5.97	22.10	0.00	592.00
DifCatRatingVal	0.68	2.06	0.00	5.00
MissingDifCatRatingVal	0.84	0.37	0.00	1.00

2.4.3.2 Results and Discussion

We focus on new mobile apps released in 2011 to examine the popularity spillover between developers' existing and new apps. More than 200,000 new apps were released by 82,010 developers in 2011. From these large numbers of new apps and different developers, we draw a random sample of 3,396 developers, which comprised about 4.1% of the entire developer population. Our unit of analysis is application-week pair. We consider an app in the first four weeks after its release as a new app. After that we treat the app as part of existing apps. We choose the first four weeks as our observation period for new apps because performance in the early period after the launch has been recognized as the most critical period for the success of a new app (Sangaralingam et al. 2012). As the popularity of existing and new apps influences each other simultaneously, the three-stage least squares estimator has been used to estimate the system of equations (10), (11) and (12). The model estimation results are shown in Table 2-11.

Table 2-11 Estimation Results of New App Releases

Variable		Model (10) Focal New App	Model (11) Apps in the Same Category	Model (12) Apps in Diff. Categories
Portfolio-level Factors	*SameCatRatingVol*	0.098*** (0.017)		
	DifCatRatingVol	0.094*** (0.032)		
	SameCatNewRatingVol	-0.054*** (0.003)		
	DifCatNewRatingVol	0.007 (0.007)		
	RatingVol		0.553*** (0.048)	0.035 (0.025)
	SameCatApps	0.018*** (0.006)		
	DifCatApps	-0.078*** (0.014)		
	SameCatNewApps	0.040*** (0.003)		
	DifCatNewApps	-0.016*** (0.005)		
Own Characteristics	*Free*	0.046 (0.029)		
	SameCatFreePerc		0.373*** (0.014)	
	DifCatFreePerc			0.615*** (0.012)
	Price	-0.012 (0.009)		
	SameCatPrice		0.004*** (0.000)	
	DifCatPrice			0.058*** (0.002)

	SameCatSize		0.002*** (0.000)	
	DifCatSize			-0.001*** (0.000)
	RatingVal	0.050*** (0.012)		
	MissingRatingVal	-0.173** (0.075)		
	SameCatRatingVal		0.012** (0.006)	
	MissingSameCatRatingVal		-0.180*** (0.024)	
	DifCatRatingVal			0.032*** (0.004)
	MissingDifCatRatingVal			-0.008 (0.017)
	Promotion	0.146*** (0.026)		
Competition Intensity	*NewAppsInCat*	-0.077*** (0.019)		
Constant		0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Week Dummies		Yes	Yes	Yes
R-squared		0.229	0.152	0.227

Notes: 1. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
2. Number of observations = 38,154, number of new apps = 9,976.
3. A fixed-effects estimator is utilized to account for app-specific heterogeneity.

The coefficient of *SameCatRatingVol* is significantly positive, suggesting that existing apps in the same category have a positive spillover to the focal new app in terms of popularity. A one percent increase in the popularity of these existing apps translates into a 0.098 percent increase in the new app's popularity. H3a is thus supported. The coefficient of *DifCatRatingVol* is also significantly positive, suggesting a popularity spillover from existing apps to the new app across categories. H3b is unsupported. *RatingVol* has a significantly positive coefficient in Model (11), indicating that the popularity of the new app boosts the popularity of the same developer's existing apps in the same category. However, the coefficient of *RatingVol* in Model (12) is insignificant and fails to support the popularity spillover from the new app to existing apps across categories. Therefore, H4a is supported but H4b is not. Combining H3a and H4a together, we can find a positive popularity reinforcement loop between a new app and the existing apps within the same category. Interestingly, the popularity spillover from the new app to existing apps within category is much larger than the effect in the reverse direction (i.e., 0.553 vs. 0.098). We conducted a t-test (Baum 2006) to formally test the relative magnitude of the effects and it confirms a difference of 0.455 between the two coefficients with a statistically significant z value of 8.94.

Differing from our expectation, consumers extend the popularity of existing apps to the new app by the same developer regardless of the category relatedness between the existing and new apps, whereas the popularity of the new app only spillovers to existing apps within the same category. This might be caused by the nature of brand equity, which refers to the value and a set of liabilities linked to a brand name or symbols (Aaker 1991). High brand equity increases consumers' confidence in product quality and makes consumers loyal to the products, even across markets (Aaker 1996). Thus, popular existing apps enhance a developer's brand equity, which helps consumers to better evaluate and diagnose a new app's quality even across categories. As brand equity is more of a forward marketing metric (Petersen et al. 2009), consumers more rely on the knowledge embedded in a brand to assess future products. Thus, the popularity of a new app does not necessarily boost existing apps' popularity from the perspective of brand equality. Instead, relevance between products may play an important role in transferring consumers' favor of one product to another (Hui et al. 2003). That is, the popularity spillover effect from the new app to existing apps is influenced by their similarity.

Therefore, we observed a positive popularity carryover effect from the new app to existing apps within the same category but not across categories.

2.5 Discussion and Implications

Our study investigates the impacts of developers' portfolio choices and market characteristics on their app performance in the context of the Apple App Store. Since app quality and app popularity, as perceived by consumers, are crucial elements of success for developers in the mobile app markets, we focus on these latent performance variables. For app portfolio management, we first examine the influence of portfolio size and portfolio diversity on app quality. Our empirical result on the relationship between portfolio size and quality does not support our contention that the more apps a developer has amassed in its portfolio, the higher the average quality of its apps would be. This finding implies that learning by doing does not necessarily translate into excellence in app development. This unexpected result can be explained as follows. Unlike more structured tasks, such as in the manufacturing and service sectors, software development is knowledge intensive and requires a higher cognitive capacity (Boh et al. 2007). Simple repetition without planned summarization, abstraction and contemplation may not be useful for quality improvement of mobile apps. For example, releasing several "copycat" apps quickly into the market with a hope that at least one of them would be a success cannot be the right strategy for developers. This wishful thinking leaves insufficient room for developers to carefully evaluate the flaws and shortcomings of their apps and to take the appropriate corrective actions to improve quality. Hence, ample experience in publishing apps does not necessarily lead to quality advances.

Our results show that the diversity of a developer's app portfolio negatively influences the developer's app quality, and this negative effect further exacerbates with a larger app portfolio size. Most app developers are small-scale entrepreneurs or individuals with limited resources. It is difficult for them to handle development tasks of apps with distinct functionalities, especially when they have a relatively large app portfolio. Even company developers are unable to benefit from a diversified app portfolio though they bear smaller negative impacts brought by portfolio diversity compared with non-company developers. Hence, our findings suggest that it is better for mobile developers to concentrate on as few app categories as possible. The findings in this study greatly differ from those in the study by Lee et al. (2014), who suggest that extending app portfolio to more app categories improves developers' performance. Different ways of sample construction might be the reason for the disparity. We include almost all developers who joined iOS between January 2011 and March 2012, except those not interested in publishing apps as a business. However, Lee et al. (2014) only account for developers who have top ranked apps. It is fair to suspect the existence of reverse causality of the relationship between app portfolio diversity and developer performance. Namely, successful developers are more likely to diversify their app portfolios in order to reach more customers.

Our results reveal that a developer's existing and new apps can mutually influence each other's popularity due to a spillover effect, but this effect is contingent on the direction of influence (i.e., from existing apps to new apps or from new apps to existing apps) and category relatedness between apps. . For newly released apps, consumers' usage experiences with existing apps provide a good reference for them to infer the quality of new apps released by the same developer. Hence, users extend their prior interactions with the developer's app portfolio to the recently released apps in the process of resolving the initial uncertainty. Such impact exists regardless of whether the new app is in the same category as existing apps or not. Our results also suggest that consumers' positive experience with the new apps subsequently spillovers into existing apps in the same category. Hence, there is a positive reinforcement loop between existing apps and new apps in the same category in terms of popularity, creating a virtuous cycle. One important implication is that developers can use existing apps, which are in the same category as new apps, as a vehicle to promote the new apps. The new apps, in turn, enable users to discover the existing apps of the developers and this effect is much larger than the spillover in the reverse direction. For apps across categories, we only find a positive popularity spillover from existing apps to new apps, but no effect in the other way around. Thus, releasing apps to the same category enables popularity synergies among apps in a portfolio. Taken together, our findings on the popularity spillover effects between the new and existing apps within and across app categories indirectly support our claim on app production that focusing on fewer categories is conducive for developers in cultivating their core competencies in order to improve product quality.

This study contributes to the literature in the following ways. Our work extends the study of portfolio management from traditional industries, such as manufacturing, to an emerging mobile app industry, helping us in understanding how portfolio management choices influence developers' performance in this new market of the digital economy. Our results indicate that extending the scope of an app portfolio without a proper scale does more harm than good for the app quality. Hence, mobile developers are advised to focus on fewer app categories to make the best use of their limited tangible and intangible resources.

Our study sheds light on how app portfolio management benefits from the branding effect in terms of signaling a developer's reputation on the popularity of mobile apps. We provide strong evidence that users draw quality inferences from existing apps to new apps irrespective of category relatedness. Interestingly, such a spillover effect in terms of popularity also works from new apps to existing apps, but only available within the same category. Furthermore, the popularity spillover from new apps to the existing apps within the same category is substantially larger (i.e., more than five times) than the effect in the reverse direction.

This study offers several important insights for practitioners. While the proliferation of electronic exchanges such as eBay, Taobao for physical goods and the Apple App Store and Google Play for information goods, provides many small- and medium-sized enterprises with ample business opportunities, these online exchanges have been criticized as being highly overcrowded, hypercompetitive and lacking viability for newcomers. Our study suggests that fostering core competencies is crucial for mobile app developers to cope with the stiff competition. Instead of engaging in many categories to appeal to different market niches, focusing app development on fewer categories enables developers to utilize their limited resources more effectively.

In addition, app developers should take advantage of popularity spillovers between existing and new apps while managing their portfolio. If mobile app developers have a well-received app, releasing a new app in the same category as the successful app increases users' receptivity to the new app. Releasing a new app is also a good way to attract new customers, whose attention may subsequently be directed to developers' existing apps. This attention-direction effect from new apps to existing apps is only available within the same category. Hence, developers should harness the power of mutual interactions between existing apps and new apps in choosing what categories of apps to develop in their portfolio. Combining the impacts of app portfolio on app quality, developers are advised to release apps in the same category to reduce the adverse effects brought by category diversification and to benefit from the maximum spillover effect between new and existing apps.

Furthermore, the popularity spillovers between existing and new apps have implications for developers' app release calendar as well. While mobile app developers aim to maximize market shares for their apps with timely app releases, they also need to minimize releases of premature, buggy apps. Releasing an app early may succeed in preempting potential competition, but the ensuing app quality may not be guaranteed as successful due to shortened development cycles. Fortunately, mobile app stores allow developers to update their existing apps by releasing new versions. Under such circumstances, releasing an app early and marketing it along with the release of other new apps in the same category later, offers developers extra time to refine and improve the app. Early release of apps may decrease the extent of potential competition and yet help to shape users' preferences in favor of the early entrant. Once an existing app is capable of providing superior user experiences, the app developer can cross-advertise it with its new app releases. This asynchronous product release and marketing plan can be a feasible approach for mobile app developers' new product strategies.

2.6 Conclusions

In this study, we assess the impacts of app portfolio management strategies on developers' performance. Specifically, we examine the influence of app category assortment on developers' app quality and popularity using a large dataset from the Apple App Store. Our analyses reveal a number of novel and insightful results. We find that, unlike our expectations, portfolio size does not directly influence the quality of apps released by developers. Our results reveal that increasing the diversity of an app portfolio negatively impacts the quality of developers' apps. Hence, utilizing their limited resources on a narrow production scope initially not only increases specialization in app development but also brings about quality improvements. We also show that the popularity of existing apps of a developer positively influences the popularity of its new apps both within and across categories. Interestingly, the popularity of a developer's new app also promotes the popularity of its existing apps within the same category. Therefore, a new app release not only expands a developers' app portfolio but also facilitates the discovery of the developer's existing apps in the same category as the new app. Overall, we conclude that there is a positive reinforcement loop between the existing apps and the new apps of a developer in terms of popularity spillover, thus creating a virtuous cycle.

Our study is not without limitations. First, we used the category classification scheme defined by the Apple App Store to quantify the diversity of developers' app portfolios. The classification of each app under available categories is determined by developers. It may reflect developers' perception of category affiliation of their apps. It may also be a result of developers' intentional marketing strategies. For instance, some developers may categorize their apps into popular categories (e.g., Games, Entertainment) rather than the most relevant ones so as to reach a possibly larger user base. To the extent that a large number of developers follow deceiving practices in categorizing their apps, our results should be taken with some caution. Second, although we controlled for portfolio-level and market-level characteristics, developers' portfolio management strategies may also be influenced by factors that we cannot observe, such as the size of the development team, experience levels of team members and funding conditions. Though we have used dynamic propensity score matching and Heckman selection model to address the endogeneity of portfolio diversity and the censoring issue of app ratings respectively, the findings in the current study are more of associations rather than causations due to our inability to control for these unobserved factors. Finally, we investigated the impacts of portfolio-relevant factors such as size and diversity on app quality and app popularity. Although these two quantities are important metrics for developers, app downloads and revenues from app sales are probably the primary focus of developers. Since the Apple App Store keeps app downloads and revenue data confidential, we are unable to access this crucial information, which is also acknowledged by other studies (e.g., Liu et al. 2012; Zhong et al. 2013). Though Garg et al. (2013) proposed a method to infer app downloads from daily rankings, this method is not useful for unranked apps, which is the case for most apps in our dataset. Instead, we relied on user ratings to measure developers' latent performance. Nevertheless, future studies would immensely benefit from proprietary app download or sales data, if they become available. Despite these limitations, we hope that our study would pave the way for further research to study the success factors in the mobile app markets.

