Understanding the Determinants of Success in Mobile Apps Markets

by

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ABSTRACT

Mobile applications (Apps) markets with App stores have introduced a new approach to define and sell software applications with access to a large body of heterogeneous consumer population. Several distinctive features of mobile App store markets including – (a) highly heterogeneous consumer preferences and values, (b) high consumer cognitive burden of searching a large selection of similar Apps, and (c) continuously updateable product features and price – present a unique opportunity for IS researchers to investigate theoretically motivated research questions in this area. The aim of this dissertation research is to investigate the key determinants of mobile Apps success in App store markets. The dissertation is organized into three distinct and related studies. First, using the key tenets of product portfolio management theory and theory of economies of scope, this study empirically investigates how sellers' App portfolio strategies are associated with sales performance over time. Second, the sale performance impacts of App product cues, generated from App product descriptions and offered from market formats, are examined using the theories of market signaling and cue utilization. Third, the role of App updates in stimulating consumer demands in the presence of strong ranking effects is appraised. The findings of this dissertation work highlight the impacts of sellers' App assortment, strategic product description formulation, and long-term App management with price/feature updates on success in App market. The dissertation studies make key contributions to the IS literature by highlighting three key managerially and theoretically important findings related to mobile Apps: (1) diversification across selling categories is a key driver of high survival probability in the top charts, (2) product cues strategically presented in the descriptions have complementary relationships with market cues in influencing App sales, and (3) continuous quality improvements have long-term effects on App success in the presence of strong ranking effects.

This work is dedicated to my wife, Hyoeun Kim,

who steadfastly supported and encouraged me,

&

to my lovely son, So-ul Lee, and my respectful parents

who have been a source of encouragement and inspiration for me throughout my life.

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CHAPTER 1

1. INTRODUCTION

Mobile applications are one of the fastest growing segments of downloadable software applications markets. Many mobile application markets such as Amazon Appstore, Blackberry App World, Google Play Store, and Apple App Store have emerged and grown rapidly in a short amount of time. Since Apple App Store launched with only 500 Apps and a dozen developers in July 2008, the market has increased to over 1,810,000 Apps and 388,470 unique sellers in April 2015[1]. This rapidly growing market has in turn led to over 600 million App consumers downloading around 75 billion Apps in 155 countries and the platform had paid out over 10 billion dollars to App developers in 2014[2].

The competitive dynamics and market interactions in consumer-focused mobile applications (Apps) markets exhibit the key characteristics of 'long tail market' (Anderson 2006). Unlike other long-tail markets covering books, DVD and music, however, App developers do not have established alternate channels to position or brand their creations. In addition, they compete more directly with other developers since consumers are better able to compare product features across Apps. The intense competition along with the remarkable growth in the number of Apps creates "survival"

[1] Apple's App Store Report (April, 1st, 2015), 148Apps, available at http://148apps.biz/app-store-metrics/
[2] iTunes App Store Now Has 1.2 Million Apps, Has Seen 75 Billion Downloads To Date (June 2nd , 2014), TechCrunch, available at http://techcrunch.com/2014/06/02/itunes-app-store-now-has-1-2-million-apps-has-seen-75-billion-downloads-to-date/

problem for even well-established Apps. However, theoretical and managerial understanding of the determinants of success in this hyper-competitive market is still limited. As such, the theoretical underpinnings of strategic market positioning and impacts are as yet unclear. This research develops theoretical and empirical insights into the determinants of success in Mobile Apps markets.

Several distinct characteristics of mobile Apps markets make them a theoretically interesting research context to examine. First, App developers can reuse features and codebase from one App to another, thereby enabling the creation of App portfolios across various App categories. Second, mobile App markets enable developers to deliver an array of App-related attributes and/or marketing messages through the first few lines of product descriptions. This strategic presentation of App product cues has the potential to reduce consumer cognitive burden and perceived risk related to purchase quality uncertainty in the search dominated purchase process. Third, unlike content creators in other long-tail markets, mobile App developers have opportunities to promote their products in the market post-release by responding to dynamic consumer demands. Hence, a developer can strategically utilize price-based or quality-based updates to overcome slow adoption rates or declining sales.

Consequently, these key characteristics of mobile App markets require developers to formulate long-term sales strategies such as App product portfolio, the presentation of App product cues, and pricing and feature updates at multiple periods in order to compete with other developers.

1.1. Research Questions

The overarching goal of this dissertation is to identify the key determinants of mobile App success. App store market structure has several key differentiating characteristics that set it apart from a number of previously examined long-tail market contexts such as books (Brynjolfsson et al. 2006), music (Elberse 2008), and movies (Hinz et al. 2011). I evaluate how the theories and findings drawn toward the conventional long-tail markets are applied in the context of mobile App markets. This dissertation is organized into three chapters that address three distinct yet interrelated research questions.

App Portfolio Management and App Success

Research Question 1: Are Seller's Product Portfolio Decisions Influential in Determining App Survival?

Mobile App Developers can easily create various Apps, thereby quickly building a portfolio of Apps across various (and often unrelated) App categories. The portfolio perspective, in fact, is the most distinguishing facet of mobile App markets. It is evidenced as developers in Apple App Store offered an average of 6.8 Apps across 2.7 categories in 2012. More interestingly, nearly 40% of sellers offer more than 10 Apps and about 60% of the sellers have Apps in more than one category. While developers can address heterogeneous consumer preferences by offering Apps across different categories (Rothaermel et al. 2006), specialization within categories can allow sellers to develop distinct competencies and benefit from scope economies through reduced product development costs (Baumol et al. 1982). Using key tenets of product portfolio management theory and theory of economies of scope, this study empirically investigates how sellers' App portfolio strategies are associated with sales performance over time.

App Product Description and App Success

Research Question 2: Do App Product Descriptions Matter?

The unique characteristics of App store markets increase consumer cognitive burden in evaluating an App's value/quality prior to actual purchase as compared with traditional online markets. First, a large number of Apps contributes to high search costs. In 2014, an average of 1,339 new Apps appeared every day, and even worse many Apps share similar features and functionalities. Second, inherent factors in mobile App transactions such as a smaller screen size and constrained user-interface capabilities further exacerbate the cognitive load during valuation of the offerings (Ghose et al. 2012). Third, the presence of external information (via social media and other sources) on an App from third-parties creates information overload and makes it difficult for users to accurately judge the true utility of the App. As a result, strategic representation of information cues has the potential to reduce a consumer's perceived risk related to purchase quality uncertainty, to reduce cognitive burden, and to increase willingness to purchase. App developers have capabilities to strategically present App product cues in the descriptions to attract more consumers. This study evaluates the role of product cues presented in the descriptions in shaping App consumers' purchase decisions.

App Quality Update Decision and App Success

Research Question 3: What is the Value of Quality in Mobile App Markets?

In such search-intensive markets, a product's successful prior ranking (popularity) has the pivotal role in stimulating new consumer demands for the already successful product as evidenced in the long-tail markets selling songs (Yoo and Kim 2012) , movies (De Vany and Lee 2001), and digital software products (Duan et al. 2009). However, no superstars, bestsellers or blockbusters last forever. Strong popularity effects driven by consumers may not necessarily lead to lasting success in the mobile App market. While most digital products are not updatable in terms of their quality after their releases, the quality of mobile Apps can be easily modified and updated by content creators after observing consumers' purchase behaviors and competitors' strategies. Thus, the success of App is managed by a developer's continuous endeavor throughout the whole life cycle of an App.

The three phases of this dissertation share the common underlying theme of evaluating the distinctive aspects of mobile App markets and identifying key factors that affect the success of App sales. This dissertation aims at contributing to the extant literature on information goods management, and managerial insights for market participants.

The remainder of this dissertation is organized as follows: In Chapter 2, extant literature and theories on information goods management are summarized to find the theoretical explanations for the three research questions. Chapter 3 investigates an association between an App developer product portfolio strategy and sales performance. Chapter 4 examines whether product cues in App descriptions significantly impact App sales and whether they can complement or substitute the cues offered from a market. Chapter 5 evaluates the value of quality improvement in stimulating dynamic App consumer demands. Finally, Chapter 6 concludes with a summary of key findings and managerial implications of this dissertation, along with a discussion of the limitations and future research directions.

CHAPTER 2

2. RESEARCH CONTEXT AND RELATED WORK

This chapter provides theoretical explanations for the three research questions. A brief summary of the relevant literature and theories is presented. The theories of product and scope economies are presented to explain the impact of App assortment strategies on App sales. Then, the key tenets of market signaling and cue utilization theories are adopted to evaluate the role of product cues in shaping consumer App purchase decisions. To answer the third research question, the theories relating to information goods management in the long-tail markets are presented.

2.1. App Portfolio Management and App Success

Product portfolio theory suggests that heterogeneous consumer tastes and scope economies are two important factors in determining portfolio decisions. While developers can address heterogeneous consumer preferences by offering Apps across different categories (Rothaermel et al. 2006), specialization within categories can allow sellers to benefit from scope economies through reduced product development costs (Baumol et al. 1982). However, past research has found no evidence of a positive relationship between product concentration and sales performance (Cooper 1985). Many studies applying financial portfolio theory to product portfolio management (Cardozo and Smith 1983; Devinney 1988) show that correlations across similar product categories lead to a higher risk profile for the firm. In line with this, the theory of scope economies provides a rationale for associating broadening product selections with sales performance (Lancaster 1979; Panzar and Willig 1981). Bailey and Friedlaender (1982) argue that firm-level scope economies are crucial for multi-product industries and present that, in a competitive market, multi-product firms better survive as compared to single-product competitors since the economies of scope bring about a significant cost advantage (e.g., transaction costs) to those firms. Therefore, consistent with main tenets in theory of product portfolio management and theory of scope economies, we predict that a large selection of mobile Apps (i.e., the number of products) and diversification across selling categories (i.e., product diversity) increase the success of App sales. Based on these theoretical explanations, I investigate how mobile App seller product portfolio is associated with sales performance. In addition, App-specific properties such as pricing, update, user reviews are considered for evaluating the success of App sales.

2.2. App Product Description and App Success

Mobile Application software is generally characterized as an experience product (Nelson 1970). Consumers use an array of extrinsic and intrinsic cues to assess the quality/value of such a product (Alba et al. 1999). In mobile App markets. The extrinsic and intrinsic cues that consumers can consider when they evaluate an App are offered through both product descriptions and product page view formatted by the market. While the cues in product descriptions are voluntarily selected by developers and deliver subjective information on Apps (i.e., low fidelity), those presented through market formats are mandatory and provide objective clues (i.e., high fidelity). Although a large volume of prior literature has examined the synthesized effects of multiple cues such as price and brand (Dawar and Parker 1994) and warranty and reputation (Boulding and Kirmani 1993) from a single source (a retailer or a market), there is still no study investigating complementarities among product cues from multiple sources in influencing a consumer' perceived value and product sales. In line with this, this study evaluates whether extrinsic and intrinsic cues in App descriptions have significant impacts on the success of App sales and whether they can complement or substitute market cues.

2.3. App Quality Update Decision and App Success

While digital product pricing has been considered as the key driver for creating a positive user network (Aliawadi et al. 1998; Shapiro and Varian 2013; Smith et al. 2001), the appraisal of product quality in shaping digital content consumer purchase decisions has not been identified yet. Prior studies argue that quality-based differentiation and versioning strategies are effective practices to create network externalities (Parker and Van Alstyne 2000; Jing 2003) and to accommodate heterogeneous consumer demands segmentations (Bhargava and Choudhary 2008; Shapiro and Varian 1998) in digital product markets. However, these approaches are generally made prior to the product launch and are considered at the market level. In addition, the versioning of a product is considered as a pricing scheme charging different price for the same product/service based on its quality, and thus it does not mean the improvement in product quality exerted by a content provider. For mobile App developers, product updates require continuous endeavor and need a strategic approach along with dynamic consumer demand in the market.

The expected contributions to the extant literature from the perspective of strategic positioning of Apps in long-tail markets are as follows. First, I show that specific portfolio properties affect sales performance sustainability in high velocity markets. Second, this research suggests that prudent selection and presentation of App product cues in the descriptions has the potential to increase sales performance. Third, the appraisal of App update strategies will highlight the importance of strategic App quality management along with heterogeneous consumer demand in highly competitive mobile App markets.

CHAPTER 3

3. APP PORTFOLIO MANAGEMENT AND APP SUCCESS

Variety's the very spice of life, That gives it all its flavor

- William Cowper, 1785

3.1. Research Objective and Questions

Mobile App store markets exhibit key characteristics of "long tail market" (Anderson 2006) such as a large selection of digital products and relatively low user search costs. However, App store market structure has some key differentiating characteristics that set it apart from a number of previously examined long-tail market contexts such as books (Brynjoffson and Smith 2010a), music, and DVDs (Elberse 2008). First, sellers in mobile App markets have a single channel for selling their product (especially in the case of Apple App market) and terms of access to the market are uniformly determined for all sellers. Second, unlike creators of music and DVDs, App developers/sellers have the opportunity to change not only price, but also the features and characteristics of the App based on user feedback and reviews. Third, sellers in mobile App markets compete more directly with other developers, irrespective of whether Apps are intended for hedonic consumption (such as crossword puzzles) or utilitarian purposes (e.g., teleprompters). Comparing competing Apps within a category is easier than, say, comparing music offerings within a genre. Fourth, while in many long-tail markets versioning is restricted to release times or superficial features (such as hard-cover vs. paperback), mobile Apps offer a greater range of flexibility to sellers in versioning strategies (e.g., feature based or price based differentiation, in-app purchases, subscription length, etc.). Finally, sellers can reuse features and codebase from one App to another, thereby quickly building a portfolio of Apps across various (and often unrelated) App categories. The portfolio perspective, in fact, is the most distinguishing facet of mobile App markets that we intend to explore in this research.

It is evident from a quick look at mobile App offerings on the AppStore that a portfolio approach to mobile App offerings is quite common. Sellers in AppStore offer an average of 6.8 Apps across 2.7 categories. More interestingly, nearly 40% of sellers offer more than 10 Apps and about 60% of the sellers have Apps in more than one category (see Table 1).

Number of Apps	Cumulative Percent of Sellers	Number of Categories	Cumulative Percent of Sellers
1	17.8%	1	38.0%
2 ~ 5	45.7%	2 ~5	81.3%
6 ~ 10	59.8%	6~10	94.1%
10 ~100	88.5%	11~15	98.4%
> 101	100.0%	> 15	100.0%

Table 1. Number of Apps and Categories in Apple App Store

While sellers can address heterogeneous consumer preferences by offering Apps across different categories (Rothaermel et al. 2006), specialization within categories can allow sellers to develop distinct competencies and benefit from scope economies through reduced product development costs (Baumol et al. 1982). Using key tenets of product portfolio management theory and theory of economies of scope, this study empirically investigates how sellers' App portfolio strategies are associated with sales performance over time. Utilizing a longitudinal panel data of sales performance over 39 weeks, we model App survival in the weekly charts within App categories. We consider the impact of both seller-level and App-level properties on an App's survival in the top charts. Our main research objective is to understand how sellers' App portfolio affects sales sustainability in the AppStore. We also intend to develop insights into how App specific decisions (such as free offerings, price changes and updates) affect sales performance and sustainability of individual Apps.

3.2. Theoretical Foundation

Product Portfolio Management:

Day (1977) defines product portfolio as "*a decision on the use of managerial resources for maximum long-run gains.*" Extant marketing literature identifies two different product portfolio management strategies: product proliferation and product concentration. By offering highly divergent product lines, firms can satisfy consumers' desire for variety seeking (Aribarg and Arora, 2008; Quelch and Kenny 1994) and meet customer need in a manner superior to competitor's product offerings (Rothaermel 2006). However, in spite of these merits of product diversification, some firms successfully pursue the opposite strategy of concentrating on specific product lines. The narrower product line helps the firms to lower unit production costs when scale economies are present by lowering inventory costs, and reducing complexity in assembly. Hence, the success of product proliferation depends not only on the firm's market, but also on firm specific properties.

However, past research has found no evidence of a positive relationship between product concentration and sales performance (Cooper 1985). Many studies applying financial portfolio theory to product portfolio management (Cardozo and Smith 1983; Devinney and Stewart 1988) show that correlations across similar product categories lead to a higher risk profile for the firm. Therefore, diversification of Apps over selling categories has the potential to improve product portfolio's risk-return profile.

There is still lack of research in understanding the association between information goods portfolio management and sales performance. Extant research on long tail markets of information goods such as DVDs and books have not considered product portfolio effects, but only long tail properties and intermediation/disintermediation effects (Brynjofsson et al. 2010a; Oestreicher-Singer and Sundararajan 2010). Although Brynjolffson et al. (2010b) suggested a research agenda that studies shifts in product variety and concentration patterns driven by information technology, their research focus is still limited to an issue of shaping a long tail (broadening niche products for product variety) or Superstar effect (concentrating on a few popular products for product concentration). However, as Brynjolffson et al. (2010b) suggest, technological (changes in search, personalization, and online community technologies) drivers and non-technological drivers (price premium and social interactions with other consumers) have shifted the consumption and production patterns of niche and popular products. In App store markets, technological drivers are playing an especially important role in increasing sellers' incentives to create various Apps with a lower barrier to entry and a large network of users, while also increasing users' incentives to purchase Apps that satisfy their tastes with lower search costs and a large selection of Apps.

A key driver of portfolio decisions in App store markets will be the ability to create scope economies by developing and leveraging product development capabilities across a number of different categories of mobile App offerings. We argue that the lower barriers to entering different category segments enables sellers to expand their offerings beyond what has been considered in product portfolio literature. Additionally, the ability to alter App offerings based on specific information gleaned from sales, usage patterns, and user feedback enables sellers to update their product offerings almost on a constant basis, thus setting up a high velocity market environment. We expand on the notion of scope economy in the following paragraphs.

Scope Economies

The theory of scope economies provides a rationale for associating broadening product selections with sales performance. Economies of scope refer to the cost and revenue benefits through the production of a wider variety of products across related settings rather than specializing in the production of a single product (Lancaster 1979; Panzar and Willig 1981). A firm's ability to leverage investment experience and knowledge from one setting to another can confer significant performance benefits. Bailey and Friedlaender (1982) argue that firm-level scope economies are crucial for multi-product industries and present that, in a competitive market, multi-product firms better survive as compared to single-product competitors since the economies of scope bring about a significant cost advantage (e.g., transaction costs) to those firms. In this context, Cottrell and Nault (2004) utilized the theory of scope economies in production and consumption to examine the association between product variety and scope economies in the microcomputer software industry in the 1980s by using firm- and product-level information on bundling of functionalities over application categories and computing platforms. The main results indicate that there are scope economies in the consumption of microcomputer software, and so firms with software that includes more application categories (e.g., database, graphics, and word processor) have better sales performance and product survival since a customer may prefer to purchase a variety of products from the same vendor. There are several distinctive characteristics of the App market that warrant examination of scope economies in App markets. For example, at the outset, scope economies in production appear to be much stronger in App markets because of the predominant focus on hedonic consumption as opposed to utilitarian consumption (Babin et al. 1994). On the other hand, hedonic consumption can also contribute to a diminished importance of scope economies in consumption since interoperability between Apps may not yet be of great importance to consumers (Childers et al. 2001; Hartman et al. 2006). App markets are also distinct from software markets of the 80's in that there is a single distribution channel today for Apps and channel access is not constrained for any single type of sellers. Examination of App portfolio related issues is still nascent in IS literature. Most recently, Lee and Raghu (2011) used a cross-sectional analysis of portfolio decisions in the App market to demonstrate that App portfolio diversification over multiple categories is positively correlated with success in App sales. In this research, we utilize data at multiple levels (seller and App properties) to examine longitudinal impacts on sales performance.