CHAPTER 3. STUDY II
– TARGETED ADVERTISING OUTLETS

3.1 Introduction

According to the InteractiveAdvertisingBureau (2015), 2014 has been a record-setting year for digital advertisement (ad) revenues in the United States. Marketers' ad spending on mobile, digital videos, social media, and search engines all surpassed past records, indicating the rapidly soaring importance of digital marketing in the modern business landscape. Continuing with this upward trend, digital ad spending worldwide is estimated to hit $200 billion this year (Moyo 2015). One reason for firms' growing preference for online advertising is its targetability. The increasingly sophisticated and advanced information technologies enable advertisers to target their customers more accurately and track customers' click histories in real-time (Goldfarb et al. 2011b; Hu et al. 2014). The other reason includes its wide availability and performance-based pricing (Asdemir et al. 2012; Feng et al. 2012), which greatly reduce the entry barriers and ease the marketing activities for small business owners such as the e-commerce entrepreneurs.

As a vehicle to attract consumers' attention, targeted advertisements can be shown in various contexts when people are surfing online. Sponsored search advertising (e.g., Chan et al. 2011; Rutz et al. 2011b) is one of the most popular ad forms that utilize targeting techniques. Other application contexts include contextual banner advertisements (e.g., Goldfarb et al. 2011a; Yeun Chun et al. 2014), customer retargeting (e.g., Bleier et al. 2015; Lambrecht et al. 2013) and others. The e-commerce giants like Amazon, eBay and Taobao provide targeted advertising in many outlets[7] both within and beyond the e-commerce websites, where consumers engage in different online activities such as searching for product information or reading news. However, the impacts of advertisements in these different outlets on consumers' product demand are still an open question. Without such knowledge, it is difficult for advertisers, especially emerging online entrepreneurs whose marketing budgets are limited, to plan their advertising portfolios according to their specific needs.

Unlike the advertisements in traditional media such as television, magazines and outdoor media, which often involve intricate designing by professional advertising studios, online targeted advertisements can be much simpler. The extreme case only contains a textual ad copy, which is the prevalent form for sponsored search advertising (Rutz et al. 2011b). Ad copy is an important element that influences ad viewers' responses to the advertisement (Agarwal et al. 2011; Elder et al. 2010). Advertisers can include various types of information in the ad copy. Understanding consumers' responses to the information in the ad copy would be of great value for them to design an effective ad. Various types of information can be included in an ad copy, such as price, discount information, design information and even call for action (Jacobson 2011; Rutz et al. 2011b). As the most fundamental factor of a transaction, price directly determines the utility that consumers derive from a deal (Mas-Colell et al. 1995). As a result, price related information in the ad copy would be eye catching and serve as a stimulus to drive purchases

[7] Advertising outlets are the places that support ad display to advertisers' prospective consumers. They can be either individual websites such as New York Times, Amazon and Google, or a set of places that share similar properties (e.g., the bottom part of product information pages in Amazon). Advertising outlets in this study refer to the second type.

(Google 2015b; Pechmann 1996). However, the varying impacts of such information in the ad copy in different online targeted advertising outlets on consumer responses have not been addressed by the previous literature. All these unsolved problems motivate us to examine the research questions below:

(1) How and to what extent do online targeted advertisements in different advertising outlets influence the product demand in platform-based e-commerce markets?

(2) How does the price related information (i.e., price discount and free delivery information) in the ad copy influence the performance of these online targeted advertisements in different advertising outlets?

To answer these questions, we focus our study on an e-commerce brand of female leatheroid apparel in Taobao, which is the largest platform-based e-commerce website in China (iResearch 2012). Taobao has an advanced and mature targeted advertising system, Zhitongche[8] that provides Taobao sellers with various choices to market their stores or products both within and beyond Taobao. There are four outlets advertisers of Zhitongche can choose from, i.e., keyword search advertising, category search advertising, internal banner advertising and external banner advertising. Advertisers can select any combination (keyword search advertising is mandatory) of these four advertising outlets to display a particular advertisement. Such a setting is not unique to Taobao, many e-commerce platforms such as Amazon, eBay and Rakuten[9] have similar systems that enable advertisers to show advertisements within the e-commerce platforms or through their affiliate ad networks. The Amazon Associates is most similar to Taobao's, providing advertisers with

[8] Please check http://zhitongche.taobao.com/index.html for more information.

[9] Please check https://affiliate-program.amazon.com, https://www.ebaypartnernetwork.com and http://marketing.rakuten.com for the details on Amazon, eBay and Rakuten, respectively.

advertising opportunities both within and outside Amazon.

We focus on the impacts of the four targeted advertising outlets (i.e., internal keyword search advertising, internal category search advertising, internal banner advertising and external banner advertising) in Taobao as well as the role of the price related information (i.e., price discount and free delivery) in the ad copy on the demand of advertised products. Consumers in the advertising outlets of keyword search and category search are actively searching for information, while consumers in the advertising outlets of internal banners and external banners are not. Compared with category search advertising, keyword search advertising is supposed to support a higher level of goal specificity in information seeking. We therefore expect keyword search advertising to generate higher product demand than category search advertising. Compared with external banner advertising, internal banner advertising is supposed to support a higher level of targetability for customers. Hence we hypothesize that internal banner advertising is able to generate more product demand than external banner advertising. Due to these different characteristics of the four targeted advertising outlets, we contend that consumers' responses to the price related information (i.e., price discount and free delivery) in the ad copy may also differ from one targeted advertising outlet to another.

To empirically test our hypotheses, we propose a two-level hierarchical econometric model based on the detailed information of the product sales and targeted advertising campaigns in four Taobao stores of the focal e-commerce brand. The model also takes the price related information (i.e., price discount and free delivery) in the ad copy into account. We measure the demand of a product with its quantity sales, which is not sensitive to the unit price of the product. The results, based on a panel-level ordinary least square estimator with a first-order autoregressive disturbance structure, show that targeted ads in category search produce more product demand than keyword search, and that internal banner ads generate higher product demand than external banner ads. Specifically, compared with a visit from the baseline group, which contains the places beyond the four advertising outlets, such as generic listings of the search results and direct visits, an additional visit from category search advertising increases product demand by 0.484%, while an additional visit from keyword search advertising decreases product demand by 0.082%. This outcome differs from our expectation, which might be caused by the identity of the advertiser who is an emerging brand owner. In comparison with the baseline group visit, one more visit from internal banner ads is associated with a 0.146% increase in product demand, but no significant difference has been found for the visits from external banner ads. In addition, the presence of price discount messages in the ad copy of keyword search advertising increases product demand by 0.091% whereas the presence of the messages in the identical ad copy of category search advertising decreases product demand by 0.220%. The presence of free delivery messages in the ad copy only influences the advertising outlet of external banners, boosting product demand by 0.042%. Besides, visitors from different targeted adverting outlets present differential price sensitivities. The consumers attracted by keyword search advertising are the least sensitive to price, followed by the consumers from external banner advertising and internal banner advertising, whereas the consumers from category search advertising show the highest price sensitivity. These findings have profound implications for practitioners to implement personalized pricing schemes. Moreover, we find a negative relationship between the click-through rate of the ads and the demand of the advertised products, which has not been discussed in previous studies.

Our study makes significant contributions to the online advertising literature. First, while targeted advertising heavily relies on consumers' behavioral contexts (e.g., actively or passively seeking for information) in which targeted ads are displayed, prior targeted advertising literature does not differentiate these contexts. To the best of our knowledge, this is the first study that compares the influences of different targeted advertising outlets on product demand. Second, in addition to the aforementioned consumers' information seeking modes, we venture further to analyze the goal specificity of consumer search when consumers are actively searching for product information and examine the targetability of targeted advertisements when consumers are engaging in activities that are less relevant to purchase. This granular typology provides a good theoretical perspective to analyze the features of targeted advertising outlets and would benefit future research in this stream. Third, we examine a hitherto unexplored issue, i.e., the moderating effects of price related information in the ad copy on the demand of online visitors from different targeted advertising outlets. The effects differ across outlets, emphasizing the necessity to design ad copy according to the outlets where the targeted ads are shown.

Our study also provides valuable insights for practitioners. First, the value of targeted advertising outlets is not equal. Marketers should consider both costs and benefits of a potential advertising outlet when planning their advertising portfolio. Second, the price related information in the ad copy has differential impacts across online targeted advertising outlets. It is suggested that practitioners design the ad copy according to the distinctive properties of each advertising outlet. Third, the price sensitivity of the visitors from different online advertising outlets differs. This provides opportunities for practitioners to offer personalized prices to maximize profits.

3.2 Related Studies

This study investigates the impacts of online targeted advertising display outlets on consumers' product demand, and thus is closely related to the literature on targeted advertising. The delivery of targeted advertisements can be achieved through various approaches such as contextual advertising and retargeting. These approaches are based on ad viewers' current or previous search or browsing behavior, but have different emphases, which will be elaborated later on.

An early study by Yan et al. (2009) defined targeted advertising as "the delivery of advertisements to targeted users based on information collected from each individual user's web search and browsing behaviors". They found that the click-through rate of the online advertisements was increased by 670% with targeting techniques. Furthermore, targeting strategies based on short-term user search behaviors outperformed those based on long-term user browsing behaviors. Subsequent studies (Beales 2010; Farahat et al. 2012) confirmed the high effectiveness of targeted advertising in attracting clicks and converting potential customers to actual buyers. To increase targeting effectiveness, Chen et al. (2009) further recommended incorporating more categories of user browsing behaviors into the targeting algorithms.

The delivery of targeted advertisement can be achieved in many ways, such as delivering ads based on consumers' current or previous search or browsing behaviors. The earliest version of targeted advertising is simple contextual advertising, where ad delivery is based on the relevance between the content that users are currently browsing and the ad itself. This ad form focuses on the match between contents. The study of Goldfarb et al. (2011a) investigated the influence of this type of targeting and obtrusiveness of advertisements on ad campaign performance. They found that targeting and obtrusiveness worked well independently, but failed to increase purchase intention when paired together. Given the positive effects of contextual advertising on ad performance, some studies have further discussed the moderators that may influence the effects of this form of content-based targeted advertisement. Yeun Chun et al. (2014) found that the complexity of banner ads moderated the effectiveness of the contextual advertisements while Segev et al. (2014) found that the consumers' involvement level moderated the effects of the congruency between the advertisements and webpage content.

Recently, a burgeoning stream of literature has investigated an advanced version of contextual advertising, i.e., sponsored search advertising, which delivers advertisements to users when they are engaging in active information search. The sponsored ads are shown along with the organic search results returned by the search engines. This form of contextual advertising emphasizes the match between users' current search query and the ad itself. For example, Ghose et al. (2009) studied how the various factors such as ad display position, cost per click, and keyword type in sponsored search advertising affected the click-through rates and consumer purchase conversion.

Yang et al. (2010) examined the interdependence between the organic listings and sponsored search listings in the search results pages. They found that the click-through rates of organic listings and sponsored search listings positively influenced each other, but that the influences were asymmetric. The study by Xu et al. (2012) also investigated the relationship between organic listings and sponsored search listings. Their analytical model suggested that the presence of organic listings altered firms' incentives to bid for sponsored listing slots, which gave the weaker firms the opportunities to win the sponsored bidding. Rutz et al. (2011a) evaluated the spillover effects between generic search keywords and branded search keywords. A unidirectional positive spillover effect has been found from generic search activities to branded search activities.

Besides the aforementioned contextual advertising, another popular type of targeted advertising is retargeting, which is a variation of normal display banner ads. It is used to deliver relevant advertisements to the users according to their historical search or browsing behaviors. This ad form highlights the match between the ad viewers' interests and the ad itself, and takes little consideration of the contexts where the ads are shown. Goldfarb et al. (2011b) found the enactment of a privacy regulation in the European Union which aims to protect the privacy of online users' information decreased the ad campaigns' effectiveness. Though they did not explicitly discuss the advertisement types in their study, the results implied that publishers' weakened ability to track users' historical behaviors was a major reason for this effect. Another study by Lambrecht et al. (2013) suggested showing targeted banner ads to consumers who had formulated specific purchase intentions, and showing generic advertisements to consumers whose purchase goals were vague. These studies demonstrated the critical role of the knowledge on individual consumers in improving the advertisement delivery quality. The studies by Tucker (2014) and Bleier et al. (2015) even found such personalized advertisements failed to help under certain circumstances.

The aforementioned three types of targeted advertisements have been widely adopted in practice. The delivery of sponsored search ads and retargeting ads is based on the users' current or historical behaviors, and these two types of targeted advertising are instances of behavioral targeting (Chen et al. 2014; Yan et al. 2009). As we can observe, the existing literature mostly focuses on one particular advertising form, which makes comparisons across different advertisement forms an untapped research area. Without such knowledge, it is difficult for advertisers to plan their advertising portfolios when confronted with many advertising forms and outlets to select from. One exception we noticed in the existing literature is a recent study by Xu et al. (2014). They empirically evaluated the impacts of search advertisements and display advertisements on consumers' purchase conversions. The results suggested that compared with search advertisements, display advertisements throughout a consumer's information search and shopping process had a relatively smaller direct influence on consumers' purchases, but significantly increased consumers' awareness of the advertised item. The increased awareness stimulated the subsequent visits through other advertising formats. Thus, the value of display advertisements has been underestimated in most studies.

Though the study by Xu et al. (2014) investigated multiple online advertising forms, our study differs from theirs in the following aspects. First, we primarily focus on the ad delivery (for both search and display advertising) based on consumers' behaviors (i.e., behavioral targeting), whereas their study did not explicate the delivery methods of the display advertisements, which may not be targeted advertisements at all. Given this difference, our study is able to provide a more in-depth understanding of targeted advertisements in both search and display outlets. Second, while both studies include search advertising and display advertising, ours has a more granular typology for advertisement types. For sponsored search advertising, we have two outlets that support different levels of goal specificity in consumer information seeking, while for display advertising, we have two outlets that support different levels of targetability for customers. Such granular analyses enable us to discover more underlying factors that influence the performance of targeted advertisements in both the search and display formats. Third, our research focus differs considerably from theirs. The current study investigates the value of different online targeted advertising outlets, while their study emphasizes the dynamic effects of advertisements on individual consumers' responses without differentiating the display outlets of the advertisements. Thus, our study enables a direct assessment of the value of each advertising outlet, which facilitates practitioners' advertising portfolio planning.

Consumers' information search behavior in different advertising outlets varies and it may further impact their responses to the advertisements they have viewed. As a crucial component of advertisement, the ad copy plays an important role in influencing consumers' attention and purchase intention. Polyorat et al. (2007) compared the influence of narrative versus factual print ad copy on consumers' evaluation of the same product. Consumers who viewed the narrative print ad responded with more favorable product evaluation. Elder et al. (2010) found that multisensory advertisements produced higher taste perception than advertisements focusing on taste alone. Rutz et al. (2011b) took the textual features of the advertisements into account when investigating the effects of ad position on the performance of sponsored search advertising. They found several impactful features of the advertisements, such as keyword position within the ad copy, density of the ad and the presence of call to action. While these studies demonstrate that the content of the ad copy does influence the ad effectiveness, they remain confined to a single advertising outlet. Whether the textual features of the ad copy would have differential influences on consumers' responses across advertising outlets remains unexplored. This hence is another research gap that the current study attempts to address.

3.3 Research Settings and Hypotheses Development

3.3.1 Research Settings

Our research context is Taobao, which was founded in 2003 and consists of Taobao Marketplace and Tmall. Taobao Marketplace currently is the largest consumer-to-consumer e-commerce platform in China with a 95% market share (iResearch 2012). Tmall is a business-to-consumer e-commerce platform which was spun off from Taobao Marketplace in June 2011 (AlibabaGroup 2011).

Taobao has a mature targeted advertising system Zhitongche, which provides sellers in both Taobao Marketplace and Tmall with a convenient venue to market their businesses and products. Sellers can create advertisement campaigns with this system by specifying the keywords that they want to bid as well as the bidding price. The system works similarly to Google's Adwords, which uses second price sealed-bid auctions to determine the cost per click (CPC). The advertisements would be pushed to consumers who are either searching for product information or browsing webpages. Figure 3-1 shows an example of actual advertisements, which consist of a pictorial ad creative and a text copy[10].

Figure 3-1 Example of Advertisement

An advertisement can be displayed in multiple advertising outlets. Specifically, there are four outlets from which advertisers of Zhitongche can select to display their advertisements. The ad creative and copy are identical across all the advertising outlets that are selected by the sellers. In the advertising outlets of keyword search and category search, consumers are searching for product information. The targeted advertisements are displayed along with the organic search listings on the search result pages. The ad display areas in the search results page are shown in Figure 3-2. Targeted advertisements can be presented on the right panel and in the bottom panel of the page, depending on the auction ranking of a particular advertisement. In

[10] There was no price information in the advertisement during our observation period. However, Taobao now automatically displays price information with the advertisement.

contrast, the advertising outlets of internal banners and external banners feed targeted advertisements to the pages where consumers are browsing instead of actively searching for product information.

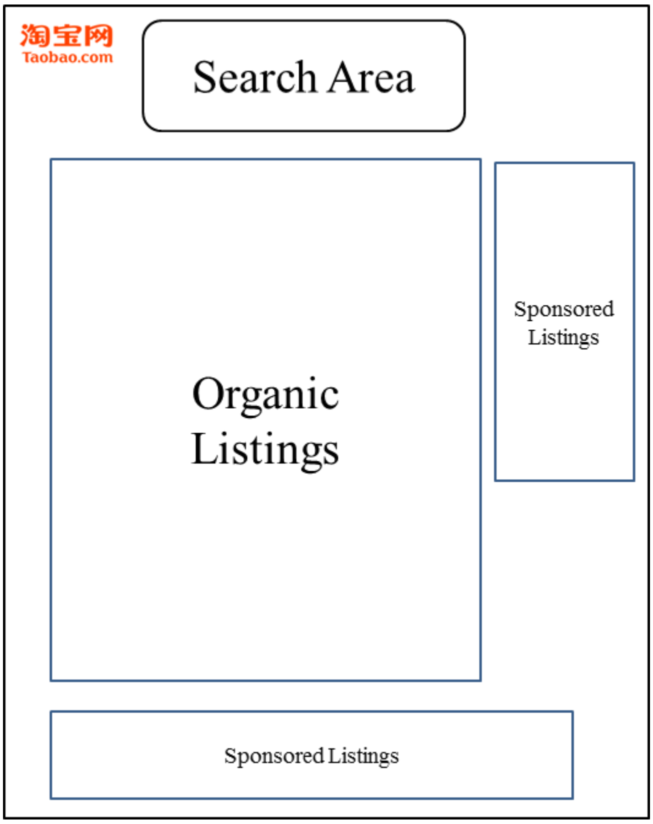

Figure 3-2 Search Results Page

The first targeted advertising outlet is keyword search advertising (shown in Figure 3-3), where advertisements are displayed when consumers search through the search box inside Taobao. This is the typical sponsored search advertising. The second targeted advertising outlet is category search advertising (shown in Figure 3-4), where advertisements are displayed when consumers search for products by browsing the hierarchical category tree predefined by Taobao, which is similar to that in Amazon. Taobao determines which advertisements are to be shown according to the relevance between the current category and the advertisements' keywords as well as the bidding price of the keywords.

Figure 3-3 Keyword Search

Figure 3-4 Category Search

Figure 3-5 Internal Banners

Figure 3-6 External Banners[11]

The third targeted advertising outlet (shown in Figure 3-5) is to display banner advertisements on some specific webpages within Taobao, such as Taobao users' order management pages, delivery status pages and pop-up windows in Aliwangwang[12]. Taobao pushes targeted advertisements to the

[11] The host website in this picture is Sina Blog. There are various external websites, not limited to this one.

[12] An instant messenger provided by Taobao to facilitate communication between buyers and

webpages according to each user's personal profile as well as historical browsing, search, bookmark and purchase behaviors in Taobao (Taobao 2012; Weng 2012). The last targeted advertising outlet (shown in Figure 3-6) is to display advertisements in external websites that are Taobao's alliance partners, which are similar to the program of Amazon Associates. These advertisements may or may not be targeted, depending on the ad viewer's cookie information. If the viewer visited Taobao previously and the information has been stored in the cookie, the advertisements displayed in the external websites would be targeted to the viewer's potential purchase interests derived from his or her previous browsing and search history. However, for the viewer who has never visited Taobao or lacks cookie information, the advertisements displayed in the external websites would be generic and served without any behavioral targeting[13].

3.3.2 Hypotheses Development

The Internet nowadays has become a major source for people to collect information. Hollis (2005) contended that potential purchasers may actively search for product information or passively receive product related information in the online environment, which often happens when consumers are browsing webpages without any purchase plan. Based on this classification scheme and consumers' information search mode (i.e., whether actively searching for information or not) in each targeted advertising outlet, we categorize the four outlets into two groups. The first group contains keyword search and category search, where consumers are actively seeking for information (Ghose et al. 2009; Yang et al. 2010). The second group contains

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sellers. Please refer to http://wangwang.taobao.com/ for more details.

[13] For convenience, we use keyword search, category search, internal banners and external banners to refer to advertisements in the first to the fourth outlets respectively hereafter.

internal banners and external banners, where consumers are browsing webpages and passively seeking for information (Wilson 1999). For the first group, the level of consumers' goal specificity is supposed to differ from one outlet to the other. For the second group, the targetability of the advertisements is expected to differ from one outlet to the other. These differences may influence consumers' responses to an advertisement as well as their interpretation of the information contained in the ad copy, which finally affects purchase decisions.

To attract consumers' attention, the text copy of the targeted advertisements is an important vehicle to convey the product value to potential consumers. Various types of information such as price, promotional information and call for action can be included in an ad copy (Jacobson 2011; Rutz et al. 2011b). As one of the first to explore the differential effects of the content of the ad copy across targeted advertising outlets, we are particularly interested in the roles of the fundamental price related promotional information in the ad copy in shaping consumers' purchase decisions. E-commerce business owners often provide two types of price related promotions to attract consumers. One is price discount and the other one is free delivery. The presence of such price related information enhances the attraction of the targeted advertisements for customers. Therefore, this study mainly examines consumers' responses to these two types of price related promotional information in the ad copy. To demonstrate the theoretical perspective of our research and the hypotheses to be developed, we present a research model in Figure 3-7. We will elaborate on it in the following paragraphs.

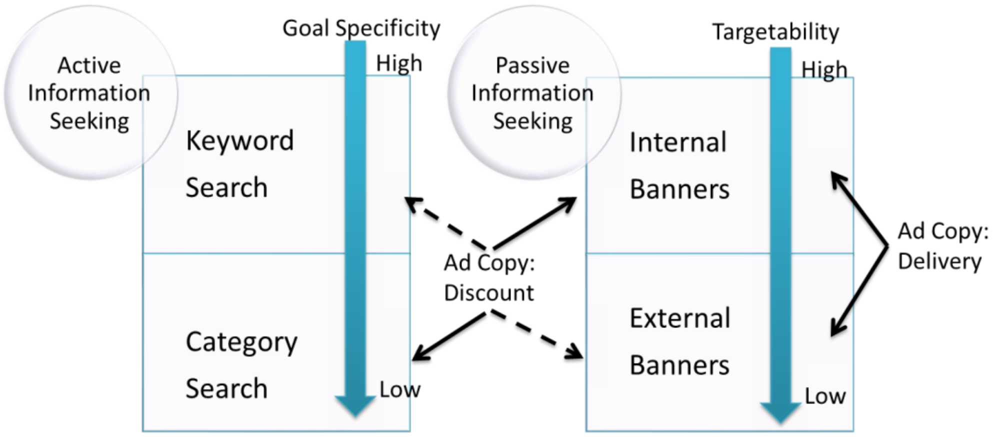

Figure 3-7 Research Model

Consumers in both keyword search and category search are actively seeking for information and thus involve in a goal-directed action (Janiszewski 1998). In keyword search, consumers type in keywords that are related to their shopping interests to explore potential products. Category search provides consumers with another way to search for products. Products are grouped into categories according to the similarities they share. Each top-level category can be further divided into many subcategories based on certain properties or attributes possessed by the products within this focal category (Hepp et al. 2007). Such a hierarchical category structure aids consumers in exploring potential products and refining their purchase goals (Baty et al. 1995). Compared with category search, keyword search gives consumers an easier way to tailor search queries to describe the exact products they want. To do so, consumers should have a clearer understanding about the products they aim than those from category search.

In contrast to the majority of the visitors from category search advertising who are still formulating consideration sets, the visitors from keyword search advertising possess more specific goals. Their clicks on the targeted advertisements exhibit their potential shopping interests in the products. The higher level of goal specificity indicates that these consumers are closer to the purchase phase (Rutz et al. 2011c). Compared with the visitors who come from category search advertising and are at an early stage of information search, the visitors from keyword search advertising have a higher probability of purchasing the advertised product. Therefore, we hypothesize:

> *Hypothesis 1 (H1): In the context of active information seeking by consumers, the advertising outlet of* ***keyword search*** *(which supports a higher level of goal specificity in information seeking) generates* ***more product demand than*** *the advertising outlet of* ***category search*** *(which supports a lower level of goal specificity in information seeking).*

Construal level refers to the abstraction degree at which goal-directed actions are presented in cognitive hierarchy (Liberman et al. 1998). A goal-directed action with a more specific goal is considered to be of a lower construal level. The construal level of a goal-directed action influences individuals' self-regulatory focus (Higgins 1997). When consumers' goals are of a lower construal level, they are prone to hold a prevention-oriented self-regulatory focus. Prevention-oriented regulation refers to individuals' intention to pursue stability and security, and these individuals thus tend to avoid risk and loss (Liberman et al. 1999). Consumers with goals of a higher construal level, are more predisposed to hold a promotion-focused regulation and engage in exploratory search (Janiszewski 1998). Promotion-focused regulation refers to an individual's inclination to take actions that can change and improve the current state (Liberman et al. 1999). Consumers with a promotion-focused regulation are generally more receptive to available information, as compared to those with a prevention-oriented regulation (Lee et al. 2006).

Visitors from keyword search advertising have a clearer understanding about their goals, in comparison to visitors from keyword search advertising, and thus are more likely to hold a prevention-oriented regulation. They often ignore available information other than their purchase goals for the sake of maintaining their current state. In contrast, the visitors from category search advertising have goals of a higher construal level and hence are more promotion-focused. They are more open-minded toward available information that can improve their purchase decisions. Because of this discrepancy between the visitors from these two advertising outlets, price discount messages as one type of promotional information in the ad copy are more capable of increasing the response probability of the visitors from category search. Thus, we postulate that the visitors from category search respond more positively to price discount messages in the ad copy, compared to the visitors from keyword search. Therefore, we hypothesize:

> *Hypothesis 2 (H2): Further in the above context,* ***price discount messages*** *in the ad copy of the advertising outlet of* ***category search*** *lead to a* ***higher extent of product demand increase****, as compared to identical messages in the ad copy of the advertising outlet of* ***keyword search****.*

Consumers in the advertising outlet of internal banners are browsing webpages related to their product orders (e.g., order management pages and delivery status pages), which do not contain any product information, whereas consumers in the advertising outlet of external banners are browsing webpages that are mostly unrelated to shopping, given that the majority of the external websites are news portals, e-book platforms and delivery service providers (Alimama 2015). In these contexts, the consumers are not actively searching for product information with a purchase goal, and thus we deem that these consumers are in passive information seeking mode (Wilson 1999).