3.3. Data and Research Design

Survival Analysis

The main empirical question in this study is the sustainability of sales over time. To establish the association between a seller's App portfolio characteristic and Apps' sustainability in the top charts, we utilize multiple approaches. Our definition of success is restricted to appearance/reappearance of Apps in the top-charts over time. Since Apps can frequently appear and disappear on top charts, both survival duration (between an appearance and disappearance) and the total length of time spent on the top charts are relevant measures of success. Therefore, we use survival analysis techniques to measure sales performance (Cottrell and Nault 2004; Srinivasan et al. 2008). We observe survival (or exit) for all products and all sellers, and survival of the App in the top charts is a necessary condition for success. Finally, the exit of an App for extended durations from the top charts can indicate poor performance (Sorenson 2000).

In our empirical model, the success of App sales is influenced by a seller's decisions at two levels. At the App-level, seller decisions frame certain App-specific properties before launch such as category, price, and certain properties after launch such as quality and price updates. A seller's effort on App development is reflected in users' review scores and initial popularity (Dellarocas et al. 2007). For example, an App's initial popularity (a debut rank) could be influenced by a seller's promotion and advertising efforts prior to the release of App, and users' reviews on Apps also could be affected by sellers' ability to manage consumer expectations and preferences. For seller-level decisions, a seller having multiple Apps formulates a macro-level sales strategy. Determining whether to create Apps across various categories or in a few categories is made at the seller-level. We summarize the main aspects of our empirical approach in Figure 1.

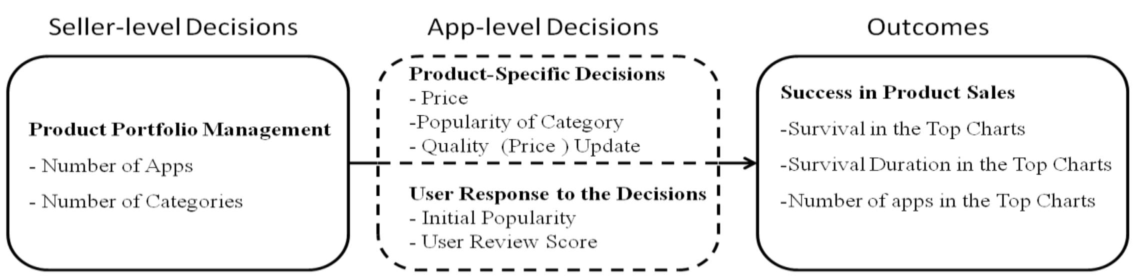

Figure 1. Empirical Approach

Data Description

Data for our analysis were collected for the top 300 Apps provided by the AppStore. AppStore provides three different charts of Apps: Free, Paid, and Top Grossing charts. Although Apple does not release the specific way it computes the rankings, it reveals how ranking is usually determined. The rank is calculated based on downloads in the most recent window of time (typically a week, but the window itself creates a moving average) for free and paid Apps, overall and within the 20 offered App categories.[3] A large portion of free Apps (80%) also includes in-app-purchase options. In order to complement the limitations of free and paid charts, we used the top grossing charts, thus combining free and paid Apps in a single chart.

We collected the top-charts data for each week, on a specific day of the week, from December 2010 to September 2011. During this period of 39 weeks, a total of 17,697 Apps offered by 8,627 unique sellers appeared on the chart (a total of 530,503 observations). To observe an App's and a seller' discrete survival at a specific study week and survival duration in the top 300, 200 and 100 charts, we tracked an individual App's (seller's) elapsed time to list in the top 300 by using data from Apple's iTunes. Every App in the dataset has its release time and the first time to hit the top 300. The Apps released before the starting date of data collection were censored since we are not able to observe key App properties in the past. Therefore, Apps that made the top 300 chart before the study period were dropped from the dataset. However, an App released after our data collection date (Week 1) has both (1) valid released date and (2) the first

[3] Apple App Store provides 20 different categories (as of September 2011): Book, Business, Education, Entertainment, Finance, Games, Healthcare-fitness, Lifestyle, Medical, Music, Navigation, News, Photography, Productivity, Reference, Social-networking, Sports, Travel, Utilities, and Weather.

date to hit the top chart. Time (1) and time (2) could be the same when an App was ranked in the top 300 at its debut week.

The iTunes store provides individual App's rank, seller (or publisher), title, price, category, released date, updated date, description, user review score, and number of user reviews. From given information on Apps, we tracked the survival of individual App at each study week, calculated elapsed time of individual App to exist in the top charts, and obtained data on each seller's specific properties such as total number of Apps and number of categories in the top 300, 200, and 100 charts. Finally, we validated our data by comparing the actual figures (e.g., a portion of free Apps, a seller's number of Apps/categories, and a portion of (un)popular categories in AppStore) produced by popular mobile application tracking websites: App148.biz (information on the number of Apps under different categories and prices) and AppStoreHQ.com (seller's information), and we confirmed our descriptive statistics were very close to those figures.

Data for Survival Analysis

We created two different sets of data for analyzing App success (an App's survival) at each discrete point in time and survival duration in the top charts). To record the survival of an App as a discrete time event, we tracked all Apps that Appeared in the top 300 charts during the study period, and coded an App that appeared in the chart as a survival ("1"), or otherwise as an exit ("0") if the App dropped from the charts. The discrete event approach does not pose censoring issues.

Survival duration relied on a continuous time scale and therefore had to censor some observations. When survival data is analyzed on a continuous time scale (e.g., hazard models), all observations in the sample may not have terminated or the exact initial times of all events may not be known (Oakes 2000). This was an issue in our data as well. For the 300 top grossing charts, we censored 66.3% from the observed Apps as follows: Apps that already appeared before the study (left-censoring), were still alive at the end of study (right-censoring), and exited and reappeared over the study period (interval-censoring) were cut off. Thus, the final dataset for continuous survival time analysis consisted of 7,579 Apps in the top 300 charts provided by 3,882 sellers. The set of variables extracted from our dataset is shown in Table 2.

Variable Names	Description of Variables	Mean (S.D.)	Min.	Max.
Dependent Variables				
	Generalized Mixed Model (Model I)			
App_survival_top100	1 if an App was listed in the top 100 at time t	.109(.312)	0	1
App_survival_top200	1 if an App was listed in the top 200 at time t	.223(.416)	0	1
App_survival_top300	1 if an App was listed in the top 300 at time t	.338(.473)	0	1
	Survival Analysis Model (Model II)			
Seller_survival_time_top300	Seller survival time in the top 300 charts	30.372(8.267)	1	39
Seller_censor_top300	1 if a seller is censored in the top 300 charts	.554(.497)	0	1
App_survival__time_top300	App survival time in the top 300 charts	19.708(9.009)	1	39
App_censor_top300	1 if an App is censored in the top 300 charts	.662 (.475)	0	1
	Count Regression Model (Model III)			
Seller_num_apps_top100	Number of Apps in the top 100 charts	.976(2.169)	0	22
Seller_num_apps_top200	Number of Apps in the top 200 charts	2.334(4.371)	0	37
Seller_num_apps_top300	Number of Apps in the top 300 charts	4.211(7.007)	1	55
Seller-specific Explanatory Variables				
Seller_num_app	Total number of Apps offered by the same seller	128.721(751.947)	1	6049
Seller_num_cate	Total number of categories offered by the same seller	3.425(3.165)	1	20
*Seller_num_app * num_cate*	An interaction of *Seller_num_app* and *Seller_num_cate*	1075.145(7193.508)	1	83623
App-specific Explanatory Variables				
App_free _price	1 if an App offered is for free	.121 (.296)	0	1
App_initial_rank	An App's initial debut rank.	182.679(87.049)	1	300
App_popular_cate	1 if an App is in the most 3 popular categories	.149 (.342)	0	1
App_unpopular_cate	1 if an App is in the least 3 popular categories	.138 (.356)	0	1
App_price_promotion	1 if an App's price was decreased in week t	.110 (.344)	0	1
App_quality_update	1 if an App's quality indicators were updated (adding more App features or fixing bugs)	.250 (.433)	0	1
App_review_avr	Averaged user review points (1 to 5 scale)	2.437 (1.230)	0	5
App_review_num	Total number of user reviews	1561.362 (14153.106)	0	626439
App_age_of_app	Time elapsed after initial release date	412.074(270.454)	0	1162
App_util_hedonic	1 if an App is in the hedonic categories 0 if an App is in the utilitarian categories	.593(.491)	0	1

Table 2. Summary Statistics of the Dataset

3.4. Empirical Approach

In order to investigate the association between a seller's App portfolio management strategy on successful App sales (product-level) and overall sales performance (producer-level), we have utilized three different models: a generalized hierarchical linear model (GHLM), a Cox hazard model with frailty, and a count regression model. Since many Apps move in and out of the top charts, modeling just the survival without re-entry can limit the analysis. Further, since sales performance is affected by variables at multiple levels (e.g., time, App properties and seller level properties), a hierarchical approach to analyzing performance would be appropriate. Thus, we mainly rely on GHLM approach. The other two models are used here to augment and support the main results from GHLM.

Generalized Hierarchical Linear Model (GHLM)

Generalized hierarchical linear model is widely used in social and behavior research that have a hierarchical data structure, with individual observations nested within groups. The multilevel regression model is most appropriate for data structures that have many levels because it is more flexible and more parsimonious than analysis of variance-type models (Frees, 2004).

Our data at the first level include the repeated measures (survival of an App in the top charts) over 39 weeks, the second level predictors account for the variation in mean of survival within Apps, and the third level accounts for variation in intercepts and slopes among sellers. Consequently, we set up a logistic mixed linear regression to predict the survival of an App from the multilevel explanatory variables

$$\text{Level-1(Time}_t\text{):} \quad logit(App\_survival_{ijt}) = \ln\left(\frac{P_{App\_survival_{ijt}}}{1 - P_{App\_survival_{ijt}}}\right) = \pi_{ijt} \tag{1}$$

Equation (1) is a binomial model with a logit link function (i.e., a logit transformation function) providing the relationship between the linear model and the mean of the logit distribution function. In other words, this transformational link connects the untransformed dependent variable, which is bounded by 0 and 1 and is non-normal (i.e., $App\_survival_{ijt}$), to a new transformed variable π_{ijt}. $App\_survival_{ijt}$ indicates the survival of App *i* offered by a seller *j* at time *t*. Since for binary variables, the variance is determined by the mean, there is no residual term for the first-level error variance.

One of the biggest challenges with a logistic model is that the results of this analysis are highly vulnerable to the assumption that observation (measures) is independent. Since the data involves 39 repeated measures of an App's survival in the chart, there might exist correlations among the observations made from the same App. If the independence of observations fails to hold but a maximum likelihood logistic regression is used to estimate the standard errors of parameter estimates one may conclude that something is significant when it actually is not. Thus, we introduce a correlation structure among the repeated measures to account for correlations among the events of an App. The correlation among the repeated observations made from the same App (nested within an App) was assumed to be autoregressive. We assume that the current survival of an App at *t* is influenced by its survival at *t-1*, autoregressive (1). Therefore this model specification controls for whether an App is shown in the top chart in the last period.

The regression coefficient (π_{ijt}) varies across the App, and we model this variation with predictors at the App level. Then, model for the (π_{ijt}) becomes:

$$\begin{aligned}\text{Level-2 (App}_i\text{)}: \pi_{ijt} = {} & \beta_{00j} + \beta_{01j}(App\_free\_price)_{ijt} + \beta_{02j}(App\_minus\_initial\_rank)_{ijt} + \beta_{03j}(App\_price\_promotion)_{ijt-1} \\ & + \beta_{04j}(App\_quality\_update)_{ijt-1} + \beta_{05j}(App\_popular\_cate)_{ijt} + \beta_{06j}(App\_unpopular\_cate)_{ijt} \\ & + \beta_{07j}(App\_review\_avr)_{ijt-1} + \beta_{08j}(App\_log\_review\_num)_{ijt-1} + \beta_{09j}(App\_age\_of\_app)_{ijt-1} + \tau_{0ij}\end{aligned} \quad (2)$$

In equation (2), β_{00j} and β_{0ij} are the intercept and slopes for the regression equation used to predict (π_{ijt}). τ_{0ij} is error term for App_i and assumed to be normally distributed (i.e., mean of 0 and variance of σ^2_τ). It accommodates un-modeled variability for the App-level part.

It is also desirable to construct a time-lagged dataset through which the impacts of App-level explanatory variables on a subsequent survival event could be longitudinally assessed. Time-varying variables at *t-1* were used to examine whether an App_i is listed in the top chart at *t*. It takes account of the effect of endogeneity (reverse causation) into the presented model.

Similarly, equation (3) includes seller-level predictor variables and accounts for variation among sellers.

$$\begin{aligned}\text{Level-3 (Seller}_j\text{)}: \; & \beta_{00j} = \gamma_{000} + \gamma_{001}(Seller\_num\_app)_{jt-1} + \gamma_{002}(Seller\_num\_cate)_{jt-1} + \gamma_{003}(Seller\_num\_app * num\_cate)_{jt-1} + u_{00j} \\ & \beta_{01j} = \gamma_{010} + u_{01j}; \;\; \beta_{02j} = \gamma_{020} + u_{02j}; \;\; \beta_{03j} = \gamma_{030} + u_{03j} \\ & \beta_{04j} = \gamma_{040} + u_{04j}; \;\; \beta_{05j} = \gamma_{050} + u_{05j}; \;\; \beta_{06j} = \gamma_{060} + u_{06j} \\ & \beta_{07j} = \gamma_{070} + u_{07j}; \;\; \beta_{08j} = \gamma_{080} + u_{08j}; \;\; \beta_{09j} = \gamma_{090} + u_{09j}\end{aligned} \quad (3)$$

Equation (3) indicates that while seller-level predictors for App portfolio management only influence the mean of App's survival (β_{00}), App-level predictors have unconditional random intercepts (μ) and slopes (γ) at seller-level to examine how App-specific properties vary under different sellers. Thus, we assume that App-specific decisions are not affected by variables at the seller-level. The residual term of u_{00j} accommodates the un-modeled variability at the seller-level.

Finally, substituting (2) and (3) into (1) yield a combined multilevel model as follows:

$$\begin{aligned}
logit(App_survival_{ijt}) = \gamma_{000} \\
&+ \gamma_{001}(Seller_num_app)_{jt\text{-}1} + \gamma_{002}(Seller_num_cate)_{jt\text{-}1} + \gamma_{003}(Seller_num_apps*num_cate)_{jt\text{-}1} \\
&+ \gamma_{010}(App_free_price)_{ijt} + \gamma_{020}(App_minus_initial_rank)_{ijt} + \gamma_{030}(App_price_promotion)_{ijt\text{-}1} \\
&+ \gamma_{040}(App_quality_update)_{ijt\text{-}1} + \gamma_{050}(App_popular_cate)_{ijt} + \gamma_{060}(App_unpopular_cate)_{ijt} \\
&+ \gamma_{070}(App_review_avr)_{ijt\text{-}1} + \gamma_{080}(App_review_num)_{ijt\text{-}1} + \gamma_{090}(App_age_of_app)_{ijt\text{-}1} \\
&+ \tau_{0ij} \\
&+ u_{01j}(App_free_price)_{ijt} + u_{02j}(App_minus_initial_rank)_{ijt} + u_{03j}(App_price_promotion)_{ijt\text{-}1} \\
&+ u_{04j}(App_quality_update)_{ijt\text{-}1} + u_{05j}(App_popular_cate)_{ijt} + u_{06j}(App_unpopular_cate)_{ijt} \\
&+ u_{07j}(App_review_avr)_{ijt\text{-}1} + u_{08j}(App_log_review_avr)_{ijt\text{-}1} + u_{090j}(App_age_of_app)_{ijt\text{-}1} \\
&+ u_{00j}
\end{aligned} \tag{4}$$

The combined equation shows the single mixed-model equation and reveals that our model has 13 fixed effects (coefficients of Υ) and 11 random effects (coefficients of μ and τ). Notice that there is no cross-level interaction effect, because seller-level predictors are allowed to affect only the intercept in Level-2.

Hazard Model

We measure the impact of a seller's product portfolio strategy and App-level properties on Apps' and sellers' survival times in the charts by using a set of hazard models. Traditional survival analysis approaches assume homogenous populations and the same hazard of having an event for individuals. Consequently, they do not account for the problem of dependence caused by unobserved heterogeneity (Wong 2012). Thus, the standard errors may become too small, and may subsequently lead to misleading significance of estimates and high *p*-values (Allison 2010). Therefore, we conduct the survival analysis of nested data, and use a *frailty* term to account for unobserved heterogeneity at seller level. We utilize four distinct hazard models. The first two models are Cox semi-parametric models, and the other two are parametric models with Weibull and logit functions.

A Cox proportional hazards (PH) model assesses the relationship of predictor variables to survival time *t* of App *i*. Cox PH model allows us to handle both continuous and categorical variables and to estimate the parameters for each covariate without specifying the baseline hazard (Cox 1972).

The first model is a reference model that examines the net effect of each explanatory variable on the hazard function to measure the App's survival in the chart. The hazard function of App in the top 300 is presented as:

$$h_i(t \mid X_j, Z_{ij}) = \exp(\beta X_j + \delta Z_{ij}) \cdot h_0\ (t) \tag{5}$$

$$, where\ X_j = \begin{bmatrix} Seller\_num\_app_j \\ Seller\_num\_cate_j \\ Seller\_num\_app_j * num\_cate_j \end{bmatrix}\ and\ \ Z_{ij} = \begin{bmatrix} App\_free\_price_{ij} \\ App\_minus\_initial\_rank_{ij} \\ App\_price\_promotion_{ij} \\ App\_quality\_update_{ij} \\ App\_popular\_cate_{ij} \\ App\_unpopular\_cate_{ij} \\ App\_review\_avr_{ij} \\ App\_log\_review\_num_{ij} \\ App\_age\_of\_app_{ij} \end{bmatrix}$$

$h_0(t)$ is a non-parametric baseline hazard, and X_j and Z_{ij} are the vectors of the covariates for the seller *j* and App *i* offered by seller *j*, β and $\boldsymbol{\delta}$ are coefficients of the covariates estimated from Maximum Partial Likelihood Estimates (MPLE) and it represents the effect of the covariates on hazard rate. When the parameter estimate of an explanatory variable is positive (negative), we can conclude that an App *i*'s hazard rate (or rates of exiting from the top charts) increases (decreases) with the variable.