The internal banners are displayed within the e-commerce platform and only visible to the registered consumers. These consumers' personal profiles and historical activities (e.g., browsing, search, bookmark and purchase behaviors) recorded by the e-commerce platform assist the platform in feeding tailored advertisements that are more relevant to each consumer's shopping interests (Taobao 2012; Weng 2012). The match between the advertised product and the purchase interests exhibited by consumers previously attracts them to click the advertisement and view the details of the product. Though they do not actively search for products at the moment, the advertisement helps them to discover what they are interested in and has a high possibility of converting them into buyers. However, regarding the external banners, the e-commerce platform only has access to a small proportion of the total consumers' historical activities, since not all the consumers who view the advertisements are registered users or previous visitors of the focal e-commerce platform[14] (CNNIC 2012). For the registered consumers and previous visitors who are browsing external websites, the targeted

[14] According to Alibaba's prospectus (AlibabaGroup 2014), the number of active buyers in Taobao by the end of 2011 was 114 million, whereas the number of Internet users in China then was 513 million (CNNIC 2012). It demonstrates that Taobao at most has information about 1/5 of the potential advertisement viewers in a random external website.

advertisements are pushed to them in the same way as internal banners, with the aim of attracting them back to the e-commerce platform. For the consumers who have no records in the database of the e-commerce platform, the advertisements pushed to them are generic ones, without any behavioral targeting. Some of these consumers are perhaps merely curious about the advertised product and want to acquire and retain knowledge for future purchase decisions. According to a typology developed by Moe (2003), this type of users is knowledge builder, who has little immediate purchase intention. Moreover, the unregistered consumers have to make purchases with a valid account, which potentially inhibits their purchase conversion due to the hassles of the registration process. Hence, the visitors from external banners are a mixture of returning consumers attracted by their previously exhibited shopping interests and knowledge builders. Compared with the visitors from internal banners, who are attracted by their previously exhibited shopping interests, the visitors from external banners, on average, have lower demand for the advertised product. Therefore, we hypothesize:

> *Hypothesis 3 (H3): In the context of passive information seeking by consumers, the advertising outlet of* ***internal banners*** *(which supports a higher level of targetability for customers) generates* ***more product demand than*** *the advertising outlet of* ***external banners (****which supports a lower level of targetability for customers).*

Visitors from internal banners are browsing webpages that are related to their extant product orders, instead of seeking for product information in search pages. Though they are not actively engaging in product search, they tend to have a purchase intention of a high construal level because they have previously displayed shopping interests in the advertised product. This general purchase intention renders them receptive to available information related to the potential purchase targets (Lee et al. 2006). Similar to the visitors from keyword search advertising who also have a purchase intention of a high construal level, the visitors from internal banners would be positively influenced by the price discount messages in the ad copy. However, the situation is different for the visitors who are attracted by external banners. External banners could be either targeted or non-targeted, depending on whether the e-commerce platform has the records of the users' historical activities. Some of the users without records might be knowledge builders (Moe 2003), who have low immediate product demand even with a price discount. This consequently weakens the impacts of discount messages in the ad copy on the visitors who are attracted by external banners. Thus, the visitors attracted by internal banners may respond more positively to the stimuli engendered by the discount messages in the ad copy, compared with the visitors attracted by external banners. Therefore, we hypothesize:

> *Hypothesis 4a (H4a): Further in the above context,* ***price discount messages*** *in the ad copy of the advertising outlet of* ***internal banners*** *lead to a* ***higher extent of product demand increase****, as compared to identical messages in the ad copy of the advertising outlet of* ***external banners****.*

Researchers previously contended that the low search costs would reduce the product price to the marginal cost in the e-commerce environment (Bakos 1997; Brynjolfsson et al. 2000). Despite the gradual maturity of e-commerce, price dispersion still remains substantial in online markets. One of the various reasons for this phenomenon is the sellers' utilization of partitioned pricing (Burman et al. 2007; Lee et al. 2002). Unlike offline in-store shopping, online consumers are affected not only by the product price but also by the shipping charges (Hamilton et al. 2008; Marco 2008). Decomposing the total price of products into product costs and delivery costs enables sellers to take advantage of consumers' biased perception of price, which refers to the situations where consumers' perceived total price of the partitioned prices is not equal to the actual combined price (Burman et al. 2007; Hamilton et al. 2008; Lee et al. 2002). If the perceived total price is lower than the actual combined price, sellers can benefit from such a pricing tactic.

As a device to promote product demand, online advertisements now can include delivery information to attract consumer attention. A strategy that e-commerce sellers usually employ is to provide free delivery. However, the effects of such information in the ad copy may depend on the context in which the advertisements are displayed. Petty et al. (1986) proposed two routes, central route and peripheral route, to understand human's information processing. The central route is used when the information recipient is highly motivated and has the ability to process the information while the peripheral route is used when the information recipient has little or no interest in the information (Petty et al. 1986). The visitors from the advertising outlets of keyword search and category search are actively seeking for product information and are thus more likely to process the advertisements via the central route. In contrast, the visitors from the advertising outlets of internal banners and external banners are browsing webpages that are not directly related to product information, and thus are more predisposed to process the advertisements via the peripheral route.

Under the peripheral route, individuals are more stimuli-driven and tend to use simplifying heuristics to make decisions (Evans 1984). Adjustment and anchoring is one heuristic that consumers frequently use to deal with partitioned prices (Hamilton et al. 2008). This heuristic suggests that when confronted with multiple pieces of information, decision makers start from one initial value that is adjusted stepwise to make final estimates (Morwitz et al. 1998). A frequent bias made by people using this heuristic is to overweight the anchoring value and adjust the remaining values insufficiently (Tversky et al. 1974). Visitors from the advertising outlets of internal banners and external banners are more predisposed to take the free delivery messages in the ad copy as the anchoring value and adjust this value with the price that they view from the product page after clicking through the focal advertisement. According to the theory of Tversky et al. (1974), this adjustment is often lower than the actual value due to consumers' biased perceptions. Therefore, after viewing the free delivery messages in the ad copy, the visitors from the advertising outlets of internal banners and external banners are more likely to underestimate the total price. As a result, the presence of free delivery messages in the ad copy increases the product demand generated by the ads in both internal banners and external banners. Therefore, we hypothesize:

> *Hypothesis 4b (H4b): Further in the above context,* ***free delivery messages*** *in the ad copy* ***positively increase*** *the* ***product demand*** *for the advertising outlets of both* ***internal banners*** *and* ***external banners****.*

3.4 Research Methodology

3.4.1 Data Description

To empirically test our hypotheses, we use a dataset obtained from a Taobao-based entrepreneurial e-commerce brand Lolita[15] of female leatheroid apparel. The products of this emerging brand are sold in four stores in Taobao, including a flagship store in Tmall and three stores in the Taobao Marketplace. The four stores are operated independently. The dataset consists of daily advertising and sales information of the four stores from April to December 2011. The stores ran both shop-level and product-level ad campaigns. Since our research focus in this study is product demand, we mainly discuss the impacts of product-level advertisements. Product-level advertising information includes ad copy, outlets where an advertisement has been displayed, the numbers of impressions and clicks, and costs of that advertisement in each display outlet, as well as the average display position of that ad in the advertising outlet of keyword search. Besides the information on targeted advertising, the sales information contains the numbers of page views and unique visitors, promotion information, as well as the quantity and dollar sales of each product.

Before examining the impacts of each targeted advertising outlet on product demand, we would like to know whether targeted advertising boosts product sales. In other words, we first assessed the value of the targeted advertising service provided by Taobao, namely the Zhitongche program, to brand Lolita. We regressed the number of product page views (*PV*), the number of unique visitors (*UV*) and quantity sales (*QSales*) respectively,

[15] At the brand owner's request, we masked the real brand name.

against the stores' decision of using the targeted advertising service. We controlled for relevant product-level and store-level factors as well as time trends. The results are shown in Table 3-1 and the definitions of variables in the models can be found in Table 3-3. The binary indicator of the usage of targeted advertising service (i.e., *TargetedAd*) has significantly positive coefficients in all the three models. This means that compared with products that did not use the targeted advertising service, products with targeted advertisements received significantly more visits and sales.

Table 3-1 Effects of Targeted Advertising

VARIABLES	(1) *ln(PV)*[16]	(2) *ln(UV)*	(3) *ln(QSales)*
TargetedAd	1.492***	1.467***	1.007***
	(0.334)	(0.330)	(0.335)
Price	-0.004***	-0.003***	-0.006***
	(0.001)	(0.001)	(0.001)
*TargetedAd*Price*	-0.003**	-0.003**	-0.003*
	(0.002)	(0.002)	(0.002)
Favorites	0.005***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)
NewArrival	0.177***	0.157**	0.014
	(0.064)	(0.063)	(0.025)
ShopAds	-0.052**	-0.044*	-0.002
	(0.026)	(0.025)	(0.012)
SpecAds	-0.174***	-0.161***	-0.093***
	(0.034)	(0.033)	(0.015)
NormAds	0.019	0.016	0.002
	(0.013)	(0.012)	(0.006)
Constant	4.819***	4.596***	1.551***
	(0.194)	(0.188)	(0.115)
Weekday Dummies	Y	Y	Y
Month Dummies	Y	Y	Y
Observations	72,178	72,178	72,178
Overall R-squared	0.174	0.180	0.184
Number of Products	649	649	649

1. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
2. Store-product specific effects have been controlled.

However, the stores may intentionally select the well-received products to advertise. If so, the impacts of targeted advertising would be biasedly estimated. To account for marketers' strategic selection of products to be

[16] All log transformations in this study have been conducted with an addition of one before taking logs to avoid ln(0).

advertised, we used Arellano-Bond estimator (Arellano et al. 1991), which is able to take into account the marketers' performance-based product selection into account. The results are presented in Table 3-2. Consistent with our previous finding, Model (1) suggests a positive effect of targeted advertising service usage on product quantity sales, while the magnitude is greatly attenuated. The shrinking coefficient of *TargetedAd* confirms the selection issue of the advertised products. Nevertheless, switching on the targeted advertising service in general increases product quantity sales by 29.563% (i.e., $e^{0.259}$-1). Additionally, the research model enables us to compare the consumers' price sensitivities of products with and without the targeted advertising. We find that in Model (2), after adding an interaction term between the usage of targeted advertising and price to Model (1), *TargetedAd* becomes insignificant whereas the interaction term is significantly positive. The positive coefficient of the integration term suggests that consumers of the products with the targeted advertising service, on average, are less price sensitive than those of the products without the targeted advertising service.

Table 3-2 Arellano-Bond Estimation for Advertising Effects

VARIABLES	(1) *ln(QSales)*	(2) *ln(QSales)*
l. ln(QSales) †	0.290***	0.289***
	(0.013)	(0.013)
l2. ln(QSales) †	0.073***	0.073***
	(0.009)	(0.009)
TargetedAd	0.259***	-0.348
	(0.079)	(0.353)
Price	-0.003***	-0.003***
	(0.001)	(0.001)
*TargetedAd*Price*		0.004*
		(0.002)
Favorites	0.004***	0.004***
	(0.001)	(0.001)
NewArrival	0.105***	0.104***
	(0.036)	(0.036)
ShopAds	-0.020***	-0.020***
	(0.006)	(0.006)
SpecAds	-0.023**	-0.024**

	(0.011)	(0.012)
NormAds	0.055***	0.054***
	(0.005)	(0.006)
Constant	0.538***	0.590***
	(0.172)	(0.165)
Weekday Dummies	Y	Y
Month Dummies	Y	Y
Observations	64,413	64,413
Number of Products	649	649

1. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
2. Arellano-Bond estimator is able to control for advertisers' strategic ad planning.
3. The "l" in the entries with † denotes lag operators.

Given the preceding findings of the positive impacts of targeted advertising, it is meaningful to further explore the effects of each advertising outlet on product demand. Our following main analyses will concentrate on the products that were advertised with targeted advertisements. The analysis unit is shop-product-day and each unit corresponds to a targeted advertisement. Our dataset contains 1,562 shop-product-day entries, of which 851 are from the flagship store in Tmall, 544, 163 and 4 are from the remaining three stores, respectively. Keyword search advertising is the default and mandatory option for each targeted advertisement. Advertisers can add any one of the remaining three outlets to their ad display portfolio. We operationalize product demand as quantity sales, since this measurement is less sensitive to the unit price of a product.

3.4.2. Econometric Model

$$QSales_{pst} = \alpha_{0pst} + \sum_{j} \theta_{pso_j t} * Visits_{pso_j t} + \eta_{pst} \tag{1}$$

$$\begin{aligned} &\alpha_{0pst} = \alpha_{00} + \omega_p + \psi_s + \varepsilon_{pst}, \\ &\varepsilon_{pst} \sim N(0, \sigma_e^2) \end{aligned} \tag{2}$$

$$
\begin{aligned}
\theta_{pso_jt} &= \boldsymbol{\gamma}_{o_j}\mathbf{X} + \zeta_{pso_jt} \\
&= \gamma_{o_j1} + \gamma_{o_j2}DiscountMsg_{pst} + \gamma_{o_j3}FreeDeliveryMsg_{pst} \\
&\quad + \gamma_{o_j4}CTR_{pso_jt} + \gamma_{o_j5}CPC_{pso_jt} + \gamma_{o_j6}Price_{pst} + \gamma_{o_j7}PosInPage_{pso_jt} \\
&\quad + \gamma_{o_j8}AvgDisPage_{pso_jt} + \zeta_{pso_jt}, \\
\zeta_{pso_jt} &\sim N(0, \sigma^2_{o_j})
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
\eta_{pst} =& \beta_1 Price_{pst} + \beta_2 Favorites_{pst} + \beta_3 NewArrival_{pst} + \beta_4 MultiColor_{pst} \\
& + \beta_5 AutumnDesign_{pst} + \beta_6 WinterDesign_{pst} + \beta_7 ShopAds_{st} \\
& + \beta_8 SpecAds_{st} + \beta_9 OtherAds_{pst} + WeekdayDummies \\
& + MonthDummies
\end{aligned} \tag{4}
$$

where p denotes product, s denotes shop and t is day indicator. O_j *denotes targeted advertising outlet and j can be 1 (keyword search), 2 (category search), 3 (internal banners) and 4 (external banners). PosInPage and AvgDisPage are only for keyword search advertising.*

To estimate the impacts of targeted advertisements in the four outlets on product demand, we specify a multilevel model as shown in Equations (1) to (4). Variable definition and operationalization are presented in Table 3-3. α_{0pst} is a random intercept, where α_{00} captures the mean value of product demand without targeted advertisements, ω_p and ψ_s are product-level and shop-level unobserved heterogeneities that influence product demand respectively, and ε_{pst} is an idiosyncratic error term with standard assumptions. Product demand is affected by the traffic from different targeted advertising outlets O_j. θ_{pso_jt} is the random coefficient for the visits from targeted advertising outlet j. Its effects are contingent on the related factors $\boldsymbol{X}$ in a particular shop-product-day. The factors include the presence of price discount and free delivery messages in the ad copy, click-through rate and cost per click of the ad in each targeted advertising outlet, product price as well as the ad display position for keyword search advertising. We let the random component ζ_{pso_jt} capture the unobserved random effects for outlet *j*. Besides the clicks from the targeted advertisements, products may have visits from other venues (e.g., generic listings of the search results and direct visits) and these visits also influence the product demand. We incorporated various product characteristics and shop-level information to model these impacts, which are shown in Equation (4). Weekday effects and time trends are accounted for with weekday and month dummies.