The second model is a Cox model with a frailty term. It examines how Apps' survivals in the top charts vary at the seller level. The hazard rate for Cox model with frailty is as follows:

$$h_i(t \mid X_j, Z_{ij}) = \exp(\beta X_j + \delta Z_{ij}) \cdot r_j \cdot h_0(t) \tag{6}$$

r_j represents the random (frailty) term for a seller *j* who offers individual App *i*. The frailty components of r_j are assumed to be distributed as *gamma* with mean one and an unknown variance θ (Andersen et al. 1997; Fan and Li 2002; Gutierrez 2002). The penalized partial likelihood approach was used for fitting the frailty model (Ripatti and Palmgren 2000). Since the baseline hazard for the first two models is not specified (i.e., non-parametric baseline hazard) and the true underlying model is not given, we introduce two parametric hazard models (a Weibull random-effects hazard model and a discrete-time logit random-effects hazard model) with frailty to check if the frailty term in a Cox frailty model (i.e., the third model) is significant. The random terms in the Weibull hazard model and the discrete-time logit model are assumed to follow the *gamma* distribution (Liu 2012) and the *normal* distribution (Allison 2010) respectively

For a hazard model, the inclusion of time-varying variables can introduce endogeneity (Bennett 1999; Bennett and Stam 1996; Kalbaeisch and Prentice 2002). Endogenous time-varying covariates cause bias in coefficient estimates (Goodliffe 2005). Since our hazard models include both time-independent (e.g., *App_free_price*, *App_popular cate*, and *App_minus_initial_rank*) and time-varying (e.g., *Seller_num_app*, *Seller_num_cate*, and *App_review_num*) covariates, the estimates from those time-dependent covariates are subject to the effect of endogeneity.

Goodliffe (2005) suggested a set of approaches that fix the problem of endogenous time-varying covariates in a hazard model based on relevant prior literature: (1) drop the covariate only; (2) ignore the problem (Bartels 1985); (3) jointly model the duration and the time varying covariate (Cox and Lewis 1972); (4) use the ideas of simultaneous equations to duration models (Bartels, 1991); (5) include the covariate, but drop the time-varying portion (Goodliffe 2005). While the first four approaches have statistical problems of omitted variables, bias in coefficient estimates, complexity in modeling, and difficulty in finding a true instrument, the fifth approach works best by "taking away the part of the covariate that is mostly likely to be tainted by reverse causation" (Goodliffe 2005). In line with his suggestion, we used the time-invariant explanatory variables. In other words, we used the averaged values of time-dependent covariates (e.g., averaged review score and review number) over an App's survival duration and introduced dummies for time-varying variables such as *App_price_promotion* and *App_quality_update* (i.e., if an App's quality indicators / price were changed at least once), and ignore the changes in those covariates. This approach resulted in no major changes to parameter estimates and therefore we conclude that endogeneity bias is not likely impacting our results.

Count Regression Model

In order to reexamine the main results from GHLM, we have run a pooled count regression model for individual sellers across 39 weeks. One-week time lag is used for estimating associations between seller-level explanatory variables at *t-1* (X_{jt-1}) and a seller's number of Apps in the top chart at *t*, $Seller\_num\_apps\_top_{jt}$.

$$E\,[Seller\_num\_app\_top_{jt} \mid X_{jt-1}] = \beta X_{jt-1} + \varepsilon_j \quad (7)$$

The two supplemental models have some potential limitations for fitting the data into a multilevel framework. The hazard model censors Apps not having continuous durations over the study period (55% of the Apps were censored). Hierarchical survival analysis approach has not been well established due to its complex estimation procedure where the solutions are not usually expressed in closed form (Rodriguez and Goldman 1995). With GHLM, it is possible to utilize a discrete survival time approach, in which the survival to an event at a discrete time is a binary dependent variable, and incorporate hierarchical structure in the data (Allison 2010).

Since the dependent variable of a count regression model is numbers of Apps in the charts of individual seller, the model does not include App-level explanatory variables, and so the App-specific properties that may affect the sales performance are ignored in the modeling setting. In the GHLM, since the survival time of a seller in the top chart does not consider the presence of multiple Apps in the top chart, the seller's exact sales performance in a specific period may not be taken into account. The count regression model allows us to examine how a seller's assortment of Apps across various categories affects the total number of Apps in the top charts.

3.5. Results

The results from fitting a generalized hierarchical linear model appear in Table 3.

While we have not reported the correlation matrix, we did not find any strong correlations between explanatory variables; the highest correlation (ρ=-.350) among explanatory variables is between *App_minus_initial_rank* and *App_price_promotion*. Further, we tested for the presence of multicollinearity by means of Variance Influence Factors (VIF) of each explanatory variable. The largest VIF was below 2.0, which indicates that multicollinearity was not a problem in the models.

In order to examine model explanation power due to the addition of random and fixed explanatory variables, we sequentially ran Model I in five iterations. Model I(0) is a confound logistic regression model that included all predictor variables without controlling cross-level interactions. As a baseline (null) model, Model I(1) includes an unconditional intercept only. Model I(2) and Model I(3) incorporate level-2 and level-3 fixed and random effects respectively. Finally, Model I(4) combines all fixed and random effects across Level-2 and Level-3. The ability of a model to predict better than a baseline model was used as an index of Goodness of Fit. In hierarchical linear model, the deviance test is mostly used to compare the fixed and random effects of competing models (Luke 2004). Improvements in predictability were determined by the proportional reduction of deviance compared with the null (baseline) model (Bryk and Raudenbush 1992).

We also compared the resulting model with no lag effect to one with a one-week lag effect in explanatory variables. The model with a lag effect had a lower deviance (from 391687.24 to 387891.21) as compared to the model with no lag. Since larger sample size generally leads to increased significance, we used a more stringent p <.005 as the significance limit. Additionally, we considered practical significance of the coefficients in interpreting the findings.

	Model I (0) (Confound model) N=530,503	Model I (1) (Intercept only) N=530,503	Model I (2) (+ Level-2) N=530,503	Model I (3) (+ Level-3) N=530,503	Model I (4) (+ Level-2 +Level-3) N=530,503
Fixed Effects					
Intercept (r_{000})	-.993(.012)***	-.909 (.017)***	-.673(.040)***	-1.161(.022)***	-.404(.041)***
Seller_num_app (r_{001})	.000(.000)			-.001(.000)***	.002(.000)***
Seller_num_cate (r_{002})	.024(.001)***			-.054(.003)***	.152(.006)***
*Seller_num_app*num_cate* (r_{003})	-.000(.000)***			.000(.000)***	-.0002(.000)***
App_free_price (r_{010})	.408(.016)***		.573(.067)***		.536(.067)***
App_minus_initial_rank (r_{020})	. 004(.000)***		.004(.000)***		.004(.000)***
App_price_promotion (r_{030})	.687(.093)***		.322(.104)		.321(.104)
App_quality_update (r_{040})	1.775(.010)***		1.069(.023)***		1.077(.023)***
App_popular_cate (r_{050})	-.533(.013)***		-.531(.075)***		-.504(.075)***
App_unpopular_cate (r_{060})	.262(.011)***		.346(.069)***		.365(.069)**
App_review_avr (r_{070})	.127(.006)***		.061(.012)**		.046(.012)*
App_log_review_num (r_{080})	.281(.004)***		.332(.009)***		.328(.009)***
App_age_of_app (r_{090})	-.000(.000)***		-.006(.000)***		-.006(.000)***
Random Effects					
Intercept-1 ($\sigma^2 \tau$)		2.330(.041)***	2.708(.102)***		1.876(.050)***
Intercept-2 (σ^2_{u00})		2.732(.034)***		3.459(.062)***	2.397(.091)***
App_free_price (σ^2_{u01})			60.594(.000)***		1.979(.179)***
App_minus_initial_rank (σ^2_{u02})			.139(.000)***		.000(.000)
App_price_ promotion (σ^2_{u03})			.000(.000)		.334(.293)
App_quality_update (σ^2_{u04})			485.811(.002)***		.842(.038)***
App_popular_cate (σ^2_{u05})			.000(.000)		1.706(.192)***
App_unpopular_cate (σ^2_{u06})			.000(.000)		1.867(.189)***
App_review_avr (σ^2_{u07})			126.030(.000)***		.048(.004)***
App_log_review_num (σ^2_{u08})			101.870(.001)***		.034(.002)***
App_age_of_app (σ^2_{u09})			.000(.000)		.000(.000)
Deviance	397535.01	502897.05	388464.19	462559.23	387891.21

*= p <.005, ** = p <.001, ***= p <.0001

Table 3. Analysis Results from Model I

Overall, the deviance decreases when we incorporate the hierarchical structure into the baseline model. The unconstrained model, Model I(1), provides empirical and statistical evidence of the need for multilevel model. The intra-class correlation (ICC) between the App-level variability and the seller-level variability, $\frac{\sigma^2_{\mu 00}}{\sigma^2_{\mu 00} + \sigma^2_{\tau}}$ =.53, represents that 53% of the variance in the presence of Apps in the top charts can be accounted for by sellers (Level-3). This moderately high ICC suggests not only the violation of the independence assumption (i.e., the observations are not independent from one another due to a nested data structure), but also the need for a multilevel model incorporating seller-level properties (Luke, 2004).

Model I(2) explains the association between App-specific properties and an App's success consistent with our expectation. When only seller level variables are considered (Model I(3)), coefficients of *Seller_num_app* and *Seller_num_cate* are negative, thus contradicting theoretical prediction. This result indicates how a mis-specified multi-level model can lead to erroneous conclusions (Snijders and Bosker, 1999). It also shows the effect of number of Apps to be insignificant. However, the deviance in this model was relatively high. Finally, the combined three-level Model I(4) allows us to obtain the correct estimates by incorporating intra-class random effects with the lowest deviance. The coefficient signs in Model I(4) confirm the theoretical predictions related to portfolio characteristics in that the number of Apps and number of categories both improve outcome. It clearly demonstrates the need to consider both sellers' portfolio decisions and App characteristics in sales performance measurement.

Because this model specification assumes that seller-level explanatory variables are not correlated with unobserved seller-level fixed properties in the error term, controlling for seller-level heterogeneity is important. In the context of our study, however, it is difficult to identify strong and valid instruments that are correlated with seller-level App assortment decisions. A fixed effects modeling approach might be a technique to correct for such omitted variables at the seller-level, but this is generally difficult to accomplish for a model with a nested data structure. Inclusion of seller-level dummies for fixed effects will introduce the incidental parameters problems (Wooldridge 2001). We employed a conditional fixed effect logistic regression model to account for seller-level fixed effects[4]. The estimation results showed that the signs and significance levels across the models are qualitatively identical. Although the estimates of App-level estimates are slightly different from that of GHLM, these differences are likely due to differing model assumptions. It leads us to confirm that our estimates from GHLM on seller-level Apps portfolio decisions are highly robust to an alternative model specification that handles seller-level endogeneity problems. The results of the other two supporting models are presented in Tables 4 and 5. Model II examines the impact of explanatory variables on survival time of an App *i* and a seller *j* using a hazard modeling approach. Table 4 presents the estimates of App/seller-level covariates of the six hazard models.

Explanatory Variables	**Model II (0)** Cox Main Effect (Survival of Sellers)	**Model II (1)** Cox Main Effect (Survival of Apps)	**Model II (2)** Cox with Gamma Frailty (Survival of Apps)	**Model II (3)** Weibull with Gamma Frailty (Survival of Apps)	**Model II (4)** Logit with Normal Frailty (Survival of Apps)
Total Cases	7,579 sellers (100%)	17,697 Apps (100%)			
Events	3,426 sellers (45.2%)	5,964 Apps (33.7%)			
Censored Cases	4,153 sellers (54.8%)	11,733 Apps (66.3%)			
Intercept				-2.481(.155)***	5.632(.657)***
Seller_num_app	-.0033(.000)***	-.0035(.000)***	-.0062(.000)***	.0017(.000)***	.0012(.000)***
Seller_num_cate	-.1180(.006)***	-.1218(.006)***	-.1893(.004)***	.2070(.007)***	.1470(.005)***
*Seller_num_app*num_cate*	.0012(.000)***	.0005(.000)***	.0008(.000)***	-.0001(.000)***	-.0001(.000)***
App_price_free		-.254(.055)**	-.190(.003)***	.651(.081)***	.565(.055)***
App_minus_initial Rank		-.002(.000)***	-.003(.000)***	.005(.000)***	.004(.000)***
App_price_promotion		-1.407(.105)***	-1.590(.126)***	2.606(.157)***	1.935(.105)***
App_quality_update		-2.814(.082)***	-3.108(.104)***	4.844(.129)***	3.486(.082)***
App_popular_cate		.186(.035)**	.199(.048)**	-.398(.052)***	-.328(.035)***
App_unpopular_cate		-.265(.047)***	-.250(.062)**	.608(.069)***	.499(.047)***
App_review_score		-.070(.012)***	-.067(.016)**	.124(.019)**	.088(.013)***
App_log_reivew_num		-.179(.013)***	-.199(.014)***	.042(.020)***	.350(.014)***
App_age_of_app		.000(.000)***	.000(.000)***	-.002(.000)***	-.000(.000)***
Random Effect			2.034(.032)***	9.188(.324)***	8.176 (.053)***
AIC	149484.59	96719.92	52478.41	31403.18	32855.63
BIC	149505.63	96792.17	52485.58	31504.80	32949.43

*= p <.005, **=p <.001, ***=p <.0001

Table 4. Analysis Results from Model II

[4] Since the data includes 8,627 unique sellers (a total of 530,503 observations), the estimation of seller-level fixed effects is not tractable and requires enormous computational power. As a result, we randomly sampled sellers from our original dataset based on unique identification numbers (AppIDs) of Apps. We selected sellers who have apps ending in '7' in their IDs. The resulting sample for a fixed effects model includes 1,015 sellers (a total of 51,599 observations). Given the smaller dataset, we used the bootstrapping procedure to derive estimated standard errors with 500 replications of the sample.

Model II (0) involves only seller-level covariates to examine the main effect of App portfolio management on a seller's survival in the top 300 chart, where a seller was considered to have survived ($App\_survival_{jt}$ = 1) if at least one App of a seller appeared in the chart at *t*. Other four survival models include both seller/App-level covariates as discussed in Section 4.2. The estimates from Model II(1) and Model II(2) present similar results. The random (frailty) term in Model II(2) is significant and shows the variability among sellers. The estimates in other two parametric random models show similar pattern and significant random effect at the seller-level, but inconsistent with the COX models. Such differences are mainly due to (1) the unspecified baseline hazards of a Cox model, (2) the approximation of the true parametric models (i.e., different distribution assumptions), and (3) the shape parameters in the two parametric models (Wong 2012). Moreover, the sign reversal of estimates is because of different estimation formats. While the estimates from a Cox regression model are in log-hazard format, the estimates from a parametric survival model are in log-survival time format (Allison 2010). In other words, a Cox model with a frailty term and the two parametric models have the same sign implications for hazard rates and trends. Finally, the estimates of the Cox hazard model with a frailty term (i.e., Model II (2)) are validated by the parametric survival models, so we use the estimates from Model II (2) for explaining the association between a seller' App portfolio management and corresponding App survival in the top chart. Model III (a count regression model) only considers seller-level properties under the different rank charts (top 100, 200, and 300) as shown in Table 5.

Explanatory Variables	Model III Parameter Estimate (S.D.) N=3,882 sellers		
	Top 100	Top 200	Top 300
Constant	-.698(.014)***	.349(.008)***	1.037(.006)***
Seller_num_app	.001(.000)***	.001(.000)***	.001(.000)***
Seller_num_cate	.081(.003)***	.077(.002)***	.075(.001)***
Seller_ num_app num_cate*	.0017(.000)***	-.0013(.000)***	-.0008(.000)***
AIC	61267.09	107235.80	142212.15
BIC	61306.17	107274.88	142251.24
*=$p<.05$, **=$p<.01$, ***=$p<.001$			

Table 5. Analysis Results from Model III

In Model III, the large ratio of deviance to degree of freedom (12.229) indicated the problem of overdispersion. In other words, observed variance is greater than the mean since the mean of Poisson distribution is equal to its variance. Although we expect the residual deviance / degree of freedom to be approximately 1.0, the deviance is almost 10 times as large as the degree of freedom. In order to adjust the problem of over-dispersion, we used a negative binomial regression model. By allowing for more variability in the data, this approach accounted for over-dispersion. Overall, the deviance / degree of freedom value is much closer to 1.0 than that in Poisson regression model. As shown in Tables 4 and 5, the results from a Cox hazard model with frailty and a count regression model support our findings in Model I.

Seller-level Properties (App Portfolio Management): The positive and significant estimates of r_{001} and r_{002} in Model I(4) indicate that there is a positive association between broadening App offerings over multiple categories and an App's presence in the top 300 chart. When it comes to the negative and significant interaction effect (r_{003}) of these two predictors, there is a relatively small diminishing marginal impact. To examine the marginal effects of seller-level covariates, we converted the log odds (i.e., estimates) to predicted probabilities. Then we computed the marginal effects of *Seller_num_cate* (and *Seller_num_app*) on the survival of Apps at different values of *Seller_num_app* (and *Seller_num_cate*) holding the App-level explanatory variables at their means. Table 6 summarizes how much the effect of *seller_num_cate* for an App's survival changes according to *seller_num_app*, and vice versa in GHLM and Cox hazard models.

Marginal Effects	Number of Apps / Categories	Model I (4)	Model II (2)
A one-unit increase in number of categories	2 Apps	.1514	-.1877
	5 Apps	.1509	-.1851
	10 Apps	.1500	-.1809
	20 Apps	.1482	-.1724
A one-unit increase in number of Apps	1 Category	.0014	-.0054
	5 Categories	.0007	-.0019
	10 Categories	-.0002	.0023
	20 Categories	-.0019	.0107

Notes: the predicted marginal probabilities in Model II (2), a Cox hazard model, are presented as probabilities exiting the top charts with negative signs.

Table 6. Changes in Sales with Increases in Number of an App and a Category

The predicted probabilities provide the changes in the probability of an App's survival with a one-unit increase in *Seller_num_app* or *Seller_num_cate*. Overall, the marginal effects are largely stable at different numbers of Apps and categories. The marginal effects of adding a category, $\frac{\partial Prob(App\_survival_{ijt} = 1)}{\partial Seller\_num\_cate_{ijt-1}}$, are positive at different numbers of Apps. The marginal effects of adding an additional App, $\frac{\partial Prob(App\_survival_{ijt} = 1)}{\partial Seller\_num\_app_{ijt-1}}$, are much smaller than those of *Sell_num_cate* and practically insignificant.

Overall, the results indicate that expanding across categories has greater practical significance to sellers. The scope economy argument seems to therefore apply to the Apps market quite significantly. The hazard model also supports the positive association between broadening Apps over multiple categories and successful App sales. The marginal effects of seller-level App portfolio decisions in this case are expressed in terms of predicted probability of exiting the top charts. A one-unit increase in *seller_num_cate* decreases an App's probability of exit by 18.77% when a seller offers the second App in a new category as compared to doing nothing. Thus, sellers who provide Apps in various categories (i.e., diversify Apps over multiple categories) and have larger variations in choosing categories (i.e., large selection of selling categories) survive longer on the top charts and as a result have better sales performance. The marginal effects remain stable as the number of Apps increase.

A look at some notable sellers supports this observation as well. Table 7 illustrates App vendors' App portfolio management (number Apps/ categories) and their overall performance. While first three sellers have lower overall sales performance and offer multiple Apps in a few categories, other sellers have relatively higher sale performance with Apps diversified over various categories. For instance, Iceberg Reader, an online media publisher, offers 6,049 Apps on AppStore with only 6 categories, and has 55 Apps in the top 300 charts. Meanwhile, Oceanhouse Media, an individual developer, has listed 49 of her 141 Apps in the top chart by selling Apps in 12 categories.