Table 3-3 Variable Definition and Operationalization

<table>
<tr><th colspan="2">Variable</th><th>Definition and Operationalization</th></tr>
<tr><td colspan="2">$QSales_{pst}$</td><td>Total number of product p in shop s that were sold in day t.</td></tr>
<tr><td colspan="2">PV_{pst}</td><td>Total number of page views received by product p in shop s in day t.</td></tr>
<tr><td colspan="2">UV_{pst}</td><td>Total number of unique visitors who viewed product p in shop s in day t.</td></tr>
<tr><td colspan="2">$TargetedAd_{pst}$</td><td>= 1 if product p in shop s used the targeted advertising service provided by Taobao in day t; =0, otherwise.</td></tr>
<tr><td colspan="2">$Visits_{pso_jt}$</td><td>Total number of visits (in 1,000) from outlet j in day t for product p in shop s. If outlet j was not switched on in day t, this variable is coded as 0.</td></tr>
<tr><td colspan="2">$DiscountMsg_{pst}$</td><td>= 1 if the ad copy of product p in shop s contains information on price discount (usually presented in percentage form) in day t; = 0, otherwise. As all advertising outlets for product p in shop s in day t had the identical ad copy, this variable is outlet invariant.</td></tr>
<tr><td colspan="2">$FreeDeliveryMsg_{pst}$</td><td>= 1 if the ad copy of product p in shop s contains free delivery information in day t; = 0, otherwise. As all advertising outlets for product p in shop s in day t had the identical ad copy, this variable is outlet invariant.</td></tr>
<tr><td rowspan="8">Control Variables</td><td>$Price_{pst}$</td><td>Average transaction price of product p in shop s in day t. If there was no sales in day t, we impute this variable with the mean value of average transaction prices in previous days. If no price information is available before day t, we impute this variable with the average transaction price in the first non-missing day that followed.</td></tr>
<tr><td>CTR_{pso_jt}</td><td>Click-through rate of the targeted ad in outlet j for product p in shop s in day t. If outlet j was not switched on in day t, the value is coded as 0.</td></tr>
<tr><td>CPC_{pso_jt}</td><td>Cost per click of the targeted ad in outlet j for product p in shop s in day t. If outlet j was not switched on in day t, the value is coded as 0.</td></tr>
<tr><td>$PosInPage_{pso_jt}$</td><td>Average page number where the keyword search ad of product p in shop s was displayed in day t.</td></tr>
<tr><td>$AvgDisPage_{pso_jt}$</td><td>Average position where the keyword search ad of product p in shop s was displayed within the search result page in day t.</td></tr>
<tr><td>$Favorites_{pst}$</td><td>Total number of favorites (similar to Twitter’s favorite function) product p in shop s had received till day t</td></tr>
<tr><td>$NewArrival_{pst}$</td><td>= 1 if it is less than 10 days since the first day product p was sold in shop s; =0, otherwise.</td></tr>
<tr><td>$MultiColor_{pst}$</td><td>= 1 if there were multiple colors to choose from for product p</td></tr>
</table>

		in shop s in day t; =0, otherwise.
	$AutumnDesign_{pst}$	= 1 if the description of product p in store s in day t specifically pointed out that the product was designed for Autumn; =0, otherwise.
	$WinterDesign_{pst}$	= 1 if the description of product p in store s in day t specifically pointed out that the product was designed for Winter; =0, otherwise.
	$ShopAds_{st}$	Total number of shop-level advertisements of shop s that were on display in day t.
	$SpecAds_{st}$	Total number of special promotion advertisements of shop s that were organized by Taobao in day t.
	$OtherAds_{pst}$	Total number of other products in shop s that had targeted ad display in day t.
	Weekday Dummies	Weekday indicators (e.g., Monday, Tuesday …), capturing weekly sales pattern.
	Month Dummies	Calendar month indicators, capturing time trends over months.

Table 3-4 Descriptive Statistics (obs. = 1,562)

Variable	Mean	Median	Std. Dev.	Min	Max
1. *QSales*	40.94	5	378.13	0	14180
2. $Visits_{o_1}$ †	0.26	0.06	0.65	0	15.16
3. $Visits_{o_2}$ †	0.06	0.01	0.24	0	5.26
4. $Visits_{o_3}$ †	0.17	0.00	0.40	0	3.03
5. $Visits_{o_4}$ †	0.29	0.06	0.48	0	3.49
6. CTR_{o_1} †	0.49	0.46	0.31	0	2.87
7. CTR_{o_2} †	0.30	0.26	0.29	0	2.78
8. CTR_{o_3} †	0.24	0.24	0.30	0	4.55
9. CTR_{o_4} †	0.25	0.19	0.27	0	2.97
10. CPC_{o_1} †	1.27	0.77	0.93	0	4.49
11. CPC_{o_2} †	0.84	0.74	0.58	0	2.38
12. CPC_{o_3} †	0.69	0.59	0.62	0	3.9
13. CPC_{o_4} †	0.72	0.55	0.65	0	3.09
14. *DiscountMsg*	0.12	0	0.33	0	1
15. *FreeDeliveryMsg*	0.19	0	0.39	0	1
16. *PosInPage*	6.12	6	3.68	0	12
17. *AvgDisPage*	3.11	2	3.10	0	41
18. *Price*	177.87	174.07	57.99	86.24	782.04
19. *Favorites*	0.85	0.22	2.08	0	43.91
20. *NewArrival*	0.63	1	0.48	0	1
21. *MultiColor*	0.13	0	0.33	0	1
22. *AutumnDesign*	0.33	0	0.47	0	1
23. *WinterDesign*	0.08	0	0.27	0	1

24. ShopAds	1.59	1	1.53	0	7
25. SpecAds	0.57	0	0.88	0	4
26. OtherAds	2.37	2	1.74	0	7

† O_1, O_2, O_3 and O_4 correspond to the targeted advertising outlets of keyword search, category search, internal banners and external banners respectively.

Table 3-4 shows the descriptive statistics for each variable. Our sample is an unbalanced panel with 49 unique shop-product pairs. The product with the longest targeted ad display is from shop 1 and has targeted advertisements in 173 days, while the average on display time for the advertised products is 32 days. The covariates for each advertised product such as advertising outlet choices, product-level characteristics, would change over their display period. *QSales* is our dependent variable, which is a count number ranging from 0 to 14,180. Products with targeted advertisements, on average, were sold 41 pieces per day, but with a large standard deviation of 378. To overcome this over-dispersion, log transformation has been made for further model estimation. Furthermore, for an average advertised product, the outlet of external banners received the most clicks, i.e., 290 a day, followed by keyword search, internal banners and category search. In addition, the outlet of keyword search has the highest average click-through rate of 0.49%, twice as high as that of internal banners. Similarly, keyword search has the highest cost per click, followed by category search, external banners and internal banners. 12% and 19% of the targeted advertisements contain messages on price discount and free delivery, respectively. Moreover, the average transaction price of the advertised products is 177.87, with a standard deviation almost equal to the mean.

We also examined the correlation between variables, which was reported in Table 3-5 and Table 3-6. Six cells (only for correlations between independent variables) have values equal or larger than 0.6, implying a potential thread to unbiased model estimation. Five of them involve cost per click in different outlets and the last one is between the number of favorites and the number of visits from keyword search advertising. To avoid multicollinearity, we dropped cost per click for all outlets from the model. Consumer reviews are deemed important to control for a product's quality and popularity (Chevalier et al. 2006; Dellarocas 2003), but we have no detailed information on them. As an alternative, the number of favorites a product received is deemed closely related to customers' attitudes towards the product. Thus, we choose to keep *Favorites* temporarily and will pay close attention to it in the subsequent model estimation.

Table 3-5 Correlation Matrix (1)

Variable	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	***17***	***18***
1. QSales	1.00																	
2. $Visits_{o_1}$ †	0.63	1.00																
3. $Visits_{o_2}$ †	0.13	0.44	1.00															
4. $Visits_{o_3}$ †	0.22	0.53	0.33	1.00														
5. $Visits_{o_4}$ †	0.22	0.56	0.18	0.35	1.00													
6. CTR_{o_1} †	0.06	0.24	0.45	0.27	0.13	1.00												
7. CTR_{o_2} †	0.08	0.24	0.14	0.24	0.24	0.43	1.00											
8. CTR_{o_3} †	0.03	0.13	0.11	0.17	0.08	0.30	0.30	1.00										
9. CTR_{o_4} †	0.05	0.21	0.07	0.03	0.46	0.14	0.15	0.05	1.00									
10. CPC_{o_1} †	0.11	0.25	0.00	0.14	0.50	0.02	0.19	0.08	0.22	1.00								
11. CPC_{o_2} †	0.09	0.31	0.11	0.25	0.55	0.22	0.50	0.26	0.22	0.70	1.00							
12. CPC_{o_3} †	0.11	0.32	0.12	0.32	0.52	0.21	0.38	0.39	0.16	0.63	0.75	1.00						
13. CPC_{o_4} †	0.10	0.25	0.00	0.08	0.60	-0.07	0.05	0.00	0.50	0.68	0.52	0.38	1.00					
14. DiscountMsg	0.01	-0.03	0.13	0.02	-0.13	0.40	0.23	0.13	-0.16	-0.08	0.02	-0.04	-0.12	1.00				
15. FreeDeliveryMsg	0.04	0.23	0.12	0.12	0.51	0.21	0.26	0.09	0.51	0.28	0.37	0.38	0.40	0.10	1.00			
16. PosInPage	-0.02	-0.01	-0.05	-0.08	-0.04	-0.07	0.01	-0.04	0.01	-0.01	0.00	-0.03	-0.03	-0.08	0.01	1.00		
17. AvgDisPage	-0.05	-0.20	-0.11	-0.25	-0.25	-0.30	-0.28	-0.25	-0.10	-0.33	-0.40	-0.39	-0.23	-0.11	-0.17	0.00	1.00	
18. Price	-0.04	0.00	-0.08	-0.07	0.21	-0.22	-0.10	-0.12	0.16	0.17	0.11	0.08	0.30	-0.27	0.13	-0.02	0.18	1.00
19. Favorites	0.63	0.62	0.23	0.31	0.46	0.20	0.21	0.08	0.27	0.32	0.33	0.32	0.33	0.00	0.29	-0.03	-0.17	0.02

20. NewArrival	0.06	0.13	0.09	-0.01	0.25	0.27	0.31	0.11	0.11	0.49	0.44	0.41	0.22	0.20	0.35	-0.02	-0.15	0.05
21. MultiColor	-0.02	-0.08	-0.08	-0.15	-0.05	-0.35	-0.26	-0.25	-0.07	0.07	-0.19	-0.20	0.08	-0.14	-0.18	0.03	0.30	0.22
22. ProdAutumn	0.00	0.09	-0.03	-0.02	0.07	0.00	0.09	0.05	-0.01	0.26	0.21	0.23	0.06	-0.05	0.12	0.05	-0.02	0.08
23. ProdWinter	-0.02	-0.03	-0.03	-0.06	0.10	-0.04	-0.01	-0.03	-0.04	0.20	0.13	0.11	0.17	-0.11	-0.14	-0.02	0.03	0.34
24. ShopAds	-0.05	-0.08	-0.09	-0.04	-0.23	-0.25	-0.37	-0.07	0.03	-0.43	-0.34	-0.39	-0.11	-0.32	-0.31	0.04	0.18	0.06
25. SpecAds	0.00	-0.05	-0.01	-0.03	0.08	-0.03	0.18	0.04	0.07	0.36	0.35	0.41	0.14	-0.02	0.29	0.01	-0.05	0.10
26. OtherAds	0.04	0.03	-0.04	-0.07	0.31	-0.09	0.06	-0.06	0.33	0.31	0.24	0.23	0.31	-0.28	0.40	0.04	0.06	0.46

[†] O_1, O_2, O_3 and O_4 correspond to the targeted advertising outlets of keyword search, category search, internal banners and external banners, respectively.