App Vendors	Number of Published Apps	Number of Selling Categories	Number of Apps in the Top 300	Overall Sales Performance $\left(\frac{\textit{Number of Apps in the Top Charts}}{\textit{Total Number of Published Apps}}\right)$
Libriance Inc	1,038	1	1	.10%
Iceberg Reader	6,049	6	55	.91%
Deadly Dollar	53	1	4	7.55%
Oceanhouse Media	141	12	49	34.75%
SIS Software	17	10	6	35.29%
iHandy soft	22	5	8	36.36%

Table 7. App Portfolio Management and Sellers' Sales Performance

App-level Properties: The estimates from App- and seller-level analysis in Model I and Model II present the relationship between App-specific properties decided by a seller and an App's survival periods in the top chart. These results highlight the main features of Apps that help sellers to strategize their Apps for better sales. To interpret a one-unit change in app-level covariates on the success of Apps, we utilized odds ratios and hazard ratios of the estimates.

The estimate of *App_free_price* is positive in Model I(4), as expected, and strongly significant. It indicates that free Apps are around 1.7 (=exp(.536)) times more likely to survive in the top charts as compared to paid Apps. The estimate from Model II (2) also supports this finding. It suggests that when Apps are offered free of charge, the hazard ratio decreases by 17.2% (=100*[1-exp(-.1896)]) as compared to the paid Apps. Around 20% of top 300 Apps are free and most of them are either lite-version of paid Apps or require additional payments (e.g., in-app purchases) for more features (e.g., game money or network supports) when running Apps. Even most pure free Apps retain advertising proceeds. That is, free Apps do not mean the absence of revenues. From our observation around 8% of observed Apps in the top grossing 300 were offered for purely free. Thus, as with other information goods contexts, free Apps create opportunities for larger network of users (Bhargava and Choudhary, 2004) and increased demand in a complementary premium good (Parker and Van Alstyne 2005).

Initial popularity is an important determinant of survival. The estimate of *App_Minus_initial_rank* is positive and significant. However, the improvement due to initial rank lacks practical significance (one rank higher at its first week increases the presence of an App in the charts by nearly 0.4% in the models). The positive association of initial rank with survival is consistent with the findings from prior studies with digital goods (Burt 1987; Strobl and Tucker 2000; Yamada and Kato, 2002). Thus, there is limited evidence for returns to efforts on App advertising and promotion before release (Dellarocas et al. 2007).   Quality updates appear to have a bigger impact on App survival than price changes. In GHLM, the estimate of *App_price_promotion* is not significant while that from the hazard model is negative and significant. Apps that had offered at least one quality update (or promotional price) during the study period increased the chance of survival in the top charts 2.9 (or 1.3) times as compared to non-updated Apps, and lowered hazard rate of 95.5% (or 79.6%) than when they made no updates. Moreover, these updates have differing impact based on seller. Even though further studies on this issue are required, we empirically confirm that sellers can impact the success of Apps by making targeted updates to price and quality in mobile App markets.

The estimates from *App_popular_cate* and *App_unpopular_cate* in Model I (4) indicate that Apps offered in the popular categories have relatively lower odds of survival and shorter survival periods as compared to those in unpopular categories. In Model II (2), the estimated risk of exiting the top chart increases 1.22 times if an App is offered in the popular categories. Therefore, from the literature on long tail effects (Brynjolffson et al. 2006; Elberse 2008), we can divide categories into popular-App categories (head) and niche-App categories (tail) based on their popularity in the AppStore market. Even though the Apps offered in the popular categories may have more downloads, they could have shorter periods in the top charts since these Apps would compete with numerous popular Apps. For instance, around 716 Apps are released a day and 40% of them are provided in the popular categories (i.e., Games, Books, and Entertainments). It implies that there exists severe competition among sellers and impacts survival in top charts.[5]

Finally, Apps that gained higher volume and higher review scores have higher success and lower hazard ratios. Similarly, Apps offered by reputable sellers, who have overall higher average user review scores across their Apps in the top 300, have lower hazard rates, but the volume of reviews does not influence App's survival time. These results reveal that existing users' satisfaction from Apps can bring about new user interests to the Apps. Furthermore, we can argue that users tend to trust (purchase) Apps offered by reputable sellers who had good review scores associated with other Apps.

3.6. Robustness Analysis

Our main results are restricted to the probability of an App's survival in the top 300 charts. We conducted three different post-hoc analyses with GHLM to test the sensitivity and validity of our model.

First, we compared the estimates under different ranking charts. Since AppStore only provides Apps' information in the top 300 ranks, we could observe neither other Apps ranked outside the top 300 charts nor their properties (e.g., price, review score, and developer). Thus, to test if sampling bias is influential to our main results, we compare the estimates of a seller's App portfolio management on the successful App sales under different ranking charts. Table A1 in Appendix A shows that seller-level predictors are

[5] We also tested if different combination of (un)popular categories have the same results. The most / least popular categories (Game vs. Weather) and the four most/least popular ones (Game, Book, Entertainment, Lifestyle vs. Medical, Navigation, Weather, Finance) were selected into the analyses. The results present that the different selections of categories do not change the sign and significance of estimates from our original selection. Also, these selections do not significantly change other estimates as well.

more critical in the higher rank charts. Table 8 shows the impacts of a seller's App portfolio plan on the probability of an App under different ranking charts. The impacts of category diversification strategy on the survival of an App increase in the top 100 chart as compared to the top 200 and 300. Moreover, App-level properties like free price, user review score, and initial rank are more highly associated with survival probability in the higher rank charts.

Marginal Effects	Number of Apps / Categories	Top 300	Top 200	Top100
A one-unit increase in number of categories	2 Apps	.1520	.1523	.1747
	5 Apps	.1515	.1517	.1735
	10 Apps	.1506	.1506	.1716
	20 Apps	.1487	.1484	.1677
A one-unit increase in number of Apps	1 Category	.0018	.0032	.0030
	5 Categories	.0010	.0023	.0014
	10 Categories	.0001	.0012	-.0005
	20 Categories	.0018	-.0009	-.0044

Table 8. The Impact of App Portfolio Management under different Ranking Charts

Second, we investigated how the association between seller's App management and an App's survival differs over time. We divided the data into two periods. The first period includes the first 19 weeks, and the second period last 20 weeks. During second period Apple released a new iOS version and a new white iPhone for AT&T and Verizon. In addition, the number of iPhone users significantly increased by around 44 million compared to the first period. Thus, we expect more severe competition among sellers (or developers) in the second period. The estimates are presented in Table A2 in Appendix A. Since we used time-varying explanatory variables in GHLM, the negative intercept terms indicate the overall decrease of App survival (i.e., the mean of survival when all of explanatory variables take on the value zero) in the second period. Furthermore, the seller-level decisions play more important role in the second period.

Marginal Effects	Number of Apps / Categories	Period I (Week 1 ~ 19)	Period II (Week 20~39)
A one-unit increase in number of categories	2 Apps	.1446	.1685
	5 Apps	.1444	.1682
	10 Apps	.1441	.1678
	20 Apps	.1434	.1668
A one-unit increase in number of Apps	1 Category	.0013	.0066
	5 Categories	.0010	.0062
	10 Categories	.0007	.0057
	20 Categories	.0000	.0048

Table 9. The Impacts of Increases in Number of an App and a Category

Finally, we also incorporated App users' hedonic and utilitarian uses of Apps into the model. By adding a hedonic dummy (coded "1" if an App is offered in hedonic categories[6] and coded "0" if an App is offered in utilitarian categories), we looked for the association between App's hedonic or utilitarian uses and Apps' survival. In the first model, we included a hedonic dummy instead of (un) popular dummies, and in the second model both category-related variables were added (see Table A3 in Appendix A). The results show that the estimate of a hedonic dummy is not significant in both models and Goodness of Fit worsened. Since *App_popular_cate* (games, books, and entertainment) and *App_unpopular_cate* (medical, navigation, and weather), in general, reflect the hedonic and utilitarian Apps, our main model incorporated competitive pressures adequately. Consequently, the results from sensitivity and robustness analysis give us more confidence in the proposed empirical models.

[6] - Hedonic Categories: Book, Entertainment, Games, Healthcare-fitness, Lifestyle, Music, Navigation, News, Photography, Social-networking, Sports, and Travel
- Utilitarian Categories: Business, Education, Finance, Medical, Productivity, Reference, Utilities, and Weather

3.7. Concluding Remarks

Our findings demonstrate how mobile App seller product portfolio is associated with sales performance. Specifically, diversification across selling categories is a key determinant of high survival probability in the top charts and contributes to sales performance. Furthermore, we find that offering free Apps, higher initial popularity, investment in less popular categories, continuous updates on App features and price, and higher user feedbacks on Apps are positively associated with sales performance. Therefore, these App-level attributes lead to further potential user demand and increase the longevity of Apps.

The results of this study have several significant implications to extant literature on digital product management and business practice. From an academic perspective, our research creates new knowledge about mobile App seller's strategic decisions on product portfolio management and its impact on success in mobile App markets. Our findings firmly establish the importance of scope economies as an ingredient for success in mobile App market. Survival and sales performance was greatly higher for sellers when participating across multiple categories than otherwise. We also find that product price and quality upgrades are quite important in mobile Apps market contexts. Prior studies in software management have been restricted to cost reduction in software upgrades: optimal frequency of security patch updates (Cavusolglu et al. 2006) and the expected time to perform major upgrade to software systems (Krishnan et al. 2004). However, developers in App markets can easily change price and features with lower costs and efforts than in traditional software markets. It appears that the opportunity for frequent changes should indeed be exploited.

CHAPTER 4

4. APP PRODUCT DESCRIPTIONS AND APP SUCCESS

4.1. Research Objective and Questions

Mobile Application (App) software is an experience product where consumers are generally unable to assess the quality of a product at the time they make an actual purchase (Nelson, 1970). As such, consumer effort is needed to discover hidden information about an App before final download. Certain unique characteristics of App store markets increase consumer cognitive burden in evaluating an App's value/quality prior to actual purchase as compared with traditional online markets. First, a large number of Apps contributes to high search costs. In January 2015, there were 1,496,939 active Apps and 367,167 developers in the U.S. Apple App Store and an average of 1,339 new Apps appeared every day. In particular, the most popular Games category included 317,907 active Apps and an average of 419 Games Apps were released a day[7]. Searching through such a large number of products requires intense external costs (e.g., the opportunity costs of time taken up in searching) and internal costs (e.g., the mental effort of sorting and integrating searched information) (Smith et al. 1999). Moreover, inherent factors in mobile App transactions such as a smaller screen size and constrained user-interface capabilities further exacerbate the cognitive load during valuation of the offerings (Nunamaker et al. 1987; Ghose et al. 2012). As an additional complexity, the presence of external information (via social media and other sources) on an App from third-parties creates information overload and makes it difficult for users to accurately

[7] App Store Metrics (February 6,2015, PocketGamer) available at http://www.pocketgamer.biz/metrics/app-store/

judge the true utility of the App. Strategic representation of information cues has the potential to reduce a user's perceived risk related to purchase quality uncertainty, to reduce cognitive burden, and to increase willingness to purchase. Therefore, strategic representation of multiple information cues has the potential to reduce a user's perceived risk related to purchase quality uncertainty, to reduce cognitive burden, and to increase willingness to purchase.

Prior studies on product cues/signals have extensively examined how either market intermediaries or individual sellers can mitigate a consumer's quality uncertainty on an experience product. Online marketplaces have introduced preventive tools such as user review scores (Chen and Xie 2008; Dellarocas 2005) and escrow service (Antony et al. 2006; Hu et al. 2004). Individual sellers provide detailed information such as delivery time, money-back-guarantee, and reputation signals to convey the true quality of products and services (Li et al., 2008). An emerging stream of information systems (IS) literature has found that specific information cues, generated from early adopters, such as ranking information (Duan et al. 2009; Ghose et al. 2012; Yoo amd Kim 2012), accumulated user reviews (Dellarocas et al. 2007; Gao et al. 2006; Zhu and Zhang 2010), and the value of a product attributed from others (Gallaugher and Wang 2002; Kauffman et al. 2000; Zhu et al. 2006) are predominant in shaping a collective purchase/adoption decision among online consumers. However, the complementarities between the signal sources and types in competitive markets remain largely unexplored.

The dominant approach to discover interactions in cues is controlled experiments. However, the scope and dynamics of the relative effects among cues are typically restricted due to research design in experiments (Olsen and Jacoby 1972). Since a limited number of potential cues can be included in one experiment, a comprehensive understanding and assessment of multiple product cues in competitive product market settings is yet to be established. Moreover, product description content as an additional cue is yet to be examined in this research domain. The cues from different sources can complement or substitute each other in determining a digital product' quality. As such, the relative effects among cues from multiple sources need closer scrutiny. More importantly, the cues in a product description are intentionally selected and altered, and thus consumer evaluations are also likely to change as a result (Balboa and Marti 2007). To address these research gaps in the extant literature, we empirically analyze the dynamic impacts of cues from multiple sources over multiple periods of time in the mobile App market.

There is also a paucity of research on a seller/supplier-generated product description and its impact on product sales. A large volume of extant literature finds a significant association between user-generated reviews (i.e., description of a product from personal experience) and positive product sales growth (Chevalier and Mayzlin 2006; Dellarocas et al. 2007; Liu 2006; Zhu and Zhang 2010). The design of online/offline store with effective interfaces such as adding rich product descriptions (Simonson et al. 1994) and presenting detailed product features/information (Granados and Gupta 2013; Lohse and Spiller 1998) can influence product sales. However, product description content has not been systematically examined in depth to understand the specific aspects of descriptions that are most effective. Recent white papers and industry reports highlight the important role of App description in advertising an App to potential consumers. They commonly suggest a set of principles in formulating a good product description[8]: 1) List benefits, not features; 2) Let customer describe it; 3) Make your content unique; 4) Provide additional value. While such pragmatic suggestions emphasize a strategic formulation in writing an attractive product description, it is unclear as to whether these principles in the descriptions contribute to a successful App/product. To the best of our knowledge, no prior work has examined the impact of product descriptions on product sales, especially in a mobile App setting. This research aims to fill this gap in the literature.

The main objective of this study is to evaluate the role of dominant market information cues (henceforth, *market cues*, e.g., rankings and review scores) in shaping mobile App users' purchase decisions in mobile App markets, and to identify the alternative producer-generated product cues (henceforth, *producer cues*) that can also influence App sales performance in the presence of strong market cues. In addition, we seek to examine the interactive effects of market and producer cues on sales performance. Mobile platforms require listing of market cues that include product attributes (e.g., rankings, price, seller name, and update information) and user supplied information (e.g., user review scores/comments). Market cues deliver relatively objective information (i.e., high-fidelity). On the other hand, developers can supplement the market cues through

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Tips for Improving your Product Description (October 17, 2007, Palmer Web Marketing) available at /http://www..palmerwebmarketing.com/blog/6-tips-for-improving-your-product-descriptions/
Smart Tips for Improving your Product Descriptions (July 25, 2012, SEO Service) available at http://3in1seoservices.com/tips-to-improve-product-descriptions/
How to Write your Apple App Store Description (March 12, 2012, Toura.com) available at http://support.toura.com/kb/marketing-promotion/how-to-write-your-apple-app-store-description

product descriptions to transmit relatively subjective quality signals to users (i.e., low-fidelity). These two distinctive cues on an App contribute to consumer value perceptions. Consequently, this study answers the following key research questions:

- Do market cues have prominent effects in influencing consumers' purchase decisions in mobile App markets?
- Do producer cues have significant impacts on App sales in the presence of strong market cues? If so, what types of producer cues are associated with better sales performance?
- Are there complementarities between producer cues and market cues in influencing the success of App sales?

We utilize signaling and cue utilization theories to systematically classify the cues (or signals) in App markets. By utilizing text-mining methods, we identify commonly used App product description patterns/keywords from 7,376 descriptions of Apps that appeared in the top 300 game charts over 20 weeks from April to August 2012. We then conduct panel analyses, including predictors on both description messages (i.e., producer cues) and App-specific properties (i.e., market cues), to investigate the impact of product description formulation on App sales. We find systematic patterns of intrinsic and extrinsic cues in product descriptions. The cues in the product descriptions are found to be strong predictors of App sales. More importantly, we establish the existence of complementarities between producer and market cues. In general, irrespective of cue source, we find extrinsic cues to be stronger predictors of App sales.

4.2. Theoretical Foundation

Signaling

Information asymmetries between producer and consumer lead to unfairness perceptions between the two parties (Connelly et al. 2011), which is evidenced as problems of *adverse selection* (Akelof 1970) and *moral hazard* (Hölmstrom 1979). In information economics, signals are regarded as mechanisms to solve information asymmetry among the market participants (Kirmani and Rao 2000). Earlier IS and Economics studies in this domain examined retailer reputation and product quality in offline markets. As such, signals from a retailer such as price (Caves and Greene 1996; Gerstner 1985; Tellis and Wernerfelt 1987; Wolinsky 1983), reputation (Chu 1992; Chu and Chu 1994), brand (Dawar and Parker 1994; Erdem 1998; Rao et al. 1999; Richardson et al. 1994; Wernerfelt 1988), warranty (Boulding and Kirmani 1993; Kelly 1988; Wiener 1985), packaging (McDaniel and Baker, 1997; Zhu et al. 2012), and advertising expenditures (Archibald 1983; Basuroy et al., 2006; Kirmani 1990) have been identified as strong quality indicators. Recent research in online market contexts finds that information cues through word-of-mouth such as user review scores/comments (Dellarocas 2005; Forman et al. 2008; Godes and Mayzlin 2004; Li and Hitt 2010; Zhu and Zhang 2010), escrow services (Antony et al. 2006; Hu et al. 2004), website quality (Wells et al. 2011), and copyright enforcement (Takeyama 2009), are strong predictors of quality perceptions. Given the vast array of possible cues and cue sources, researchers have focused on how consumers utilize cues based on the cue sources and formats. In mobile App markets, however, effective signals have not yet been studied. Since most transactions in mobile App markets are made through mobile devices in a platform market, transaction uncertainties related to the platform tend to be low, whereas, transaction uncertainties related to the App under consideration tend to be high. Given the large number of Apps (even within App categories), consumer cognitive load for finding the right App from a very large selection of similar Apps can be extremely high. As such, product cues and their utilization can play a critical role in mobile App markets.

Information Flow in Digital Markets

Extant IS literature have found that a certain form of information cues such as popularity (e.g., rankings), reputation (e.g., user reviews), and the value of a product attributed from user network size (e.g., accumulated usage or total downloads) is prominent in influencing users' purchase decisions on digital products (Brynjofsson and Smith 2000, Duan et al. 2009). In this regard, the theories of information cascades, word-of-mouth, and network externalities have been extensively used to explain and understand the key drivers (cues) in shaping online users' decision making behaviors in a collective way, i.e., herding behavior. In particular, the important role of ranking information has been identified in stimulating information cascades in digital software products (Duan et al. 2009) and online music (Yoo and Kim 2012), where consumers with noisy information make decisions based on observation of others (i.e., rank of a product) without considering their own private information (Banerjee 1992). Moreover, online user reviews from early adopters have been considered as a strong quality indicator, especially for experience goods (Gao et al. 2006), and consequently reduce the perceived risk related to purchase ((Dellarocas 2005; Murray 1991) and promote followers to purchase a highly reviewed product such as movies (Dellarocas et al. 2007;

Chintagunta et al. 2010), books (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004), and software products (Zhu and Zhang 2010). Imitative behavior among individuals also arises when a particular option become more valuable of others also choose the same option (Katz and Shapiro 1985). For example, many software products (Gallaughter and Wang 2002; Kauffman et al. 2000) and electronic systems (Zhu et al. 2006) are subject to network effects, and thus users' adoption decisions are influenced by early adopters' decisions. In summary, past IS and relevant literature has studied how a certain form of market cues, mainly generated from predecessors, influences collective behavior among subsequent decision makers.