Table 3-6 Correlation Matrix (2)

Variable	***19***	***20***	***21***	***22***	***23***	***24***	***25***	***26***
19\. Favorites	1.00							
20\. NewArrival	0.19	1.00						
21\. MultiColor	-0.05	-0.13	1.00					
22\. ProdAutumn	0.01	0.54	-0.19	1.00				
23\. ProdWinter	-0.04	0.05	0.05	-0.06	1.00			
24\. ShopAds	-0.17	-0.59	0.03	-0.22	-0.13	1.00		
25\. SpecAds	0.04	0.45	-0.17	0.32	0.13	-0.53	1.00	
26\. OtherAds	0.13	0.29	0.00	0.26	0.20	-0.21	0.30	1.00

To estimate the model shown in Equations (1) to (4), we first plugged Equations (2), (3) and (4) into Equation (1). The resultant model is shown in Equation (5). The model can be understood as a two-level hierarchical model, which is illustrated in Figure 3-8. Level 1 represents the shop-product pairs and Level 2 represents the targeted advertising outlets. The cross-level effects are captured by the interaction terms between product-level characteristics and visits from each targeted advertising outlet. The composite errors in the last line of Equation (5) capture the random effects of the visits from the four targeted advertising outlets. Thus, our final model is a two-level hierarchical model with both fixed and random effects of the visits from the four targeted advertising outlets.

$$
\begin{aligned}
\ln(QSales_{pst}) = \alpha_{00} &+ \sum_j \left(\gamma_{o_j 1} * Visits_{pso_j t} \right) \\
&+ \sum_j \left(\gamma_{o_j 2} DiscountMsg_{pst} * Visits_{pso_j t} \right) \\
&+ \sum_j \left(+ \gamma_{o_j 3} FreeDeliveryMsg_{pst} * Visits_{pso_j t} \right) \\
&+ \sum_j \left(\gamma_{o_j 4} CTR_{pso_j t} * Visits_{pso_j t} \right) + \sum_j \left(\gamma_{o_j 5} Price_{pst} * Visits_{pso_j t} \right) \\
&+ \gamma_{o_1 6} PosInPage_{pso_1 t} * Visits_{pso_1 t} + \gamma_{o_1 7} AvgDisPage_{pso_1 t} * Visits_{pso_1 t} \\
&+ \beta_1 Price_{pst} + \beta_2 Favorites_{pst} + \beta_3 NewArrival_{pst} + \beta_4 MultiColor_{pst} \\
&+ \beta_5 AutumnDesign_{pst} + \beta_6 WinterDesign_{pst} + \beta_7 ShopAds_{st} \\
&+ \beta_8 SpecAds_{st} + \beta_9 OtherAds_{pst} + WeekdayDummies \\
&+ MonthDummies + \omega_p + \psi_s + \sum_j \left(\zeta_{pso_j t} * Visits_{pso_j t} \right) + \varepsilon_{pst}
\end{aligned}
\tag{5}
$$

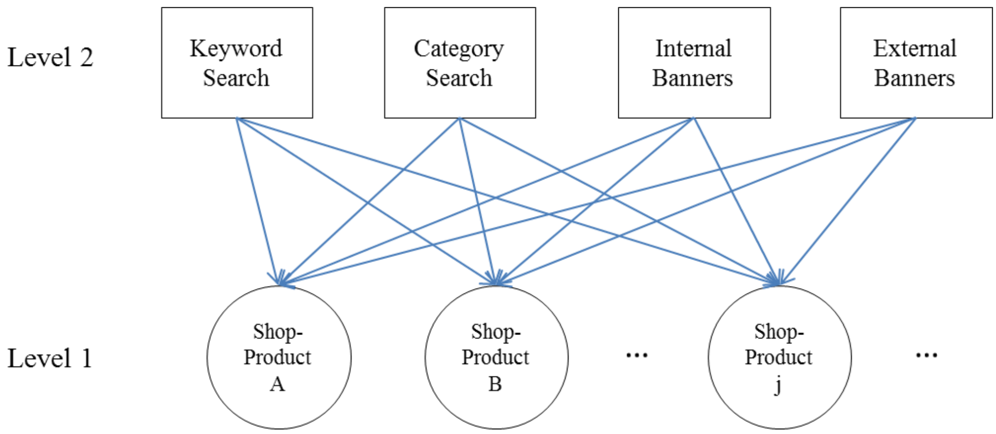

Figure 3-8 Two-level Hierarchical Model

3.5 Model Estimation and Results

To estimate the hierarchical model with mixed effects (i.e., Equation (5)), we used the maximum likelihood estimator. As the dependent variable *ln(QSales)* is a real number, the error term ε_{pst} is assumed to follow normal distribution. For simplicity, we assume the random effects of the visits from the four targeted advertising outlets are uncorrelated. Namely, all covariances between outlets are 0. The estimation results are presented in Table 3-7. Each targeted advertising outlet has one random component, which is shown in the section of level-2 random part in the table. The random component of keyword search advertising is the only significant one. The rest are either insignificant or marginally significant. These values suggest that the random effects actually are not prominent for most targeted advertising outlets. Therefore, it is not necessary to include a random component to model the impacts of each targeted advertising outlet on product demand (Hox 2010).

Table 3-7 Results of Mixed-effects Model

VARIABLES		Estimates
Fixed Part		
Intercept	*Visits_KeywordSearch*	0.532
		(0.641)
	Visits_CategorySearch	6.942**
		(3.177)

	Visits_InternalBanners	1.297
		(0.847)
	Visits_ExternalBanners	0.451
		(0.602)
DiscountMsg×	*Visits_KeywordSearch*	0.410
		(0.433)
	Visits_CategorySearch	-2.645
		(3.311)
	Visits_InternalBanners	-0.194
		(0.616)
	Visits_ExternalBanners	0.153
		(0.480)
FreeDeliveryMsg×	*Visits_KeywordSearch*	-0.004
		(0.127)
	Visits_CategorySearch	2.888
		(2.176)
	Visits_InternalBanners	-0.097
		(0.265)
	Visits_ExternalBanners	0.184
		(0.162)
CTR×	*Visits_KeywordSearch*	-0.600***
		(0.179)
	Visits_CategorySearch	-1.111
		(0.824)
	Visits_InternalBanners	-0.854
		(0.822)
	Visits_ExternalBanners	-0.069
		(0.133)
Price×	*Visits_KeywordSearch*	0.002
		(0.004)
	Visits_CategorySearch	-0.028*
		(0.015)
	Visits_InternalBanners	-0.003
		(0.005)
	Visits_ExternalBanners	-0.002
		(0.003)
PosInPage×	*Visits_KeywordSearch*	0.005
		(0.006)
AvgDisPage×	*Visits_KeywordSearch*	-0.018
		(0.034)
Price		-0.007*
		(0.004)
Favorites		0.157**
		(0.077)
NewArrival		-0.312**
		(0.144)
MultiColor		1.168*
		(0.600)
AutumnDesign		0.037
		(0.228)
WinterDesign		0.223
		(0.274)
ShopAds		-0.076
		(0.085)
SpecAds		0.162**
		(0.069)
NormAds		0.025
		(0.025)
Constant		3.019***
		(0.998)

Random Part	
Level 2	
$\sigma^2_{0_1}$ *(KeywordSearch)*	0.138** (0.111)
$\sigma^2_{0_2}$ *(CategorySearch)*	11.906* (15.558)
$\sigma^2_{0_3}$ *(InternalBanners)*	0.528 (0.710)
$\sigma^2_{0_4}$ *(ExternalBanners)*	0.027 (0.081)
$Var(\omega_p+\psi_s)$	1.634*** (0.248)
Level 1	
σ^2_e	-0.370*** (0.050)

1. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
2. Weekday dummies and month dummies have been included in model estimation.
3. There are 1,562 observations of 49 shop-product pairs.
4. "×" denotes interactions between the variable preceding it and the ones following it.

After removing the random part of the coefficients, our model was simplified to a normal linear regression. We used an ordinary least square (OLS) estimator for model estimation. The coefficients of this log-level model can be interpreted as semi-elasticity. Besides the factors specified in our model, some unobserved factors may shift the product sales. To account for such impacts, we exploited the panel structure of the dataset and panel-level estimators were used. The distribution of error term ε_{pst} might violate the standard assumption of homoscedasticity. Robust standard errors have been used where applicable, to overcome heteroscedasticity. Both fixed-effects (FE) and random-effects (RE) specifications were estimated to account for unobserved shop-product specific effects. The results are shown in Models (1) and (2) in Table 3-8. If correlation exists between the observed explanatory variables and the unobserved shop-product specific effects, the RE specification would produce inconsistent results. To test for appropriate specifications, we conducted the Hausman test (Wooldridge 2002b). The Hausman test rejected the null hypothesis that difference in coefficients of the two models was not systematic (χ^2 = 539.61, p = 0.0000). Thus, the FE model is preferred.

Table 3-8 Results of Panel-level Regression

VARIABLES		OLS (1) FE	OLS (2) RE	OLS&AR(1) (3) FE	OLS&AR(1) (4) RE	OLS&AR(1) (5) RE
Intercept	*Visits_KeywordSearch*	-0.598*	-1.393***	-0.830***	-0.822***	-0.835***
		(0.323)	(0.463)	(0.229)	(0.218)	(0.217)
	Visits_CategorySearch	4.548**	8.275***	3.135*	4.829***	4.492***
		(2.249)	(2.403)	(1.784)	(1.386)	(1.387)
	Visits_InternalBanners	1.201	1.142	1.943***	1.456***	1.399***
		(0.758)	(0.730)	(0.443)	(0.437)	(0.434)
	Visits_ExternalBanners	0.383	0.330	0.495	0.167	0.311
		(0.493)	(0.758)	(0.325)	(0.307)	(0.309)
DiscountMsg ×	*Visits_KeywordSearch*	0.303	0.774*	0.421	0.905***	0.865***
		(0.413)	(0.411)	(0.274)	(0.219)	(0.218)
	Visits_CategorySearch	-2.596**	-3.733***	-1.624	-2.200***	-1.932**
		(1.179)	(1.224)	(0.996)	(0.803)	(0.804)
	Visits_InternalBanners	0.735*	0.757***	-0.074	-0.103	-0.116
		(0.418)	(0.290)	(0.244)	(0.232)	(0.231)
	Visits_ExternalBanners	0.181	0.481	0.588	-0.101	-0.008
		(0.411)	(0.793)	(0.383)	(0.342)	(0.343)
FreeDelivery Msg×	*Visits_KeywordSearch*	-0.150	-0.582*	0.009	-0.154	-0.153
		(0.099)	(0.318)	(0.162)	(0.162)	(0.162)
	Visits_CategorySearch	-0.998	1.590	-0.353	0.881	1.069
		(0.926)	(1.050)	(0.830)	(0.806)	(0.808)
	Visits_InternalBanners	-0.328	-0.659	-0.329*	-0.262	-0.263
		(0.244)	(0.409)	(0.189)	(0.188)	(0.187)
	Visits_ExternalBanners	0.316*	0.716**	0.286	0.419**	0.422**
		(0.171)	(0.325)	(0.196)	(0.189)	(0.189)
CTR×	*Visits_KeywordSearch*	-0.165	-0.324*	-0.193	-0.364***	-0.345***
		(0.164)	(0.180)	(0.144)	(0.131)	(0.130)
	Visits_CategorySearch	-1.691*	-3.790***	-1.685*	-2.064**	-1.991**
		(0.852)	(1.257)	(1.000)	(0.910)	(0.906)
	Visits_InternalBanners	-0.741	-0.357	-1.121*	-0.790	-0.692
		(0.679)	(0.851)	(0.650)	(0.616)	(0.612)
	Visits_ExternalBanners	-0.019	0.406*	-0.041	0.042	0.031
		(0.147)	(0.217)	(0.153)	(0.153)	(0.152)
Price×	*Visits_KeywordSearch*	0.005**	0.011***	0.005***	0.007***	0.007***
		(0.002)	(0.004)	(0.001)	(0.001)	(0.001)
	Visits_CategorySearch	-0.009	-0.032**	-0.006	-0.018**	-0.018**
		(0.013)	(0.014)	(0.010)	(0.008)	(0.008)
	Visits_InternalBanners	-0.003	-0.002	-0.007***	-0.005***	-0.005**
		(0.005)	(0.004)	(0.002)	(0.002)	(0.002)
	Visits_ExternalBanners	-0.002	-0.003	-0.004**	-0.002	-0.003**
		(0.002)	(0.004)	(0.001)	(0.001)	(0.001)
PosInPage×	*Visits_KeywordSearch*	0.010	0.010	0.012	0.008	0.008
		(0.012)	(0.012)	(0.007)	(0.007)	(0.007)
AvgDisPage×	*Visits_KeywordSearch*	0.001	-0.038	0.010	0.020	0.019
		(0.024)	(0.047)	(0.070)	(0.036)	(0.036)
Price		-0.010***	-0.004	0.000	-0.002***	-0.001
		(0.004)	(0.003)	(0.001)	(0.001)	(0.001)
Discount						0.290***
						(0.066)
Favorites		0.134*	0.242***	0.203***	0.214***	0.211***
		(0.069)	(0.088)	(0.018)	(0.017)	(0.017)
NewArrival		-0.412**	0.690***	0.293	0.327**	0.364**
		(0.177)	(0.239)	(0.191)	(0.162)	(0.164)
MultiColor		0.961	-0.063	1.235***	0.874***	0.862***
		(0.593)	(0.250)	(0.265)	(0.221)	(0.224)
AutumnDesign		0.170	-0.403*	-0.550***	-0.306**	-0.314**
		(0.248)	(0.229)	(0.196)	(0.149)	(0.150)
WinterDesign		0.238	-0.428	-0.008	-0.166	-0.192
		(0.289)	(0.292)	(0.236)	(0.190)	(0.192)

ShopAds	-0.069	-0.024	0.050	-0.032	-0.041
	(0.089)	(0.104)	(0.042)	(0.038)	(0.038)
SpecAds	0.094	0.037	0.151**	0.095	0.089
	(0.061)	(0.094)	(0.069)	(0.064)	(0.064)
NormAds	0.036	-0.028	0.109***	0.059**	0.058**
	(0.037)	(0.045)	(0.029)	(0.028)	(0.028)
Constant	4.013***	1.910**	1.186***	2.012***	1.700***
	(0.919)	(0.811)	(0.105)	(0.246)	(0.256)
Weekday Dummies	Y	Y	Y	Y	Y
Month Dummies	Y	Y	Y	Y	Y
Overall R-squared	0.2675	0.7338	0.4538	0.6270	0.6135

1. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
2. The standard errors for Models (1) and (2) are robust standard errors.
3. There are 1,562 observations of 49 shop-product pairs.
4. "×" denotes interactions between the variable preceding it and the ones following it.

The aforementioned panel-level OLS estimates provide some evidence on the impacts of different targeted advertising outlets. However, the demand for the advertised products in our sample might have serial dependence. In other words, the sales of a product in previous time periods may influence its current sales, which commonly occurs in e-commerce environments (Duan et al. 2009; Ye et al. 2013). Consumers can access the historical sales and customer reviews conveniently. These statistics usually have great impacts on consumers' purchase decisions. Thus, we foresaw serial correlation existed in our panel data. To test this potential thread, we followed the approach proposed by Wooldridge (2002b) and Drukker (2003). The test rejected the null hypothesis of no serial correlation at the significance level of 0.05 (*F-Stat* =10.838 and $p>F$=0.0021). In order to account for this serial correlation, a panel-level OLS estimator with a first-order autoregressive (AR(1)) disturbance was used to estimate our econometric model. We tried both FE and RE specifications, which were presented in Table 3-8 Models (3) and (4) respectively. The Hausman test then suggested no significant difference between the two models (χ^2 = 36.85, p = 0.6558). As FE estimates are restricted within the specific data sample, RE results are preferred (Cameron et al. 2005). Compared with Model (1), the results in Model (4) in Table 3-8 have some changes in both coefficients and significance. Specifically, more variables become significant. We focus on Model (4) for results interpretation due to its consideration of serial correlation. Though the number of visits from keyword search advertising is found to be highly correlated with the number of favorites a product received, both coefficients are significantly different from 0 in all the models in Table 3-8. Hence, their high correlation merely influences the estimator efficiency and would not cause the multicolinearity problem (Wooldridge 2012).

The intercepts of the targeted advertising outlets unveil their value in attracting visits that may result in purchases. The coefficients are relative values to the baseline group, which are the visits from places beyond the four targeted advertising outlets in our study (e.g., generic listings of the search results and direct visits). Both keyword search and category search have coefficients that are significantly different from 0. The coefficients indicate that compared with the baseline group, one additional visit from keyword search advertising would reduce the product demand by 0.082% (i.e., $e^{-0.822/1000}-1$) [17], and one additional visit from category search advertising would increase the product demand by 0.484% (i.e., $e^{4.829/1000}-1$). This suggests that category search advertising generates higher product demand than keyword search advertising, which contradicts H1.

Visits from internal banners have a significantly positive intercept while the coefficient for external banners is insignificant. The coefficient of the intercept of internal banners suggests that compared with the baseline group,

[17] As the number of visits from each outlet is measured by the unit of one thousand, we divide the coefficients by 1,000 when calculating the semi-elasticity.

one more click from internal banners is associated with 0.146% (i.e., $e^{1.456/1000}-1$) higher product demand. We conducted a t-test (Baum 2006) to compare the impacts of these two outlets. The coefficient difference is 1.289, with a standard error of 0.491. The z-value (2.62) indicates that this difference is significant at the significance level of 0.05. Therefore, H3 is supported.

To understand the role of the ad copy in shaping consumers' product demand, we next examine the interaction terms between the price related information in the ad copy and the visits from different targeted advertising outlets. Discount messages in the ad copy have significantly positive effects on the visits from keyword search but negative effects on the visits from category search. The impact is again different from our expectation. The presence of price discount messages in the ad copy of keyword search increases product demand by 0.091% (i.e., $e^{0.905/1000}-1$) but the presence of the messages in the identical ad copy of category search decrease product demand by 0.220% (i.e., $e^{-2.200/1000}-1$). This implies that price discount messages motivate visitors from keyword search to purchase the advertised product. Thus, H2 is unsupported.

The unexpected results of H1 and H2 might be caused by the identity of brand Lolita, which is an emerging entrepreneurial brand, not known as well as the established brands. Lacking large scale offline and online marketing campaigns to increase brand exposure, the low brand awareness is a big challenge for Lolita's marketing activities (Dhar et al. 1997; Steiner 2004). To build brand image, the brand owner has been advised to increase the brand exposure to the masses by bidding for both generic and branded keywords (Google 2015a; Kelleher 2010). The advertisements are displayed when consumers search for either the generic or branded keywords that are bid by Lolita, given that the bidding prices are high enough to get a display slot. As Lolita is not well-known by consumers, only a small proportion of the ad clicks are from consumers who search for branded keywords, while most ad clicks are from consumers who search for generic keywords (Jacobson 2011). Using generic keywords usually implies the consumer is in the initial phase of information search. Therefore, most visits to Lolita from keyword search advertising are still at an early stage of information seeking and lack well-defined purchase targets.

Additionally, searching through the hierarchical category tree requires consumers to choose various features of the intended products at different category level. To make a choice, consumers should have some ideas about the characteristics of their intended products. In contrast to the majority of the visitors from keyword search advertising who do not possess fully formed consideration sets (Rutz et al. 2011a; Rutz et al. 2011c), the visitors from category search advertising possess more specific goals. Their clicks on the targeted advertisements exhibit their potential shopping interest in the products. The higher level of goal specificity indicates that these consumers are closer to the purchase phase (Rutz et al. 2011c). Compared with the visitors who come from keyword search advertising and are at an early stage of information search, the visitors from category search advertising may have a higher probability to purchase the advertised product. This consequently results in a larger coefficient of category search visits than that of keyword search visits. Compared to the visitors from keyword search, the visitors from category search have clearer purchase goals, which make them less prone to be affected by the discount information in the ad copy. This is the reason why keyword search visits have a larger coefficient than category search for the interaction term with the discount message indicator.

The interaction terms between discount messages and the visits from both internal banners and external banners are not significant. Despite this, we conducted a t-test (Baum 2006) to compare whether any significant differences exist between these two coefficients. The z-value (-0.00) of the t-test suggests the difference is not significantly different from 0. Thus, H4(a) is unsupported. For free delivery messages in the ad copy, we hypothesize significantly positive effects for the visits from advertisements in the context of passive information seeking. However, only the interaction term between free delivery messages and the visits from external banners is significantly positive. The presence of free delivery messages in the ad copy of external banners increases product demand by 0.042% (i.e., $e^{0.419/1000}$-1). The effects of free delivery messages on the visits from internal banners are not significantly different from 0. H4(b) hence is partially supported.

Besides the variables of our research focus, the results produce some interesting insights on targeted advertising in different outlets. Price is one of the most crucial factors influencing product demand. Without exception, Model (4) suggests that consumers are price sensitive, which can be inferred from the significantly negative main effect of *Price*. In addition to this main effect, the interaction terms between price and the visits from the four targeted advertising outlets exhibit differential properties of consumers in each outlet. The visits from keyword search are less price sensitive than the visits from the baseline group venues under our investigation. The semi-elasticity of price for the visits from keyword search advertising is -0.199% (i.e., $e^{0.007/1000-0.002}-1$), which is slightly lower than that for the visitors from the baseline group -0.200% (i.e., $e^{-0.002}-1$). In contrast, the visits from category search and internal banners are more price sensitive, showing semi-elasticity (i.e., $e^{-0.018/1000-0.002}-1$ and $e^{-0.005/1000-0.002}-1$) that is larger than that of the visitors from the baseline group. The visits from external banners have the same price elasticity as the baseline group visitors. The click-through rate has either negative or insignificant impacts on converting the visits from targeted advertising outlets to purchases, implying that a higher click-through rate is sometimes associated with lower product demand.

The number of favorites a product receives has positive impacts on product sales, which is consistent with our postulation. Additionally, products have a higher level of sales in the first 10 days after arriving. Clothes with multiple color choices sell better than those which are only available in a single color. Furthermore, relative to no provision of seasonal information, indicating design for autumn decreases quantity product sales.

Although the price related promotional messages in the ad copy have significant impacts on consumers' purchase behaviors, they may not reflect the actual price discounts and are merely a trick for sellers to increase sales. To test the effects of real price discounts on consumer responses, we added an extra variable *Discount* to our model. The variable is a binary indicator inferred from the product's historical transaction price. We compared the price change relative to the average price of the product in the past seven days. If the price reduction was larger than 5%, *Discount* was coded as 1, and 0 otherwise. We reran the panel-level OLS estimator with AR(1) disturbance and the Hausman test (χ^2 = 7.33, p = 1.0000) again favored RE specification. Model (5) in Table 3-8 shows the results of the new model. All the variables in Model (5) have qualitatively similar coefficients as those in Model (4), except for *Price*. After adding the indicator of actual price discount, the negative effects of price on product demand is eliminated. Instead, *Discount* has a highly significant positive coefficient. We have checked the correlation between *Discount* and *Price*, which is only -0.14. The multicolinearity problem is not a concern regarding this change. This means that price discount entirely absorbs the negative effects of price. The results in Model (5) highlight online consumers' great enthusiasm for price discounts and promotions in Taobao.

3.6 Discussion and Contributions

3.6.1 Findings and Discussion

In the current study that investigates the product demand generated by online targeted advertisements in different outlets, several notable findings have been observed. First, the lower value of keyword search advertising may contradict the common perception that sponsored search advertising is one of the most effective online advertising formats (Zhang et al. 2012). A caveat worth attention is that brand Lolita in our study is an entrepreneurial e-commerce brand, which unlike the established brands, greatly lacks media coverage and brand recognition. Only a small number of customers are familiar with the brand and are able to search for it with accurate branded keywords. The proportion of such visits from keyword search advertising in our dataset is only 1.329%. Most visitors from the advertising outlet of keyword search clicked the advertisement when they were searching for generic keywords, such as leatheroid apparel, female PU jackets. They might not be ready to make a purchase at that stage (Agarwal et al. 2012). This is a potential reason for the low value of keyword search advertising. To increase store traffic, brand Lolita sometimes even bid for competitors' well-known brands as keywords. About 0.850% of the visits from keyword search advertising reached the product pages by searching for such keywords. Compared with brand Lolita, those competitive brands are more established. Juxtaposition with competitors' well-known brands reminds consumers to make comparison and the contrast effects will be exaggerated (Desai et al. 2014). In other words, consumers may perceive the advertised product as of a lower quality compared with the quality perception with the absence of the established brands. This might be another reason for the reluctance of the visitors from keyword search advertising to make purchases.

Second, the values of targeted advertising outlets show large variations, which heavily depend on consumers' information search mode. Consumers may involve in either active or passive information search. When consumers are actively searching for information, such as those in keyword search or category search, goal specificity level of their information seeking may influence their final purchase decision. When consumers are not actively engaging in product information search, Lolita's advertising outlet of internal banners, which support a higher level of targetability for customers, generates more product demand than the brand's advertising outlet of external banners, which support a lower level of targetability for customers.

Second, price discount messages in the ad copy have profound impacts on visitors' decision making on purchases and the impacts differ across targeted advertising outlets. Suppose that consumers' purchase intention is a point on a continuum ranging from very low to very high. The location can be inferred from the properties of the advertising outlets. Price discount messages in the ad copy are not effective for advertising outlets where the majority of consumers have too low or too high purchase intentions (i.e., external banner advertising and category search advertising) since the consumers either have no shopping plans or know their purchase targets clearly. Regarding the advertising outlets where the majority of consumers have a general but not well-defined purchase intention (i.e., keyword search advertising), price discount messages in the ad copy considerably boost product demand by persuading consumers of a good deal. It is important to note the significantly negative moderating effects of the discount messages on the visits from category search advertising. The negative effects indicate that the visitors from category search respond negatively to the discount messages. Possibly, the consumers from category search advertising, with a clearer purchase objective compared to the purchase goal of the consumers from keyword search advertising, tend to use price discounts as quality signals. They perceive products with price discounts to be of inferior quality (Erdem et al. 2008; Zeithaml 1988), which consequently decreases the purchase probability.

Third, free delivery messages in the ad copy increase product demand for the advertising outlets having more consumers without planned purchase, such as the outlet of external banners. The purchasers from external banner advertising are most likely to be impulse buyers, who make the purchase without any plans. The unplanned property of these visitors implies that they are more likely to make decisions through the peripheral route (Evans 1984;

Hamilton et al. 2008). In this context, free delivery messages in the ad copy act as an effective impulse item to enhance consumers' interest in the advertised product (Beatty et al. 1998; Stern 1962).

Additionally, other than the findings related to our hypotheses, our analyses reveal several interesting patterns. First, the intercepts of the targeted advertising outlets exhibit the values of their visitors relative to the visitors from the baseline group. According to our communication with brand Lolita, more than 60% of the daily store visits are direct traffic or from the search engine in Taobao. These visits form the majority of the baseline group visitors. Among the four advertising outlets, keyword search is the only one with a value lower than the baseline group, indicating that the visitors from the keyword search outlet are less likely to make immediate purchases than the visitors who voluntarily visit the product pages instead of being attracted by the advertisements. Marketers' media activities usually fall into three categories – paid media, owned media and earned media (Stephen et al. 2012). Online targeted advertising is classified as paid media, which are purchased by the marketers. As a type of paid media, keyword search advertising in our study fails to be more successful than the non-paid media where the most baseline group visitors come from. However, the descriptive statistics in

Table 3-4 show that keyword search advertising has a much higher average price than the other outlets (e.g., almost twice as that of internal banner advertising). Although price discount messages in the ad copy may mitigate the negative value of the visits from keyword search, such discrepancy in performance and costs still deserves advertisers' contemplation on their advertising portfolio.

In addition, the price sensitivities of consumers from different targeted advertising outlets are shown to vary. Consumers from keyword search advertising, on average, are the least sensitive to price, followed by consumers from external banners and the baseline group; while consumers from category search advertising are the most price-sensitive. Consumers from keyword search advertising seem to show conflicting responses, being attracted by a good deal (i.e., with price discounts) on the one hand, but yet willing to pay more (i.e., lower price sensitivity) for their ideal products on the other hand. This reaction actually reflects the fact that they are engaging in exploratory search. Since they have yet to decide their target products, there is no reference price for comparison (Mazumdar et al. 2005). This results in their greater willingness to pay for their ideal products. By the same token, they are more likely to treat discount messages as relevant cues to form a consideration set (Lee et al. 2006; Tam et al. 2006). Therefore, price discount messages in the ad copy significantly increase the product demand for the visitors from the keyword search outlet.Finally, we have observed negative effects of the click-through rate on product quantity sales for the advertising outlets of keyword search and category search. Though ample literature on sponsored search advertising (e.g., Braun et al. 2013; Ghose et al. 2009; Rutz et al. 2011b) investigates the factors that influence the click-through rate and conversions of the sponsored ads, none of them has discussed the relationship between these two metrics. Our results suggest that, generally, a high click-through rate does not necessarily increase product sales, which is somewhat counterintuitive. Nonetheless, analyzing the problem from the consumers' perspective may enhance our understanding. The click-through rate could be a proxy for the quality of a targeted advertisement when the display position has been controlled. Consumers form their own expectations of the advertised product when they view the targeted advertisement. This expectation acts as an anchor point for later product evaluation (Chapman et al. 1999; Strack et al. 1997). A well-designed ad may heighten consumers' expectations. After accessing the destination webpage, consumers update their belief on the advertised product by evaluating the product characteristics presented in the page. The anchor point of product expectations will be the minimum requirement for consumers' purchase target. If the product characteristics do not match their expectations, they would rarely make a final purchase (Mussweiler 2003). Thus, maintaining consistency between the advertisement and product information presentation is pivotal for purchase conversion (Jacobson 2011).