Although the role of market-generated cues from early user groups are expected to be important in search-intensive mobile App markets, multiple attributes of an App are likely to either impact sales or complement the dominant market cues in promoting sales. In reality, the market offers a variety of product attributes (cues) to consumers as quality indicators of a product besides its ranking and review score, and consumers generally use multiple information cues to evaluate the quality of the product (Alba et al. 1999). In mobile App markets, for example, producer-generated cues such as description on content and features of an App not only help consumers evaluate whether the App meets their needs, but also influences consumers' purchase decisions even when selecting a popular and positively reviewed App by confirming the quality of the App. Therefore, strategic representation of multiple information cues has the potential to reduce a user's perceived risk related to purchase quality uncertainty, to reduce cognitive burden, and to increase willingness to purchase. To evaluate the role of App product cues and interactive effects among multiple cues, we utilize theories of cue utilization and market signaling, where product cues available in the market are classified based on a cue's type and source (Valenzi and Andrew 1971), and accordingly a consumer's perceived value from the cue is theoretically explained (Cox 1967) instead of characterizing the impact of a single cue on consumers' decision making behaviors. This research adds to the IS literature by evaluating the role of multiple producer generated information cues in the presence of dominant market cues.

Cue Utilization

Product cues can be broadly understood based on the cue type and cue source. First, product cues can be categorized into intrinsic and extrinsic cue dimensions based on information content emphasizing intrinsic and extrinsic attributes of a product (Valenzi and Andrews 1971). Intrinsic cues are physical attributes of a product such as color and size of a cloth. Extrinsic cues are product-related, but not physical components of the product such as price and brand. As such, in App markets, intrinsic App cues provide inherent information on Apps such as content/functionalities and technical features. Extrinsic cues include explicit App attributes such as price and user review scores. In addition to the cue types, App markets offer two distinctive product cue sources: from (1) market formats, the market cue, and (2) a description, the producer cue. First, the market itself presents the basic App information on the App product page views according to specific market formats/rules (e.g., price, user review, release/updated date, and technical system requirements). Second, an App developer is able to include additional App information or marketing messages through product description (e.g., content, update information, promotional price and historical sales figures, and downloads). While the market cues deliver objective information to users with high-fidelity, the producer cues presented in a product description transmit relatively subjective information to users with low-fidelity since the cues in the description are strategically formulated and selectively offered by the developer. Figure 2 summarizes the main aspects of App product cues along the dimensions of cue types and sources.

		Source	
		Producer Cue (P)	Market Cue (M)
Type	Intrinsic Cue (I)	- Selected by a Developer - Low-fidelity - Physical Attributes - Inherent Properties	- Selected by a Market - High-fidelity - Physical Attributes - Inherent Properties
	Extrinsic Cue (E)	- Selected by a Developer - Low-fidelity - Non-physical Attributes - Explicit Properties	- Selected by a Market - High-fidelity - Non-physical Attributes - Explicit Properties

Figure 2. A Categorization of App Product Cues

We hypothesize the user-perceived values from intrinsic and extrinsic cues, and product and market sources as follows. Cue utilization theory states that a product consists of an array of cues that consumers use to determine the value prior to actual purchase, and the cues provide utility (i.e., perceived quality) for consumers according to the predictive and confidence value of the cues (Cox 1962). The predictive value (PV) indicates "the degree to which an individual consumer associates a cue with product quality" and the confidence value (CV) is "the degree to which a consumer is confident in his/her ability to accurately perceive and judge that cue" (Olson and Jacoby 1972). While the PV of a cue is related to the predictive relationship between specific levels of the cue (e.g., high or low price) and various degrees of quality (e.g., high or low quality), the CV of a specific cue vary across consumers based on cue related experience, knowledge, and familiarity. From this classification, extant literature has examined the PV and CV of extrinsic and intrinsic cues, but presented conflicting results. While some studies (Allison and Uhl 1962; Zeithaml 1988) found high PV and CV from extrinsic cues such as brand, price, and store name since these are easily verified, others (Jacoby et al., 1971; Szybillo and Jacoby 1974) suggested intrinsic cues directly related to physical attributes such as product samples are more important determinants of perceived quality.

In mobile App markets, extrinsic attributes (E) (e.g., price and user review score) and intrinsic attributes (I) (e.g., feature updates and size) are readily/concurrently available for users when they make inferences for Apps. However, unlike traditional products, intrinsic attributes of Apps such as functionality and content are more difficult to assimilate and understand prior to consumer purchase (i.e., low CV). Moreover, the cues offered from market formats are more likely to contribute to higher PV than those from App descriptions. In general, the producer cues (P) in a product description are selected and alterable by a developer, and thus it makes it difficult for consumers to infer an App's actual quality. On the other hand, the market cues (M) are likely to help the users predict the value of an App by offering a set of comparative information of the App in the market context. For example, an App with good user reviews (scores) could be considered as a high-quality App and assist the users to compare it with other competitor Apps. Based on this discussion, we summarize the user-perceived values from intrinsic and extrinsic cues along with the two different product cue sources in Figure 3.

		Source	
		Producer Cue (P)	Market Cue (M)
Type	Intrinsic Cue (I)	(PI): Low^{CV}, Low^{PV}	(MI): Low^{CV}, High^{PV}
	Extrinsic Cue (E)	(PE): High^{CV}, Low^{PV}	(ME): High^{CV}, High^{PV}

Figure 3. A User-Perceived Values from App Product Cues

In understanding the effects of multiple cues, cue consistency theory proposes that multiple cues are more useful when they provide confirming information than when they present distinctive conclusions (Maheswaran and Chaiken 1991). In line with the theory, when multiple cues from one source are consistent, the signal quality among the cues are strengthened and are more effective in improving consumers' perceived quality (Gao et al. 2008). When the cues are inconsistent, consumers put more weight on negative cues (Ahluwalia 2002; Campbell and Goodstein 2001). For example, Miyazaki et al., (2005) examined the combined effects of price and warranty on consumers' perceived quality and found that when the paired cues were consistent (i.e., high price and strong warranty or low price and weak warranty), the effects became stronger. Further they suggested that when they are inconsistent (i.e., low price and strong warranty), negative cue is more salient to consumers. Nevertheless, the theory does not explain the synthesized effects of the cues from multiple sources, especially a set of cues offered by different signal senders (i.e., a market and a seller) for the same product. Based on the key tenets of cue utilization theories, we evaluate whether extrinsic and intrinsic cues in the App descriptions have significant impacts on the success of App sales and whether they can complement or substitute those in market cues. In particular, we examine complementarities *between* the cues from the different sources (i.e., producer cues and market cues, P*M).

4.3. Data and Research Design

Data Description

Our empirical analyses were conducted on the individual paid Games Apps in the Apple App Store. The Games category is the most popular among 21 categories and makes up 17.2 percent of the Apps on the Apple App Store (as of August 2013)[9]. An average of 129 new game Apps appeared every single day during the study period. As such, the growing number of Apps has led to high costs for finding and evaluating Apps, and therefore the cues provided by the market and developer are expected to influence a user's quality perception on an App. In addition, Games Apps accounted for 40% of store downloads and covered 70% of App Store revenue in 2013[10]. Such a dominant position of Games offers a market consisting of a large body of heterogeneous consumers. While Apple provides three different top Games charts: free, paid, and grossing charts, we focus on the top paid chart. Inclusion of free Apps in the charts[11] has several limitations in examining the effects of App product descriptions on App sales. First, free Apps has a strong zero price effect, where consumer demand for a zero-priced item is much greater than a price even slightly greater than zero (Shampanier et al. 2007). Therefore, free of charge can act as a big megaphone for advertising, creating a large user network regardless of other product cues. Second, free Apps are not purely free and include

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[9] 148Apps.biz (August, 2013): App Store Metrics available at http://148apps.biz/app-store-metrics/?mpage=catcount

[10] App Annie (August, 2013): App Annie Index: Market Report Q1 2013 –iOS App Store Revenue available at http://blog.appannie.com/app-annie-index-market-q1-2013/

[11] Top grossing charts include around 90% of free Apps. Although supposedly an App's rank is determined by both the number of downloads and price (i.e., ranked by gross generated), the actual ranks are determined by downloads solely like the ranks in the top free charts.

hidden costs for consumers. A large portion (90%) of free Apps in the top 300 charts includes in-app-purchase (IAP) options.

We collected Apps in the top 300 paid games chart for each week from April 2012 to August 2012. During the period of 20 weeks, a total of 787 unique Apps (a total of 7,376 observations /descriptions) appeared in the top chart datasets[12]. App product descriptions for all observations were recorded in HTML formats and we used the first two sentences in the descriptions that users can see when they select an App (Apple restricts up to 120 characters (or no more than 2 sentences) in truncated descriptions). In general, users are not likely to click 'More..' to see the rest of description before deciding whether they are installing an App or not, and therefore sellers will need to deliver intended intrinsic cues in a few lines to capture consumer interest.

For the cues delivered through market formats (i.e., market cues), we included the following elements in an App product page view: App's rank, price, released date, recent update date, user review score, size, in-app-purchase options, and the number of screenshots (as a proxy for graphical information). Finally, since we were not able to observe an App's information once it exits the top 300 charts, we focused on Apps listed in the top 100 chart at least once during the study period for longitudinal analyses. The final dataset includes a total of 325 Apps with 4,878 descriptions.

[12] The Apps in the top charts were collected every Friday at 7:00 pm during the study period. To verify potential changes in the composition of Apps and rankings in the charts, we compared data sampled on a daily basis with the sample collected on a given day of a week and found the ranking patterns to be similar in the two samples.

A key first step in the analysis was to identify the groups/clusters of keywords in the first two sentences of App descriptions from all the Apps that appeared in the top 300 charts by utilizing text-mining methods. This step empirically discovered common patterns of extrinsic and intrinsic cues about Apps. Second, a set of panel analyses including predictors on both keywords groups (i.e., producer cues) and App-specific properties (i.e., market cues) was conducted to investigate the impact of individual cues on App sales as well as the complementarities between the two sets of cues.

Textual Information from Apps Product Descriptions

Text mining methods have been widely used for investigating systematic patterns in unstructured texts in various research areas. Eliashberg and Zhang (2007) utilized text mining to explore the relationship between the presentation of keywords in a movie script and a movie's return on investment. Pavlou and Dimoka (2006) examined how online feedback comments influence trust building by distinguishing benevolence comments and credible comments in eBay user feedbacks. Lee and Bradlow (2011) used a text-mining technique for eliciting product attributes and brands' relative positions from online reviews of digital cameras. We follow the key procedures of textual information extraction used in this line of studies[13]. First, unstructured textual formats in the descriptions were converted to structured formats by ignoring words that carry little or no information (e.g., articles, pronouns, and conjunctions) and discarding extra white spaces and punctuations (a parsing phrase), and by treating the various forms of the same words (e.g., update, updates, updated, updating) and synonyms (e.g., explore, examine,

---

[13] TM (text mining) and NLP (natural language) packages in R 3.0 were used to retrieve textual information from App product descriptions.

investigate, sand search) as identical (a stemming phrase) based on WordNet database (Fellbaum, 1998). Additionally, a set of meaningful non-characters and symbols were transformed to relevant characters (e.g., #1 to NumberOne, % to Percent, $0.99 to NinetyNineCents). The preprocessed description of an exemplary App is presented in Table 10. Although the processed description reveals incomplete English words, we can easily recognize the meanings of the words. Second, we selected the most frequently appearing terms from the first two sentences of the descriptions. Figure 4 presents a word cloud of keywords with their frequency. The word cloud shows that "Play", "World", and "Time" are the most frequently appearing terms in the Game category.

Original Description
[u'**LIMITED TIME ONLY SALE - ONLY $0.99!**', u'***The #1 Free App, #1 Paid App and #1 Word Game in over 80 countries!*** ', u'Play the AD-FREE version of Draw Something, the most popular social drawing and guessing game in the App Store! Experience for yourself the laugh-out-loud game your friends are raving about! ______________
After Parsing
limited time sale ninetynine numberone free app numberone paid app numberone word game countries play ad free version draw popular social drawing guessing game app store experience laugh loud game friends raving
After Stemming
limit time sale ninetynin numberon free app numberon paid app numberon word game countri play ad free version draw popular social draw guess game app store experi laugh loud game friend rav

Table 10. Preprocessed App Product Description

Figure 4. Word Cloud of Keywords

However, this frequency-based keywords selection approach does not account for the importance of words across the descriptions. Therefore, the frequency of occurrence of each word within and across Apps is used for evaluating the relative importance of the word in the descriptions. By removing the words which have at least a 92 percentage of sparsity[14] (i.e., these words do not appear in 92 percent or higher of app descriptions), we selected the most important 30 words from a total of 5,293 terms in the descriptions as follows:

"play"	"world"	"time"	"featur"	"sale"	"countri"	"fun"	"numberon"	"experi"	"level"	"challeng"	"top"
"action"	"award"	"version"	"adventur"	"updat"	"avail"	"control"	"million"	"limit"	"download"	"hit"	
"arcad"	"addict"	"support"	"real"	"classic"	"percent"	"nintyninec"					

Table 11. Selected Keywords from App Descriptions

Third, we clustered the selected words into four meaningful keywords groups based on relevance by utilizing a hierarchical clustering method. Hierarchical clustering techniques are the most commonly used approach to identify the clusters of terms/entities in text/data-mining (Feinerer et al. 2008). The distance between two pairs of terms was measured by the Euclidian distance metric and the dissimilarity between two clusters was computed by Ward's minimum variance method (Milligan and Cooper 1988). That is, while the dissimilarity within clusters is minimized, the dissimilarity between the clusters is maximized. A dendrogram of the clusters produced by hierarchical clustering is shown in Figure 5.

[14] We created a document-term matrix (DTM), where the frequency of terms that occur in Apps product descriptions is presented in a matrix format, to remove sparse terms (i.e., terms occurring only in very few descriptions). This reduces the number of terms dramatically without losing significant relations inherent to the term matrix (Feinerer 2008). Finally, 92 percent of sparse terms (i.e., terms occurring 0 times in a product description) was removed and the most used 30 terms across Apps' descriptions were selected for the analysis.

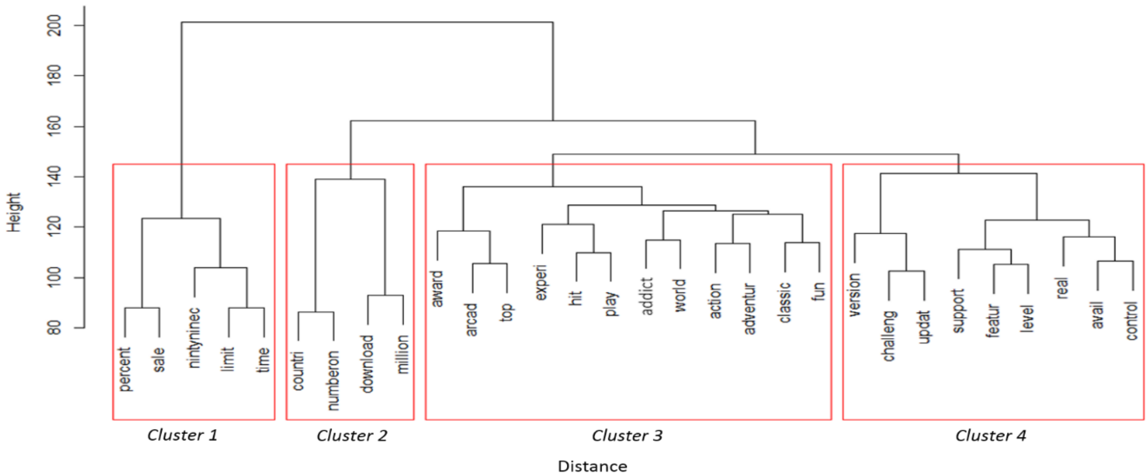


Figure 5. Clusters of Keywords

After clustering, we had the four clusters of keywords presented in App product descriptions: *Price Promotion, Sales Performance*, *User Review*, and *Feature Updates*. An illustration of the clusters of keywords and usages in the descriptions is presented in Table 12.

In order to validate the selection of 30 keywords and four clusters from App descriptions, we conducted a set of additional analyses, and found that the four clusters from 30 key terms ensure the best identification of product-related information in App descriptions (see APPENDIX B for additional details).

Finally, for an empirical analysis based on the extracted textual information from App descriptions, each cluster is considered as a single variable. A score for each keyword group of individual Apps was assigned according to the number of words used in the descriptions. Table 13 presents the cluster scores for each App.

Cluster	Term	Freq.	Description
Cluster 1 (Promotion)	*Percent (%)*	447	"Limited Time SALE! 50% OFF!"
	Sale	618	"ON SALE THIS WEEK ONLY!"
	Ninety-nine cent ($.99)	277	"Release Event! Sales $2.99 -> $0.99"
	Limit	343	"ON SALE FOR A VERY LIMITED TIME"
	Time	897	"$ 0.99 for a limited time only"
Cluster 2 (Sales Performance)	*Country*	341	"#1 Downloaded Game in 33 COUNTRIES"
	NumberOne (#1)	471	"The #1 preschool game in the app store"
	Download	271	"See why over 7,000,000 PEOPLE have downloaded…"
	Million	344	"…WHICH WAS DOWNLOADED OVER 10 MILLION TIMES IN 2011…"
Cluster 3 (User Reviews)	*Award*	390	"Feed your appetite for words in this award-winning puzzle game for all ages…"
	Play	1,450	"The Best Games I've ever Played…", "…stunning new graphics, gameplay and more!"
	Experience	468	"a high speed adventure with a silky smooth design for one of the best platforming experiences…"
	hit	230	"...one of the biggest hits on the App store!"
	Fun	546	"…definitely had a lot of fun playing the game and would highly recommend it."
	Adventure	358	"AN INCREDIBLE ADVENTURE! Leap, slide, sprint and smash your way through…"
Cluster 4 (Feature Update)	*Support*	437	"TECH FEATURES: Retina / HD support', Game Center support', Universal App"
	Feature	715	"Feature Overview: Animated Cut Scenes, Blood and Gore Animation, Retina Display Support…"
	Level	446	"Play all 60 levels, then take on 60 tests in Challenge mode…"
	Available	357	"Three different control schemes are available to suit your style!"
	Update	358	"We are aware of the Save Game issue with the latest update and are working on this."

Table 12. Clusters of Keywords in Descriptions

Cluster(s)	Apps	Description	Cluster1 Score	Cluster2 Score	Cluster3 Score	Cluster4 Score
1. Promotion	Infinity Blade	Super Summer Sale! INFINITY BLADE IS NOW ONLY $0.99. FOR A LIMITED TIME! The critically acclaimed best seller is celebrating a limited time $0.99 sale.	8	0	0	0
2. Performance	Bridge Constructor	Number 1 in the game charts for iPad & iPhone in 24 countries. Number 1 in the overall app charts for iPad in 19 countries Already Number 1 in the overall app charts for iPhone in 4 countries	0	6	0	0
3. Review	Lep's World	"Absolutely love it, big fan!" - iTunes Review (iPhone) "This is extreme fun game!" - iTunes Review (iPad) "Amazing This is a great hit!!" - Android Review	0	0	2	0
4. Update	Batman Arkham City	UPDATED WITH NEW LEVELS & FEATURES - OPTIMIZED FOR THE NEW iPAD! The inmates have escaped and Batman has his hands full defeating an army of henchmen and some of his most iconic villains.	0	0	0	3
5. Uniqueness	Epic Astro Story	Ready to test your mettle against the final frontier? Pioneer an untamed planet, building roads and houses for your fellow denizens of the future.	0	0	0	0
1. Promotion + 2. Performance	W.E.L.D.E.R	Get the best word game on the App Store for just $0.99!!! Standard price is $3.99!!! Achieved #1 DOWNLOADED GAME ON iPAD.	1	2	0	0

Table 13. Cluster Scores

For example, an App, 'Infinity Blade', has a score of 8 for the '*Promotion*' cluster while other cluster scores remain zero. The cluster of '*Uniqueness*' indicates a group of words that have not appeared in other four clusters but used in the head of a description. The terms in *Uniqueness* characterize an App's key features/uniqueness of content. For example, a product description of an App titled 'Epic Astro Story' includes 14 unique words which did not appear in the identified four clusters, but is used for describing the content/features. Moreover, most App descriptions include two or more keywords clusters (i.e., a mix of clusters) as presented in the last row of Table 13.

4.4. Empirical Approach

Table 14 lists summary statistics for the research variables extracted from both product descriptions and App-specific information available at Apple App Store.

Variable Names	Description of Variables	Mean (S.D.)	Min.	Max.
Number of Words	Total number of words in the first two sentences in an App's description in week *t*	22.419(17.374)	2	124
Description changes	Number of changes in an App product description during the study period (20 weeks).	2.493 (1.360)	0	7
Description_update	1 if an App's description was updated in week *t*	0.196(0.295)	0	1
Variables from Product Descriptions (Producer Cues: P)				
$Promotion_{it}$	Number of words relating "*Price Promotion*" (Cluster 1) in an App's description in week *t*	0.590(1.202)	0	10
$Performance_{it}$	Number of words relating "*Sales Performance*" (Cluster 2) in an App's description in week *t*	0.313(0.787)	0	8
$Review_{it}$	Number of words relating "*User Review*" (Cluster 3) in an App's description in week *t*	1.475(1.623)	0	9
$Update_{it}$	Number of words relating "*Feature Update*" (Cluster 4) in an App's description in week *t*	0.760(1.489)	0	14
$Uniqueness_{it}$	Number of words not used for other keywords groups (*Uniqueness*) in week *t*	19.281(15.848)	0	120
Variables from Market Formats (Market Cues: M)				
$Price_{it}$	Price of an App in week *t*	1.936(1.628)	0.99	6.99
$Review\_score_{it}$	Averaged user review points (1 to 5 scale) in week *t*	4.245(0.609)	1.0	5.0
$Age\_of\_app_{it}$	Week elapsed after initial release date until week *t*	56.470(52.830)	0.143	214.14
Hit_app_{it-1}	1 if an App was listed in the top 25 charts in week *t-1*	0.097(0.296)	0	1
$Feature\_update_{it}$	1 if an App's quality indicators were updated in week *t* (adding more App features or fixing bugs)	0.070(0.255)	0	1
$Size_{it}$	File size of an App (MB) in week *t*	104.244(158.399)	1	962
$In\_app\_purchase_{it}$	1 if an app includes in-app-purchase (IAP) in week *t*	0.518(0.499)	0	1
Control Variable				
$Rank_{it-1}$	An App's rank in week *t-1*	103.428(74.568)	1	300

Table 14. Summary Statistics of the Dataset

Research Variables and Model Specification

An array of information cues that users can observe from App store markets was used for the analyses. An overview of the empirical modeling approach is presented in Figure 6.

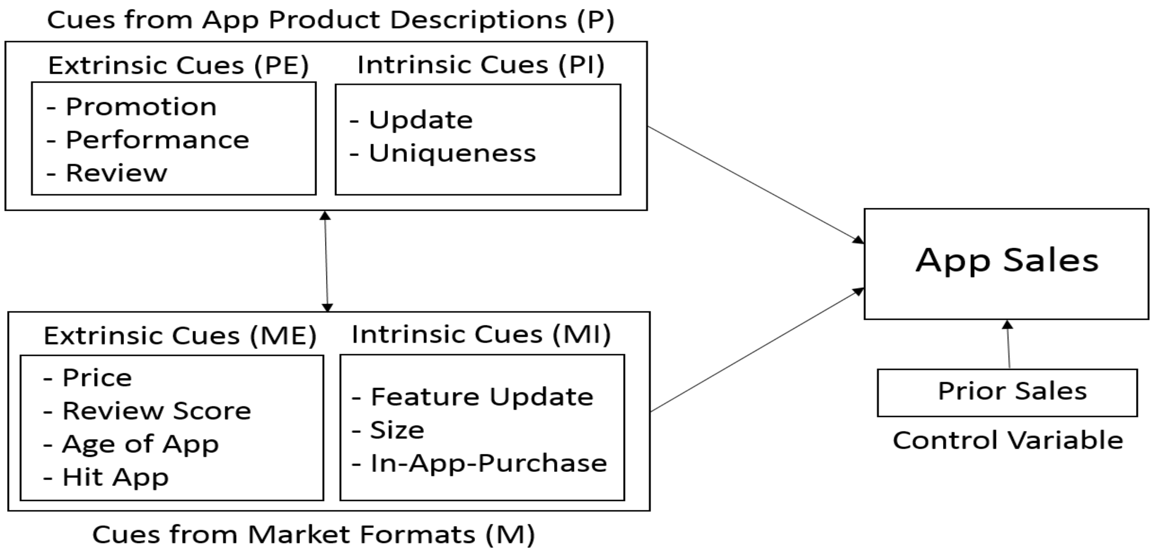


Figure 6. Empirical Model

The cues are classified as extrinsic or intrinsic to Apps. Extrinsic cues (E) are App-related attributes, but are not integral to an App. For example, price and user review scores are external to the App but influence the user's perceived quality. Similarly, the App's age and ranking information are not related to the App's physical specifications but they could signal the quality of App to the users. Conversely, intrinsic cues (I) are related to physical attributes of App such as unique features/content and size. We include the presence of in-app-purchase (IAP) option and the notification of feature updates in intrinsic cues since they indicate real changes to Apps. For instance, the inclusion of IAP option in a paid App implies limited feature availability and extra payment for more functionalities; updates on components in Apps indicate changes in features.

For producer cues (P) presented in App product descriptions, producer-extrinsic cues (PE) included keywords revealing price *'Promotion'*, prior sales '*Performance*', and user '*Reviews*'; producer-intrinsic cues (PI) included information on feature '*Update*' and '*Content*'. Similarly, market cues (M) delivered through market formats include market-extrinsic cues (ME) of *'Price'*, '*Review Score'*, '*Age of App'*, and '*Hit App'* and market-intrinsic cues (MI) of '*Feature Update'*, '*Size*', and '*In-App-Purchase*' option. To address the effect of prior sales which is prevalent in App store markets, we include '*Previous Rank'* as a control variable. The research framework presented in Figure 3 leads to the following model:

$$
\begin{aligned}
\underbrace{-ln(Rank)_{it}}_{Sales_{it}} = \beta_0 + & \underbrace{\underbrace{\beta_1 Promotion_{it} + \beta_2 Performance_{it} + \beta_3 Review_{it}}_{Producer\_Extrinsic\_Cue_{it}} + \underbrace{\beta_4 Update_{it} + \beta_5 Content_{it}}_{Producer\_Intrinsic\_Cue_{it}}}_{Producer\_Cue_{it}} \\
& + \underbrace{\underbrace{\beta_6 ln(Price)_{it} + \beta_7 Review\_score_{it} + \beta_8 Age\_of\_app_{it} + \beta_9 HitApp_{it-1}}_{Market\_Extrinsic\_Cue_{it}} + \underbrace{\beta_{10} Feature\_update_{it} + \beta_{11} ln(Size)_{it} + \beta_{12} In\_App\_Purchase_{it}}_{Market\_Intrinsic\_Cue_{it}}}_{Market\_Cue_{it}} \\
& + \underbrace{\beta_{13}(-ln(Rank))_{it-1}}_{Control_{it}} \\
& + \underbrace{\delta \sum (Extrinsic\_Cue_{it} * Intrinsic\_Cue_{it}) + \gamma \sum (Producer\_Cue_{it} * Market\_Cue_{it})}_{Interactions_{it}} \\
& + \sum Time_{it} + a_i + \varepsilon_{it}
\end{aligned}
$$

,where $Sales_{it}$ is the sales amount of an App i at time t. Since Apple does not release actual sales figures to the public, our measure of the success of App sales is based on rank information. Thus, the negative logarithm of rank of an App at week t (i.e., -$ln(Rank_{it})$) was used as a proxy of App sales, as suggested in prior research for using rank information as a proxy for sales (e.g., Brynjofsson et al. 2010a; Chevalier and Mayzlin 2006; Ghose et al. 2006; Ghose and Yang. 2009). $Producer\_Cue_{it}$ indicates a set of cluster scores derived from an App i's description at t. The cluster scores (i.e., the number of terms in clusters) in the producer cues were log-transformed to handle the variation of values (e.g., predominant zero cluster scores in the sample). A vector of $Market\_Cue_{it}$ is a set of App-specific attributes offered from a market. $Control_{it}$ includes an App's previous rank, $ln(Rank)_{t-1}$, which controls for the effect of prior sales at $t-1$ on current sales at t. The interactions of $Extrinsic\_Cue_{it}$ and $Intrinsic\_Cue_{it}$, and of $Producer\_Cue_{it}$ and $Market\_Cue_{it}$ are used for investigating the complementarities between a pair of individual cues. $\Sigma Time_{it}$ is a time-fixed effect term. α_i represents an App-specific fixed effects term incorporating unobserved heterogeneity among Apps. Finally, ε_{it} is an unobserved error term in demand.

From this model specification, we ran multiple regression models. The first set of models (Model I) investigate the main effects of individual cues on App sales and the improvement in model predictive power by adding each group of cues to the baseline model. The second set of models (Model II) examines the complementary effects between pairs of distinctive cues (i.e., P and M & E and I).

Keywords Selection and Endogeneity

It is reasonable to perceive that the keywords/messages in descriptions can be endogenously selected by developers, and therefore a fixed effects approach may not control for such a potential endogeneity problem. To address this potential confound, we conducted several different analyses to justify the empirical model.

First of all, notice that the unobserved demand shock consists of the App-specific mean level α_i and the time-varying deviation from the mean level ε_{it} in the proposed model. Suppose that α_i represents the unobserved general quality of the App and the sellers determine the levels of considered cues and/or control variables based on the general quality of the App. Then, the cues and a control variable are mainly correlated to α_i but uncorrelated to ε_{it}, and the fixed effect approach can successfully handle the endogeneity problem. If the time-varying deviation of the demand shock (ε_{it}) is also correlated with the cues and control variables, this additional endogeneity has to be appropriately tackled. However, we believe that this correlation is not likely in our data. A majority of Apps in our dataset are sold by small individual developers. As we noted, there are no easily accessible guideline or theory on key decisions associated with the cues and control variables. Therefore, it is less likely that developers react to time-varying demand shocks on a weekly basis uniformly. We expect an insignificant link between the time varying demand shocks and the cues and/or control variables. As such, the fixed effects approach can sufficiently address any App specific endogeneity issue. Alternatively, if one can obtain good instrument variables, the generalized method of moments (GMM) approach can be used for the model estimation. The main advantage of GMM estimator is that the estimates are still valid when the cues and/or control variables are correlated with ε_{it}. However, there are several problems associated with utilizing the GMM estimator in our research setting. First, it is difficult to identify good instruments that are correlated with a developer's keyword selection and control variables but are uncorrelated with sales performance (for similar arguments, see Huang et al 2012; Qian 2007). To circumvent this problem, Arellano and Bond (1991) proposed a lagged instrument based estimation approach but this method also does not guarantee a valid estimation. In a recent study, Rossi (2013) therefore advises that "if strong and valid instruments are not available, then the researcher is much better off measuring the variables in hand rather than using instruments (such as lagged variables) which are clearly invalid". Furthermore, Arellano and Bond GMM approach is designed for small T (time) and large N (subjects) but our data set has a relatively long time period (20 weeks) and a small number of subjects (325 Apps). Keeping all these shortcomings in mind, we estimate the proposed model using the Arellano-Bond (AB) difference GMM estimator to check the robustness of our findings. The results from GMM estimator are qualitatively similar to those of the fixed effect approach. The signs of all estimates are the same but as expected the significance levels of some variables are slightly different.

Model Validation

We conducted several diagnostic tests to validate our model specification. First, we checked a potential reverse causality between updates in the description and changes in App sales. The sampled Apps' descriptions were fixed at the first week of study and a dummy variable (i.e., $Description\_change_{it}$) indicating whether an App's description was changed in a given week was introduced in the models. For the estimation, we used the random effects for individual Apps with time-specific fixed effects. Then, we conducted the Granger causality tests (Granger 1969; Hood et al. 2008) using one-to-three year lags for *Rank* and *Description_update*. The test results indicated a rejection of the null hypothesis that *Description_update* did not Granger cause *Rank*. However, the results do not support rejection of the null hypotheses that *Rank* did not Granger cause *Description_update* for one-to-three lags. Therefore, we conclude that changes in App sales came *after* the description updates.

Second, the presence of multicollinearity was tested with Variance Inflation Factors (VIF) for each explanatory variable in each regression model. None of the VIF values exceeded 2.43, indicating that multicollinearity was not an issue in our models. We did not find any strong correlations between predictors; the highest correlation (ρ= 0.422) among predictors was between $Top25_{it-1}$ and $-log(Rank)_{it-1}$. Moreover, to address the multicollinearity problem due to the inclusion of multiple interactions between extrinsic and intrinsic cues from the two different sources, we estimated the interaction terms using a residual centering procedure (Lance 1988) to correct the partial coefficient distortion effects that arise from correlations between main effects and interaction terms. However, we did not find any significant changes in estimation outcomes after applying the residual centering procedure.

Third, to check if App-specific fixed effects models provide consistent and efficient estimates, we conducted two formal model specification tests: Breusch and Pagan's (1979) Lagrange multiplier (LM) test for heterogeneity effects specification and a Hausman specification test (1978) against the random effects model. The test result from Breusch-Pagan LM suggests the model specification should incorporate App-specific heterogeneity (i.e., we rejected the null hypothesis that variances across Apps are equal to zero at 1% significance level). In addition, Hausman test indicates that a fixed effects specification for our models is preferred over random effects approach (i.e., we reject the null of using random effects models at 1% significance level). To see if time-fixed effects are needed when running a fixed effects model, we conducted a joint test to check if all the time (week) dummies are equal to 0. We reject the null that all time coefficients are jointly equal to zero, therefore time fixed effects are needed in the models.

Fourth, we checked whether the inclusion of a lagged dependent variable in our fixed-effects models creates an autocorrelation, and consequently lead to a biased estimator. In this regard, we conducted a Wooldridge test for autocorrelation in fixed-effects models (Drukker 2003; Wooldridge 2002), and failed to reject the null of "no autocorrelation". In addition, we estimated the models by excluding the AR(1) term, -$ln(Rank)_{it-1}$, and there were no remarkable changes in the signs and significance levels as compared with the original model specifications. Therefore, serial correlation of residuals is not a concern.

Fifth, we diagnosed a potential endogeneity problem that can arise from the repeated entries and exits of Apps in the top charts (this creates unbalanced panel structure in the dataset). We replicated the analysis with a balanced panel that included only Apps that were continuously listed in the top charts throughout the 20 weeks. The estimation outcomes from the balanced panel data present qualitatively the same outcomes as compared to the original analysis. As such, our unbalanced panel structure is robust to the entry and re-entry of an App in the charts.

Finally, we performed a modified Wald test for heteroskedasticity in our fixed effects models, and rejected the null hypothesis of homoskedasticity (i.e., constant variance) at the 1% significance level. Therefore, we use the robust standard errors clustered by individual Apps (Rogers 1993) for all the models.

In addition, we conducted a set of post-hoc analyses to test the robustness and validity of our findings: 1) sales performance with full descriptions; and 2) the impact of App descriptions in productivity Apps. We report these additional models in a separate section.

4.5. Results

Main Effects

First, we evaluate whether market cues have dominant effect in influencing consumers' purchase decisions, and consequently lead to actual sales in the mobile App market setting. Then, the role of producer cues in promoting App sales is investigated. In this model setting, we examine the individual impacts of producer/market and extrinsic/intrinsic cues on App sales when individually separated cues are assumed to be available in the market.

To examine model predictive power due to the addition of distinctive cues, we sequentially ran Model I in four iterations. As a baseline (null) model, Model I(0) includes only control variables. Model I(1) and Model I(2) examine the main effects of producer (P) and market (M) cues respectively. Finally, Model I(3) combines extrinsic (PE and ME) and intrinsic (PI and MI) cues from product descriptions and market formats. The ability of a model to predict better than a baseline model was evaluated based on adjusted R^2 values. Overall, the model predictive power increased when we incorporated more cues into the baseline model. However, the inclusion of intrinsic cues (I) or producer cues (P) marginally increased adj. R^2 values.