3.6.2 Theoretical Contributions

This study makes significant contributions to existing literature in the following ways. First, we examine multiple targeted advertising outlets which vary in consumers' information search mode and find their distinctive impacts on the demand of the advertised products. In spite of the abundant academic studies on online digital advertising, most of them have focused on a single advertising outlet, e.g., sponsored search advertising or banner display advertising, without differentiation of consumers' information search mode. This study is possibly one of the first to take into account different types of targeted advertising outlets. We find that online targeted advertising outlets can be natural dividers to segment potential consumers and therefore the values of these advertising outlets differ.

Second, we have proposed a granular typology to analyze the properties of targeted advertising outlets based on consumers' information search mode. When consumers are engaging in active information seeking, the level of goal specificity discloses their information search stage and possibly influence their demand of the advertised product. When consumers are not actively searching for information, the targetability of targeted advertisements becomes a crucial factor affecting consumers' purchase decisions. A higher level of targetability raises the relevance level of the targeted advertisement to the viewer, resulting in an increased purchase probability. This granular typology provides a better theoretical perspective for analyzing the features of targeted advertising outlets and would benefit future research in this stream.

Third, a limited number of studies have investigated the content of the ad copy on advertisement performance, and furthermore, research on its moderating effects on advertisement display outlets is even rarer. This study identifies the unique roles of the ad copy in moderating the impacts of the visits from each targeted advertising outlet on product demand. Although targeted advertising outlets differ in their values, adjusting the content of ad copy according to the display outlet can change consumers' responses to an advertisement. Consumers exhibit distinctive properties in different targeted advertising outlets. Consumers in keyword search advertising are more responsive to price discount messages, while consumers in category search advertising tend to react negatively to such messages. Moreover, free delivery messages in the ad copy only affect the purchase decisions of the consumers who have minimal planned shopping intention (i.e., external banner advertising). These differential effects highlight the necessity to account for the differences in advertising outlets when examining the impacts of the ad copy.

Fourth, the current study takes a close examination of an entrepreneurial e-commerce brand, differing from the well-known brands that are commonly investigated by existing literature on online digital advertising (e.g., Ghose et al. 2009; Goldfarb et al. 2011a; Lambrecht et al. 2013). The fast advancing Internet technologies have empowered countless small business owners to sell products or provide services to an expanding group of customers. However, consumers' awareness of their brands is tremendously different from that of well-established brands. Such discrepancy presents great challenges to the marketing activities of these emerging brands. Our study suggests that, faced with low brand awareness, it is difficult for these emerging brands to benefit from the advertising to consumers who are actively searching for product information but remain in the exploratory phase, unless other persuasive stimuli are provided such as price discounts.

Fifth, this study provides fresh findings beyond existing literature on online digital advertising. We find a generally negative effect of the click-through rate on the sales of the advertised products. This relation has not been discussed previously and could be a new topic for future research. Furthermore, our analyses on the properties of each targeted advertising outlet (i.e., goal-specificity and targetability) provide an additional perspective that can be used to segment customers for business owners. Algorithm designers can also incorporate this factor into the algorithms that are relevant to consumer insights.

3.6.3 Managerial Implications

This study is of great relevance to practitioners, who may benefit in the following ways. First, this study demonstrates that, in practice, paid media is not of equal value. Their distinct properties influence their visitors' probability to purchase. Among the four targeted adverting outlets provided by Taobao, category search advertising possesses the highest value, followed by internal banner advertising and external banner advertising. Keyword search advertising has the lowest value, which is lower than that of the non-paid media. This is mainly due to the low brand awareness of brand Lolita, which acquires most visits from keyword search advertising with generic keywords. However, generic keywords are found to be ineffective in attracting immediate purchase visits (Rutz et al. 2011a; Rutz et al. 2011c). Thus, when choosing the advertisement media, marketers need to think about their traits carefully and make decisions based on their own characteristics.

In addition, the content of the ad copy influences consumers' purchase decisions in targeted adverting outlets differentially. When consumers have purchase goals of a higher construal level, price discount messages in the ad copy motivate these consumers' purchase intention. This suggests that marketers should include price discount messages in the ad copy of the advertising outlets that support lower levels of goal specificity in active information seeking, which is keyword search advertising in Taobao. Free delivery messages are another type of information that can be incorporated in the ad copy. Free delivery messages work well for targeted advertising outlets that support passive information seeking and have more consumers without planned purchase. This promotional information can enhance these consumers' shopping inclinations and encourage them in making a purchase without much deliberation. To summarize, it is more productive for marketers to customize the contents of their ad copies for the targeted advertising outlet where the advertisement is displayed.

Moreover, consumers from different advertising outlets present different price sensitivities. Enabled by modern information technologies, e-commerce sellers can offer personalized prices according to the customer’s willingness to pay. For example, the visitors from the advertising outlet of category search are the most sensitive to price, whereas the visitors from the advertising outlet of keyword search are the least sensitive. Such findings provide clues for marketers to design differential price schemes for the visitors from different sources.

Moreover, the click-through rate of the targeted advertisement is found to influence the product sales negatively. Practitioners need to take this observation into consideration. Marketers strive to make a well-designed and attractive ad creative that increases the click-through rate. However, the advertisement itself helps consumers to form expectations of the product. If the product information presented in the landing webpage cannot match such expectations, consumes will rarely make final purchases. Under the pay-per-click price scheme, which is one of the most frequently used pricing mechanisms today (Asdemir et al. 2012), the advertising expenditure would be wasted. Hence, keeping the advertisement consistent with the advertised product is conducive to advertisers.

3.7 Conclusions

In this study, we investigate the product demands of the visits attracted by online targeted advertisements from different outlets. The results based on a panel-level OLS estimator with a first-order autoregressive disturbance structure provide several interesting findings. In the context of active information seeking by consumers, the goal specificity level of consumers' information seeking may influence their demand of the product. In the context of passive information seeking by consumers, highly targeted advertisements are of greater capability than the advertisements with lower targetability in converting visits into transactions. In addition, price discount and free delivery messages in the ad copy have significant moderating effects on the impacts of targeted advertising outlets regarding product demand in some outlets. Specifically, the price discount messages are more capable of persuading visitors from keyword search advertising to make purchases compared with visitors from category search advertising. Furthermore, as an application of partitioned pricing, free delivery messages in the ad copy help the advertising outlet of external banners to generate higher product demand. These findings have significant theoretical and practical contributions.

This study unavoidably has several limitations. First, though we investigate the immediate impacts of online targeted advertisement on product demand, it also holds true that advertising can produce long-term effects on human memory. This effect has not been accounted for in the current study. Nevertheless, our findings are still valuable for advertisers who pursue short-term returns, which is an advantage of online digital advertising. Additionally, we only investigate two types of information (i.e., price discount and free delivery messages) contained in the ad copy due to data constraints. Usually an ad copy contains multiple facets, and future studies can consider other facets of the ad copy. Even the ad creative, which is not available in our dataset, can be incorporated into the analyses, which may produce more insightful findings. Moreover, our study is based on the dataset of a female apparel brand. Apparel belongs to experience goods, which greatly differ from search goods such as digitals and books, in product information search. Consumers may present different search behaviors for these two types of goods. Our findings may only apply to experience goods. Furthermore, the female apparel in our study is an entrepreneurial e-commerce brand, which is not well-established. Consumers' responses to such a new brand may significantly differ from those to well-known brands. Caution is needed when applying the results to famous brands. Last but not least, we have conducted aggregate analyses based on product-level information. Similar data at individual level will tremendously benefit our understanding about the impacts of different targeted advertising outlets on product demand.

CHAPTER 4. CONCLUDING REMARKS

Enabled by information technologies (ITs), platform-based e-commerce marketplaces have tremendously changed the modern business landscape. Such marketplaces facilitate the proliferation of small businesses. However, the two-sided nature of the platform-based markets fosters a positive feedback loop, which usually makes the marketplaces overcrowded. Encountered with the problem of scarce visibility, marketing has becomes the biggest challenge for these online small business owners. In this dissertation, we investigated the small business owners' marketing activities from two viewpoints, product strategies and promotion strategies. The first aspect aims at finding reasonable product portfolio designs that account for small business owners' unique characteristics and leverage on the synergy among products to achieve better marketing responses; the second aspect aims to find the appropriate ways to plan small business owners' online targeted advertising portfolios and design effective ad copies. We explored these two aspects with two studies respectively in this dissertation.

The first study investigated mobile app developers' app portfolio management strategies in the Apple App Store. Specifically, we evaluated the impacts of app portfolio on developers' app quality and popularity. For app quality, we examined the influence of mobile developers' app portfolio size and diversity on app quality. The results based on dynamic propensity score matching and Heckman selection model suggest that engaging in more app categories brings no benefit to app quality and this negative effect further exacerbates when the app portfolio size increases under certain circumstances. Regarding app popularity, we assessed the extent and direction of popularity spillover effects between developers' existing and new apps. Our empirical analyses with a simultaneous equations model show that the popular existing apps of a developer could promote the popularity of new apps both within and across categories. New apps, in turn, drive demand for a developer's existing apps within the same category and the effect is more than five times larger than that in the reverse direction. Our findings highlight the importance of specialization for mobile app developers, who are small in scale and deficient in resources.

The second study investigated the impacts of online targeted advertising outlets and the content of the ad copy on the product demand of an emerging brand. Targeted advertising is greatly appreciated by practitioners due to its situational and personalized advertisement feeds based on individual consumers' behaviors. Consumers may display different information search modes in different online advertising outlets. However, the few existing studies on targeted advertising have only focused on one single advertising outlet. How consumers' responses to targeted advertisements differ across various advertising outlets remains undiscussed. To address this research gap, we proposed a two-level hierarchical model to model the impacts of the visits from four different targeted advertising outlets provided by Taobao. A panel-level linear regression with first-order autoregressive disturbance structure was used to evaluate the model with a dataset from a Taobao-based entrepreneurial e-commerce brand of female leatheroid apparel. The results show that the goal specificity of consumer search and the targetability of targeted advertisements have significant impacts on the product demand of the visitors from different advertising outlets. In addition, the price related information (i.e., price discount and free delivery messages) in the ad copy exhibit different effects across advertising outlets. Generally, price discount messages in the ad copy increased the product demand of the visits from the targeted adverting outlet that supported a lower level of goal specificity in active information seeking (i.e., keyword search advertising). Free delivery messages in the ad copy boost the product demand of the visitors from the targeted adverting outlet that supported passive information seeking and at a lower level of targetability (i.e., external banner advertising).

Although the two studies examined small business owners' marketing strategies from different angles, the ultimate goals converged to the improvement of business performance. In these studies, we found several places that distinguished small IT enabled business owners from traditional business owners in marketing activities. First, the resources owned by these small business owners are quite limited. Making full and smart use of existing resources with the least cost is a huge challenge for them. Marketing research should never follow product development. This sequence used to be a great pitfall for most startups. A cost-saving approach to do effective marketing is to incorporate marketing effects to product design, leveraging on the synergies such as branding effects among their own products to achieve larger marketing impacts. Second, word-of-mouth transmission is extremely important for small business owners considering their limited marketing budgets. Impressing consumers with a well-designed product is much more useful than flooding the market with hundreds of mediocre products. The positive feedback for a good product will profoundly benefit the subsequent products of the same producer. Third, paid-media have different values and small business owners should plan their advertising portfolio based on their respective characteristics and the features of the specific paid-media. Brand awareness of the small business owners’ products is much lower than that of the established brands. Consumers present discrepant information searching behaviors for these two types of brands. Small business owners are advised to use more display-based advertisements to increase consumers’ memory of the brand. Fourth, the ad copy plays an important role in advertising and its impacts vary across advertising outlets. Customized ad design for different advertising outlets assists small business owners in obtaining higher returns from an investment on paid-media.

As one of the early endeavors for a better understanding of the IT enabled small business owners’ marketing strategies, this dissertation presents potential avenues for future research. While we mainly focused on the product and promotion aspects of marketing activities, the aspect of place of the 4 Ps (McCarthy 1960) recently has received overwhelming attention from the industry. To increase their market shares, online small business owners are aggressively expanding their businesses scope to offline consumers. At the same time, more traditional incumbents are starting up or expanding their online services to maintain their leading positions. Such omni-channel product presence is changing the market structure and merits further analyses.

In addition, the two studies in this dissertation have investigated product strategies and promotion strategies, respectively. As two integral elements of firms’ marketing strategies, the interaction effects between these two elements may exist. For example, the advertisement campaigns of one product might influence other products of the same producer. Questions like which product should be promoted heavily and how promotion strategies influence the synergies of the product assortment are of great relevance to marketers.

Moreover, we primarily adopted the perspective of the small business owners in the platform-based e-commerce markets in this dissertation. It is worthwhile to view the landscape from the angle of the providers of the platform-based markets. The two-sided nature of the platform-based e-commerce markets facilitates the dominant e-commerce platforms to tip the market, ultimately resulting in overcrowded markets. Besides the positive indirect network effects between sellers and buyers, negative direct network effects among the sellers will form. Should the platform providers interfere or leave the competition to proceed? What regulations or new business models can be proposed to govern the long-term prosperity of the platform-based markets? All these questions are worth further exploration by the platform market providers.

To conclude, as a unique and emerging group of participants in the modern business landscape, online small business owners are reshaping the market gradually. They have many different characteristics from the traditional firms. This discrepancy deserves continued investigation of both academics and practitioners.

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