Cue	Variable	Null	Model I(1) (Producer Cues)			Model I(2) (Market Cues)			Model I(3) (Producer + Market Cues)		
			Extrinsic (PE)	Intrinsic (PI)	Overall (P=PE+PI)	Extrinsic (ME)	Intrinsic (MI)	Overall (M=ME+MI)	Extrinsic (E=PE+ME)	Intrinsic (I=PI+MI)	Overall (E+I or P+M)
	Constant$_{it}$	-1.873***	-2.009***	-1.932***	-2.023***	-1.236***	-1.822***	-1.414***	-1.346***	-1.874***	-1.478***
		(0.155)	(0.157)	(0.267)	(0.205)	(0.309)	(0.177)	(0.298)	(0.305)	(0.272)	(0.352)
Variables from Product Descriptions (Producer Cues: P)											
PE	*Promotion*$_{it}$	.	0.528***	.	0.520***	.	.	.	0.149*	.	0.159**
			(0.059)		(0.059)				(0.062)		(0.060)
	Performance$_{it}$	.	-0.027	.	-0.027	.	.	.	-0.038	.	-0.040
			(0.077)		(0.082)				(0.070)		(0.065)
	Review$_{it}$	.	-0.060	.	-0.032	.	.	.	-0.027	.	-0.010
			(0.062)		(0.064)				(0.059)		(0.057)
PI	*Update*$_{it}$	.	.	-0.333***	-0.111	.	.	.	.	-0.341***	0.060
				(0.095)	(0.092)					(0.094)	(0.072)
	Uniqueness$_{it}$	.	.	0.067	0.015	.	.	.	.	0.077	-0.045
				(0.093)	(0.062)					(0.090)	(0.055)
Variables from Market Formats (Market Cues: M)											
ME	*ln(Price)*$_{it}$	.	.	.	.	-0.877***	.	-0.879***	-0.783***	.	-0.793***
						(0.060)		(0.060)	(0.070)		(0.073)
	Review_score$_{it}$	.	.	.	.	0.105*	.	0.109*	0.121*	.	0.128**
						(0.053)		(0.049)	(0.051)		(0.048)
	Age_of_app$_{it}$	.	.	.	.	-0.013***	.	-0.012***	-0.013***	.	-0.012***
						(0.003)		(0.002)	(0.003)		(0.002)
	Hit_app$_{it-1}$	.	.	.	.	-0.011	.	-0.005	-0.016	.	-0.011
						(0.059)		(0.058)	(0.060)		(0.058)
MI	*Feature_update*$_{it}$	.	.	.	.	.	0.193***	0.191***	.	0.197***	0.189***
							(0.050)	(0.042)		(0.049)	(0.040)
	ln(Size)$_{it}$	.	.	.	.	.	-0.004	0.030*	.	-0.009	0.034*
							(0.015)	(0.013)		(0.012)	(0.014)
	In-App-Purchase$_{it}$	.	.	.	.	.	-0.132	-0.141	.	-0.152	-0.107
							(0.114)	(0.110)		(0.124)	(0.112)
Control Variable											
	-ln(Rank)$_{it-1}$	0.538***	0.526***	0.536***	0.526***	0.510***	0.537***	0.508***	0.511***	0.535***	0.508***
		(0.036)	(0.036)	(0.037)	(0.036)	(0.034)	(0.036)	(0.033)	(0.034)	(0.037)	(0.034)
	R^2(adj. R^2)	0.369	0.443	0.379	0.444	0.531	0.377	0.540	0.536	0.388	0.544
		(0.365)	(0.439)	(0.375)	(0.439)	(0.528)	(0.372)	(0.536)	(0.532)	(0.383)	(0.540)

*= p <0.05, **= p <0.01, ***= p <0.001

Note: $\sum Time_{it}$ *variable and app-specific fixed effects were included in the analysis, but not reported here.*

Table 15. Estimation Results of Main Effects

Extrinsic vs. Intrinsic Cues: In Model I(1) and Model I(2), the addition of extrinsic cues (PE or ME) to the null model had higher adj. R^2 values than that of intrinsic ones (PI or MI) regardless of cue sources. Similarly, Model I(3) indicated that the combination of extrinsic cues (PE+ME) resulted in a 38.9% (from 0.383 to 0.532) increase in the model predictive power as compared to that of intrinsic cues (PI+MI). The findings are consistent with prior studies that have shown that consumers are more likely to rely on extrinsic cues than intrinsic cues (Dawar and Parker 1994). An App user is likely to purchase an App by evaluating its value based on extrinsic cues since extrinsic attributes of the App are more readily available and easily evaluated (i.e., high PV and CV) than intrinsic attributes such as descriptions delivering inherent features ($Update_{it}$ and $Uniqueness_{it}$) of Apps and market cues ($Size_{it}$ and $In\text{-}App\text{-}Purchase_{it}$) which are generally difficult for consumers to assess prior to actual purchase (Zeithaml 1988). As a result, a one-percent increase of price promotion-related terms ($Promotion_{it}$) in the descriptions improved the rank by 15.9%. A one-percent lower price ($Price_{it}$)[15], a one-unit increase in user review score, and a week newer App ($Age\_of\_app_{it}$) improved the App rank by 79.3%, 12.8%, and 1.2% respectively.

***Producer vs. Market Cue*:** The outcomes in Model I(1:P) show that the availability of producer cues (P) somewhat improved the predictive power (a 20.3% increase from Model I(0)). Furthermore, there was a marginal improvement in adj. R^2 when both producer and market cues are introduced in Model I (3:P+M) as compared to

[15] The majority of Apps in the Top Paid charts were offered for $0.99 and they accounted for 65.6% of Paid game Apps. To evaluate the impact of this specific price on App sales, we replaced $ln(price_{it})$ with a dummy variable, $nintynine\_cent_{it}$, indicating whether an App was offered for $0.99. The resulting coefficient estimate was 0.719*** (.0087). In other words, offering an App at the $0.99 price-point improves the ranking by 71.9%.

when only market cues were considered (Model I(2:M)). The inclusion of market cues allowed a better prediction for App sales - the adj. R^2 value by 46.8% from that of Null Model (from 0.369 to 0.536). In addition, keywords containing '*Promotion*' was the only significant predictor in producer cues, the five predictors ($Price_{it}$, $Review\_score_{it}$, $Age\_of\_app_{it}$, $Feature\_update_{it}$, and $Size_{it}$) in market cues were significantly associated with App sales.

There are several reasons why producer cues may not be strong quality signals in the context of mobile App markets. First, since the attributes in App product descriptions are selected/written by developers, the producer-driven cues are framed intentionally and thus these highly subjective cues are transmitted to users with noise (i.e., a framing effect: Anderson, 2011). For example, a developer can include a hyped prior sales information for an App ("*over 100 million downloads in 20 countries…*") not easily available in the market format, or put only extremely positive user review comments in the product description ("…*Best game ever played!!*...”). Therefore, a user's predictive value (PV) associated with producer cues is likely to be relatively low. Second, the intrinsic cues provide very content-specific and technical attributes of Apps such as "*this version enhances graphic performance with an Unreal 3D engine…*" and "*Monsters have stolen your homework and now it's payback time!.*." Consequently, users may not accurately assess the value of Apps without knowledge of App components and experience of the App at the time they purchase. This confirms the dominant prior result of lower confidence value (CV) in intrinsic cues for consumers (Richardson et al. 1994; Zeithaml 1988). Finally, some cues in the description can be easily distinguishable by the corresponding market cues such as price changes and update history. Thus, App users can reliably be expected to rely on high-fidelity and objective market cues.

In summary, market cues delivering extrinsic attributes of Apps have strong associations with App sales as past studies found in online markets and ensure a better model prediction when users can only see either producer cues or market cues. However, the key question of how the combination of producer cues and market cues can attenuate or amplify the signals of quality to consumers still remains. Therefore, we next investigate whether producer cues are complementary or substitute to market cues.

Complementary Effects

In the models presented in this section, we examine the complementarities between producer and market cues as well as between extrinsic and intrinsic cues. In reality, App users can inexpensively evaluate an App by simultaneously absorbing the cues in App product description and market formats; moreover, both cues are presented in a single screen regardless of mobile devices or PCs. Model II includes the five different combinations of the cues by introducing interactions between producer cues and the significant market cues: $ln(Price)_{it}$, $Review\_score_{it}$, $Age\_of\_app_{it}$, Hit_app_{it-1}, and $Feature\_update_{it}$. A large body of literature on extrinsic cues has introduced the first three extrinsic attributes of a product to examine their impacts on consumers' purchase decisions: price (Dodd and Monroe 1985; Erevelles et al. 1999; Miyazaki et al. 2005), review scores (Chen and Xie 2008; Dellarocas 2005; Godes and Mayzlin 2004), and ranking information (Duan et al. 2009; Yoo and Kim 2013). The cues on feature update is a strong quality indicator in a mobile App market setting. Adding new features and fixing bugs can be regarded as the continuous effort of a developer for a quality App (Lee and Raghu 2014).

Cue	Variable	Model II(1) (PE * M)	Model II(2) (PI * M)	Model II(3) (P * M)
	Constant$_{it}$	-1.794*** (0.406)	-1.102 (0.587)	-1.374* (0.638)
	Variables from Product Descriptions (Producer Cues: P)			
PE	*Promotion$_{it}$*	1.048** (0.351)	0.164** (0.063)	1.337*** (0.378)
	Performance$_{it}$	-1.199* (0.605)	-0.019 (0.070)	-1.014 (0.608)
	Review$_{it}$	0.366 (0.326)	-0.015 (0.059)	0.274 (0.330)
PI	*Update$_{it}$*	0.068 (0.074)	0.367 (0.297)	0.753 (0.397)
	Uniqueness$_{it}$	-0.009 (0.055)	-0.210 (0.218)	-0.227 (0.236)
	Variables from Market Formats (Market Cues: M)			
ME	*ln(Price)$_{it}$*	-0.883*** (0.106)	-0.976*** (0.181)	-1.209*** (0.175)
	Review_score$_{it}$	0.183* (0.074)	0.023 (0.117)	0.107 (0.130)
	Age_of_app$_{it}$	-0.012*** (0.003)	-0.009* (0.004)	-0.010* (0.004)
	Hit_app$_{it-1}$	0.104 (0.110)	-0.321 (0.272)	-0.338 (0.233)
MI	*Feature_update$_{it}$*	0.125* (0.058)	0.164 (0.130)	0.124 (0.145)
	ln(Size)$_{it}$	0.015 (0.014)	0.037* (0.015)	0.026* (0.013)
	In-App-Purchase$_{it}$	-0.071 (0.104)	-0.098 (0.113)	-0.103 (0.111)
	Interactions with *ln(Price)$_{it}$* (ME)			
PE	*Promotion$_{it}$*	0.063 (0.087)	.	0.063 (0.084)
	Performance$_{it}$	0.132 (0.139)	.	0.149 (0.144)
	Review$_{it}$	0.071 (0.098)	.	-0.063 (0.109)
PI	*Update$_{it}$*	.	0.073 (0.103)	0.078 (0.104)
	Uniqueness$_{it}$	.	0.056 (0.079)	0.147* (0.073)
	Interactions with *Review_score$_{it}$* (ME)			
PE	*Promotion$_{it}$*	-0.169* (0.076)	.	-0.237** (0.080)
	Performance$_{it}$	0.233 (0.123)	.	0.188 (0.126)
	Review$_{it}$	-0.093 (0.069)	.	-0.073 (0.070)
PI	*Update$_{it}$*	.	-0.065 (0.066)	-0.127 (0.084)
	Uniqueness$_{it}$	.	0.043 (0.047)	0.040 (0.050)
	Interactions with *Age_of_app$_{it}$* (ME)			
PE	*Promotion$_{it}$*	-0.003** (0.001)	.	-0.003** (0.001)
	Performance$_{it}$	0.000 (0.002)	.	0.001 (0.002)
	Review$_{it}$	0.000 (0.001)	.	0.001 (0.001)
PI	*Update$_{it}$*	.	-0.001 (0.001)	-0.003** (0.001)
	Uniqueness$_{it}$	.	-0.001 (0.001)	-0.001 (0.001)
	Interactions with *Hit_app$_{it-1}$* (ME)			
PE	*Promotion$_{it}$*	-0.170* (0.081)	.	-0.205* (0.094)
	Performance$_{it}$	0.244 (0.185)	.	0.255 (0.174)
	Review$_{it}$	-0.148 (0.104)	.	-0.215* (0.110)
PI	*Update$_{it}$*	.	-0.013 (0.132)	0.001 (0.126)
	Uniqueness$_{it}$	.	0.121 (0.110)	0.193* (0.085)
	Interactions with *Update$_{it}$* (MI)			
PE	*Promotion$_{it}$*	0.062 (0.104)	.	0.061 (0.108)
	Performance$_{it}$	0.045 (0.078)	.	0.040 (0.079)
	Review$_{it}$	0.051 (0.051)	.	0.056 (0.058)
PI	*Update$_{it}$*	.	-0.049 (0.064)	-0.036 (0.061)
	Uniqueness$_{it}$	.	0.016 (0.049)	0.003 (0.057)
	Control Variable			
	-ln(Rank)$_{it-1}$	0.497*** (0.031)	0.505*** (0.033)	0.488*** (0.031)
	R^2(adj. R^2)	0.557 (0.550)	0.548 (0.542)	0.564 (0.556)

*= p <0.05, **=p <0.01, ***=p <0.001

Note: $\sum Time_{it}$ variable was included in the analysis, but not reported here.

Table 16. Estimation Results of Complementary Effects

Table 17 summarizes the complementary effects between extrinsic and intrinsic cues from the difference sources.

Producer Cues (P) / Market Cues (M)		ME				MI
		$ln(Price)_{it}$	$Review\_score_{it}$	$Age\_of\_app_{it}$	Hit_app_{it-1}	$Update\_feature_{it}$
PE	$Promotion_{it}$	.	-**	-**	-*	.
	$Performance_{it}$	.	.	.	.	.
	$Review_{it}$	.	.	.	-*	.
PI	$Update_{it}$	.	.	-*	.	.
	$Uniqueness_{it}$	+*	.	.	+**	.
*= p <0.05, **=p <0.01, ***=p <0.001						

Table 17. Interactions between Producer Cues and Market Cues

Producer-Extrinsic and Market Cues: When the interactions between producer-extrinsic (PE) and market-extrinsic cues (ME) are introduced in Model II, the estimates of two producer cues ($Promotion_{it}$ and $Review_{it}$) and three market cues ($Review\_score_{it}$, $Age\_of\_app_{it}$, Hit_app_{it-1}) were significantly associated with App sales, and increased the model fit from the baseline model. The outcomes imply complementary relationships between PE and ME. A product description conveying price '*promotion'* has diminishing marginal impacts in '*review scores*' and '*the age of an App*' for App sales. In other words, developers with low review scores could improve sales by emphasizing information on price promotion in the head of the product description. Similarly, the descriptions advertising price promotion is more effective for newly released Apps than for older Apps.

Interestingly, the hit Apps that appeared in the top 25 charts did not benefit from the descriptions including price discount information and users' positive feedbacks. This indicates that the dominant informational cascades among App users for the hit Apps diminishes the role of descriptions in promoting the sale. An alternative interpretation is that the marketing messages delivering price discount and positive user reviews in descriptions can help the Apps outside the top 25 charts to improve their ranking.

Producer-Intrinsic and Market Cues: The interactions of two producer-intrinsic cues ($Update_{it}$ and $Uniqueness_{it}$) and three market-extrinsic cues ($ln(Price)_{it}$, $Age\_of\_app_{it}$, Hit_app_{it-1}) were significantly associated with App sales. The description delivering '*uniqueness*' of Apps is effective in reducing the negative effect associated with higher price. In other words, a developer offering a high-price App can attract more users by communicating the uniqueness of content and functionalities of the App. The negative and significant interaction between $Update_{it}$ and $Age\_of\_app_{it}$ indicates that newer Apps benefited from feature '*update*'-related information in the description. App markets inform the 'update date' of an App only to users through the App product page without the detailed update information. Therefore, the enriched update specifications in a product description enable the users to evaluate the quality of rookie Apps better and help making purchase decisions on the Apps.

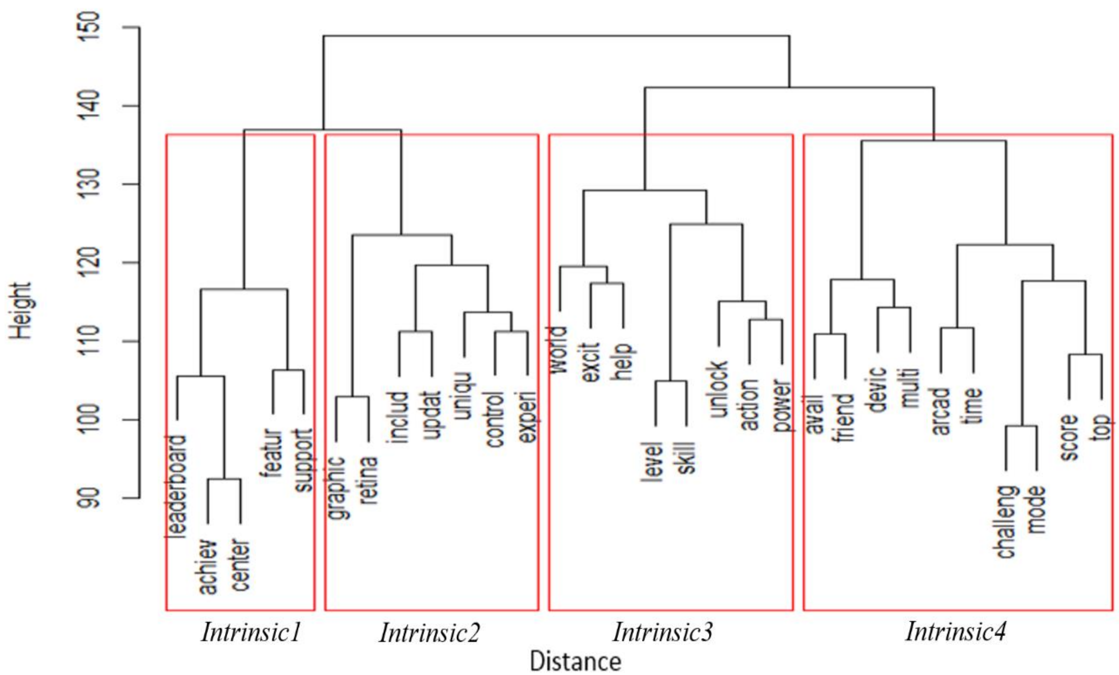
The inclusion of $Uniqueness_{it}$ in formulating a description has a positive association with Hit_app_{it-1} in terms of sales. It implies that consumers' purchase decisions for the already popular Apps highly rely on the content of an App. As we found in the moderating effects of producer-extrinsic in Hit_app_{it-1}, and sales, the descriptions stating price '*promotion*' and positive user '*reviews*' do not help the hit Apps. However, the outcome suggests that consumers' willingness to buy hit Apps are further reinforced by descriptions of inherent content/features.

The models with interaction effects empirically substantiate the important role of product descriptions in influencing App sales and suggest how App developers can strategically utilize their product descriptions. While the producer cues have limited impact on their own, they can influence App sales when coupled with market cues by enhancing the CV and PV of users.

4.6. Robustness Analysis

In the main results, we restricted text analysis to the first two sentences in the App descriptions. It is possible that information content in the complete description may improve producer cue performance. Additionally, the analyses focused solely on Game category may raise concerns on the generalizability of results to other categories in App markets. For example, while gaming Apps are generally consumed for pastime (i.e., hedonic use), some Apps in Productivity and Utility categories are downloaded for personal tasks (i.e., utilitarian use). Therefore, product cues in App descriptions are likely to be consumed differentially in different categories. To address these two threats to robustness, we conducted a set of post-hoc analyses to test the validity of our findings by 1) analyzing sales performance with full descriptions; and 2) replicating the impact of App descriptions in Productivity category.

First, we investigated how an entire App description (instead of the first two sentences) is associated with an App's sales performance. Figure 7 presents the four clusters with the 30 most frequent terms appearing in the full descriptions.



Note that if we exclude the first two sentences in the full description, the 30 most frequent keywords shown above remain unchanged.

Figure 7. Clusters of Keywords in Full Descriptions

While extrinsic cues delivering marketing messages were more frequently used in the first two sentences of App descriptions, intrinsic cues indicating App-specific content/functions were dominant in the full description model. In other words, App developers promote extrinsic attributes more prominently than intrinsic attributes in the head of App product descriptions. We present a summary comparison of estimation outcomes in Table 18[16].

[16] The detailed estimation results are presented in Tables A4 in APPENDIX B, where we labeled the clusters as intrinsic cues (i.e., *intrinsic1* to *intrinsic4*) instead of message-specific names due to difficulty in

Effect	Cue	Truncated Description	Full Description
Main	PE	*Significant*†	X
	PI	.	.
	ME	*Significant*†††	*Significant*†††
	MI	*Significant*††	*Significant*††
Complementary	PE * MI	.	X
	PE * ME	*Significant*†††	X
	PI * MI	.	.
	PI * ME	*Significant*†††	*Significant*††

Note that the number of † indicates the number of significant estimates (product cues) and 'X' indicates the estimates of producer-extrinsic (PE) cues not observed in the entire descriptions.

Table 18. Estimation Results: Truncated Description vs. Full Descriptions

The results show that none of producer cues (PE or PI) in the entire descriptions have significant main impacts on App sales. Whereas, market cues (ME and MI) remain significant. Lack of significance indicates that full descriptions are inherently noisy, and therefore the use of the first two sentences in the descriptions is able to reduce this noise.

Second, in order to evaluate the role of descriptions in other App categories, we examined the impact of App descriptions on another App category, i.e., productivity Apps. Unlike gaming Apps, Apps in Productivity category are generally consumed for utilitarian purposes. Users are more likely to weight the product value based on how a Productivity App supports task-related requirements (i.e., practical and economic benefits of the App) (Babin et al. 1994; Childers et al. 2001). Hence, it can be argued that intrinsic cues are more likely to influence sales in utilitarian categories.

To test for the differential importance of cues based on product category, we performed text mining on 6,016 descriptions of 437 Productivity Apps in the same study period[17]. As shown in Figure 7, we identified five clusters of App product cues in our

understanding the usage of terms in the descriptions. In addition, we do not have "*Uniqueness*" cluster since full descriptions have an average of 730 terms.

[17] Less number of productivity Apps appeared than gaming Apps in the study period. Since productivity Apps accounted for 2.8% of App store market (148Apps.biz, December 2012), the competition among

analysis: *Extrinsic*, *Intrinsic1*, *Intrinsic2*, *Intrinsic 3*, and *Intrinsic4* (i.e., a group of terms not used in other four clusters). While only the first cluster includes terms related to price promotion information, the other clusters deliver intrinsic cues emphasizing Apps' functionalities that emphasized task-related requirements dominantly appeared in the head of descriptions.

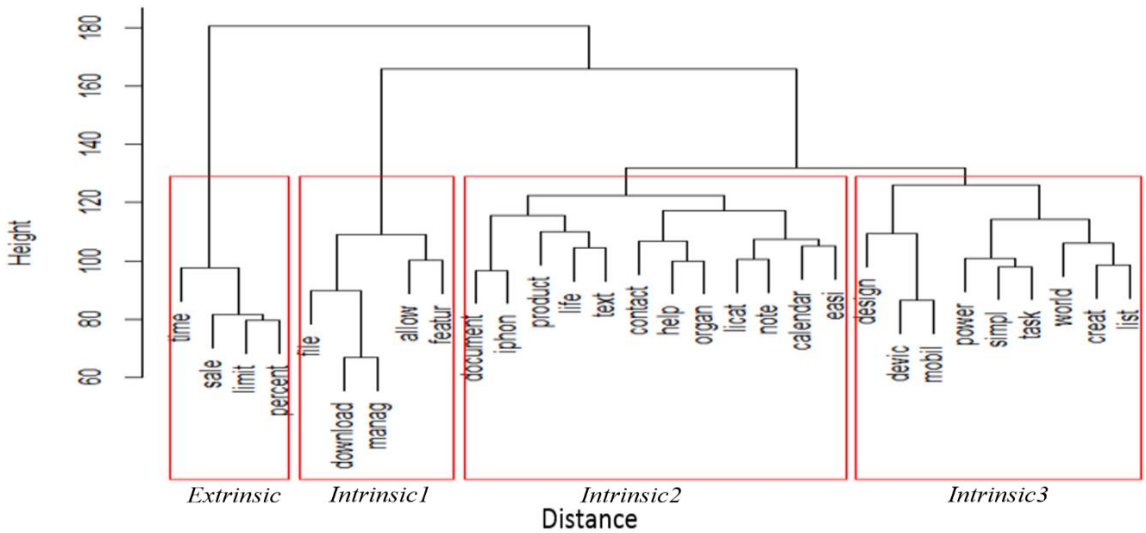


Figure 8. Clusters of Keywords in Productivity Apps' Description

The comparisons of sales performance between Game and Productivity Apps are presented in Table 19[18].

Effect	Cue	Game Category	Productivity Category
Main	PE	*Significant†*	*Significant†*
	PI	.	.
	ME	*Significant†††*	*Significant††*
	MI	*Significant††*	*Significant†*
Complementary	PE * MI	.	.
	PE * ME	*Significant†††*	*Significant†*
	PI * MI	.	*Significant†*
	PI * ME	*Significant†††*	.

Note that the number of † indicates the number of significant estimates (product cues)

Table 19. Estimation Results: Game vs. Productivity Apps

developers seems less intense. The insignificant estimates of $Age\_of\_app_{it}$ presented in Tables A5 and A6 in APPENDIX B support that the time of release date do not have significant impacts on App sales.

[18] The detailed estimation results are presented in APPENDIX B.

While producer cues (PI) in the descriptions were not significantly associated with sales except when only promotion-related messages appeared (i.e., PE ($Extrinsic_{it}$)), market cues (ME and MI) and the interaction of PE and ME remain significant. Interestingly, we found that a cluster including App-specific function (i.e., $Intrinsic1_{it}$) had a positive interaction effect with a market cue (i.e., $Update_{it}$) in terms of App sales (i.e., PI * MI). Consequently, we conclude that market cues of Apps have significant impacts on App sales performance regardless of App category whereas intrinsic cues may have differential impacts in app categories.

4.7. Concluding Remarks

In this research, we set out to investigate and identify producer/market cues that are associated with improved App sales performance. We find that extrinsic cues are more strongly related to App rankings than intrinsic ones regardless of the information source, and that consumers utilize market cues as more reliable quality indicators of Apps than producer cues as evidenced in online markets. While the producer cues have limited impact on their own, they can influence App sales when coupled with market cues.

Extrinsic cues available in the markets such as the price of $0.99, one-point higher review scores, and a one-week newer Apps improve the sales ranks by 72%, 13%, and 1% respectively. We also identify complementarities between producer cues and market cues in influencing sales performance. The findings of the study highlight the important role of seller-generated product information in improving App users' perceived quality of Apps in the search-intensive product markets. We empirically substantiate that cues in the descriptions are complementary to cues offered by the market. In particular, the extrinsic cues of price '*promotion*' and user '*review*' comments in a product description improve the sales of low review scored, newly released, and non-hit Apps. The intrinsic cues delivering information on feature 'update' and 'uniqueness' of an App enhance the sales performance of high-priced and hit Apps. Therefore, producer cues have the capability of increasing user demand for Apps in search-intensive product markets.

We believe that the findings bear significant implications to the extant literature on formulating strategic product descriptions and to business practices in the mobile application software industry. From an academic perspective, our research creates new knowledge about mobile App developers' strategic decisions on writing product description and its impact on success in mobile App markets. There is a need to recognize the important role of producer cues in the presence of dominant market cues. This research is a first step to investigate evidence for the significant associations of producer cues and market cues in stimulating product sales. From a business perspective, this research provides valuable managerial insight, not only for mobile App developers, but for platform providers. For developers, the intense competition along with the remarkable growth in the number of Apps creates 'survival' problem for even well-established Apps. For instance, more than 80% of 1.4 million Apps in Apple App Store are never downloaded by users[19]. As such, for developers, making sure that their Apps appeal to potential consumers and surface higher in the App store search results over rivals is important. Therefore, strategic App product description is critical to sales performance

[19] The Decline of the App Millionaire (February 19, 2015, Fortune) available at http://fortune.com/2015/02/19/the-decline-of-the-app-millionaire/

and sustainability of mobile Apps. The results of the study provide clear pointers on the types of keywords in App descriptions that are strongly associated with sales performance. The strong performance of market cues in our empirical results shows that platform providers have considerable influence in determining the success of Apps. Although most mobile App store market such as Google Play, Blackberry App World, and Apple App Store have large selections of Apps, they highly rely on conventional search algorithms that simply match user inputs from databases. Accordingly, customized keyword matching or personalized recommendations based on users' preferences (or purchase history) do not yet seem to be the norm in mobile platforms. In this regard, the findings in this research can motivate platform providers to design search algorithms that effectively match user wants with appropriate Apps.

CHAPTER 5

5. APP QUALITY UPDATE DECISION AND APP SUCCESS

Continuous effort – not strength or intelligence – is the key to unlocking our potential

- Winston Churchill, 1965

5.1. Research Objective and Questions

The theory of long-tail market posits that low search costs allow online consumers to meet their different tastes from various products, and thus sellers in the tail benefit from heterogeneous consumers (Brynjolfsson et al. 2011; Hinz et al. 2011). In the context of mobile markets, however, consumer costs for searching the right App are expensive due to inherent characteristics of products (i.e., Apps as experience goods, Lee et al. 2015), the medium of transactions (i.e., restricted search capabilities through mobile devices, Ghose et al. 2012), and platforms (i.e., a highly competitive market structure, Lee and Raghu 2014). In such search-intensive markets, therefore, consumer purchase decisions are generally shaped by early adopters' decisions in a collective manner (information cascades, Banerjee 1992). Specifically, a product's successful prior ranking (popularity) has the pivotal role in stimulating new consumer demands for the already successful product as evidenced in the long-tail markets selling songs (Elberse 2010; Yoo and Kim 2012), books (Elberse 2008), movies (De Vany and Lee 2001), and digital software products (Duan et al. 2009). In line with this, a few recent studies on mobile Apps also find high search costs discourage mobile users to search for low-ranked Apps (Carare 2012; Ghose et al. 2012). However, no superstars, bestsellers or blockbusters last forever. We believe in the old wisdom attributed to Aristotle - "*Success is never an* *accident. It is always the result of sincere effort."* Strong popularity effects driven by consumers may not necessarily lead to lasting success in the mobile App market. While most digital products are not updatable after their releases, mobile Apps can be easily modified and updated by content creators after observing consumers' purchase behaviors and competitors' strategies. Thus, the success of App is managed by a developer's continuous endeavor throughout the whole life cycle of an App.

As listed in Table 20, several unique aspects of mobile App markets enable sellers to take advantage of updating strategy for App success over conventional digital product markets characterized as long-tail markets.

	Mobile App Markets	Other Long-tail Markets
Timing & Scope	- Flexible in changing price and features regardless of time and scope	- Restricted to release times and superficial features
Frequency	- High Frequency - Free to update any time in a life cycle	- Low Frequency - Limited to release dates
Information Flow Velocity	- Fast information flows among consumers from various sources - Push-based information acquisition	- Slow and long idle time to get product update information - Pull-based information acquisition
Feedback Loop	- Interactive feedback loop between a seller and consumers for App updates - Assessments from individuals users	- One-way feedback from consumers to a seller - Assessments from a focal user group
Targeted Audience	- Both existing and new consumer groups	- Existing consumer groups

Table 20. Product Updates in Mobile App Markets and Long-tail Markets

First, while in many long-tail markets the alteration of a product is restricted to its release time, basic features (such as hard-cover vs. paperback) or price, mobile Apps markets offer a greater range of flexibility to sellers in pursuing product update strategies (i.e., quality updates) regardless of time and scope (Lee and Raghu 2014). In this regard, App developers have capabilities to alter prices and features more frequently during a life cycle of an App than is available for digital content creators in other markets.

Second, information flows among mobile App consumers are faster than any other forms of long-tail markets. For example, information on feature update and promotional events is instantly shared by potential consumers through various sources such as App stores, online communities, and push notifications notifying App price/feature changes. As a result, it stimulates the immediate impacts of update events on App sales by inducing a large user network in a short period of time. However, consumers in traditional product markets highly rely on pull-based information searching for a change in price/feature.

Third, an App’s update decision can be instantly made through consumers’ feedbacks. While conventional software vendors selectively reflect the assessments from a focal user group or professionals for software updates, App developers are able to utilize consumers’ opinions and review comments for the next feature updates or price changes (i.e., crowd-sourced update ideas from App users). Therefore, the immediate user responses to the products can be appropriately reflected in improvements throughout the update process.

Finally, App developer can strategically utilize price/feature update for acquisition of new customers. For instance, software product updates have been regarded as maintenance or extended services for the existing user groups only. Meanwhile, App updates allow a developer to boost the demand for new consumers by demonstrating continuous efforts in managing their products. As results of these merits in updating Apps, developers have capabilities to supplement or substitute predominant popularity effects to demand for their products.

The main objective of this study is to evaluate the role of a price discount and a quality update in stimulating App sales in the presence of predominant ranking effects. Specifically, we evaluate the value of quality in App success. While digital product pricing has been considered as the key driver for creating a positive user network (Aliawadi et al. 1998; Shapiro and Varian 2013; Smith et al. 2001), the appraisal of product quality in shaping digital content consumer purchase decisions has not been identified yet. Prior studies argue that quality-based differentiation and versioning strategies are effective practices to create network externalities (Parker and Van Alstyne 2000; Jing 2003) and to accommodate heterogeneous consumer demands segmentations (Bhargava and Choudhary 2008; Shapiro and Varian 1998) in digital product markets. However, these approaches are generally made prior to the product launch and are considered at the market level. In addition, the versioning of a product is considered as a pricing scheme charging different price for the same product/service based on its quality, and thus it does not mean the improvement in product quality exerted by a content provider. For mobile App developers, product updates require continuous endeavor and need a strategic approach along with dynamic consumer demand in the market.

To the best of our knowledge, the role of product quality updates exerted by developers have not yet been studied especially in the markets featuring strong primacy effects. Our goal is to fill this research gap. Consequently, this research answers the following key research questions:

- What are the roles of App updates of feature and price in stimulating App success in the presence of strong ranking effects?

- In what context quality updates or price discounts affect long-term App success?
- Does the value of quality matter? If so, under what circumstance quality updates outperform price discounts in App success?

A panel vector autoregresive (PVAR) model is utilized to investigate the interdependencies among the rankings, price discounts, and feature updates of 1,259 Apps appearing in the top 300 paid Games charts over 215 days from July 1, 2013 to January 31, 2014. To evaluate the effect of sizes and durations of price/feature changes on the ranks of Apps, the impulse response functions (IRFs) are introduced. To evaluate the dynamic consumer responses to changes in price and quality, we take account two distinctive consumer needs for (1) quality improvement and for (2) promotional pricing into the research. Furthermore, we consider the level of App success based on the presence of an App in the different ranking charts-expected to have distinctive ranking effects- to estimate the effectiveness of developers' effort in price/feature updates. The findings highlight the delayed but long-term effects of quality/feature updates on App success in the presence of strong ranking effects while the immediate and short-term effects of price discounts on App sales. Furthermore, we suggest the different App pricing and updating strategies corresponding to dynamic App demands for App success. We expect the findings of the study will contribute not only to related literature examining the key factors in mobile App success, but also to participants in mobile App markets by suggesting how to manage their Apps for the long-term success in the presence of ranking effects.

5.2. Theoretical Foundation

Information Goods and Heterogeneous Consumer Tastes

Online consumers enjoy various flavor of products and are likely to discover products catering to their heterogeneous tastes in long-tail markets. Prior IS literature has predominantly focused on versioning and price discrimination as the key strategic ingredients for success and largely ignored how long-tail markets react to price and quality updates. For instance, Bhargava and Choudhary (2001&2008) posit the decision of versioning is to be made based on the consumer valuation for quality of a product and to offer the products with distinctive quality to maximize profits from heterogeneous consumers. In line with this, Parker and Van Alstyne (2000) and Jing (2003) argue that the quality-based versioning can create a positive network effect (from a low-quality version) and meet high-valued customers (from a high-quality version). Sundararajan (2004a) presents an optimal pricing scheduling entailing fixed-fee and usage-based pricing for improving profits from information goods. Furthermore, Shapiro and Varian (1998) emphasize the importance of differential pricing (i.e., price discrimination) in selling digital products to consumer having different needs. In general, most versioning and price discrimination studies are motivated from the inherent characteristic of digital products and their vulnerability to piracy (Wu and Chen 2008; Chellappa and Shivendu 2004; Sundararajan 2004b). In mobile App market, the piracy of Apps has not been a major concern due to the relatively affordable price (most Apps are offered $0.99) and the separated free product market (i.e., free Apps). Moreover, the versioning and pricing decisions are generally made before the launch of product/service releases and considered at the firm/market level. For App developers, quality/price-based differentiation strategies can be made even after release to make their Apps attractive to new user groups having different tastes and needs and to get favorable reviews from early adopters.

Besides the accommodation of heterogeneous consumer needs, furthermore, a quality update strategy enables App developers not only to earn brand awareness for new consumers but also to build loyalty for existing ones. In traditional consumer product markets, product quality has been considered as a stimuli for a consumer's repeat purchase (Kirmani and Rao 2000). By adding new features/functionalities to brand-new products (e.g., new ingredients for cosmetics and enhanced cutting technologies for shavers), sellers have capabilities to make consumers return to purchase and to attract new demand (Garvin 1984). However, such quality improvements are restricted to only newer products and it is difficult to keep backward compatibility. Unlike consumers for repeat-purchase products, App consumers who made a single purchase can benefit from repeated quality updates for the same Apps without compatibility concerns. In turn, App developers can build better reputation from existing consumers through continuous effort on quality management, and consequently such endeavors impress new consumers to purchase their Apps. Therefore, the quality improvement of an App is expected to have an important role in maintaining a positive long-term relationship with various consumers in the mobile App markets. In line with this, we further discuss the distinctive aspects of a price discount and a quality update in the following section

Price Discount vs. Quality Improvement

Unlike content creators in other long-tail markets, mobile App developers have opportunities to promote their products in the market post-release by responding to dynamic consumer demands. Hence, a developer can strategically utilize price-based or quality-based updates to overcome slow adoption rates or declining sales (Lee and Raghu 2014). A developer's price-based and feature-based update decision is likely to be made based on several factors in the market. Moreover, a consumer's perceived value of a product from these two distinctive update strategies are not expected to be equivalent, and therefore they will shape different consumer purchase decisions. The key differences of two update approaches are summarized in Table 21.

	Feature/Quality Update	Price Discount
Effort Level	- More cost and time	- Less cost and time
Impact	- Delayed but Long-term effects	- Immediate and Short-term effects
Perceived Quality	- Become higher	- Become lower
Targeted Audience	- Existing and new consumers both	- New consumers only - Existing users may provide reviews
Timing	- High demands for improvements in features	- High demands for just purchasing Apps

Table 21. Comparisons between Quality Update and Price Discount

First, a quality update requires higher level of effort than a price discount. While a price change can be instantly made by a developer, a change in quality generally needs significant time and cost for adding new feature/functionalities. By the virtue of low menu cost, a digital content creator can easily change price based on consumer demand in the market (Dewan et al. 2000; Kauffman et al. 2004; Hui et al. 2007; Smith et al. 2001). On the other hand, the update cost for improving quality is expensive. Sometimes it costs as much as the initial development cost. Shapiro and Varian (2013) characterize the cost for information goods as high fixed costs for initial development stage and low variable cost in reproduction and distribution of a product, and emphasize the almost zero variable cost for digital goods. However, there is no study considering high variable costs taken in product maintenance after its release in the market (i.e., quality updates). This study evaluates when such an expensive quality update is important in attracting consumers and outperform a cheap price promotion strategy.

Second, a consumer response to a price reduction is more immediate than a feature update. Researchers have highlighted the pivotal role of a promotional price in attracting new consumer in an instant manner (Aliawadi et al. 1998; Shapiro and Varian 2013; Smith et al. 1999; Vincent 2007). Besides, the response of consumer demand to a feature update related to quality is expected to be delayed since the quality improvement of a product is not easily observable before experiencing it. As such, consumers are likely to make purchase decisions after appreciating detailed update descriptions available in the market or reading others review comments on the quality update. Moreover, we expect the long-term impact of a quality update on App sales growth over a price discount. In general, consumers use the price of a product as an indication of its quality, assuming that a higher price will have better quality (Caves and Greene 1996; Telli and Wernerfelt 1987). A price reduction may have consumers conceive less quality or less popular product (Hardie 1996). Hence, a seller can enjoy the instant benefit of a price discount in attracting new consumers but the impact will not last long. Regarding a feature update, a consumer’s perceived quality becomes higher whenever a content creator makes improvements in feature and functionalities, and consequently such continuous effort on quality has long-term impact on sales. In line with this, Lee and Raghu (2014) find that a feature update improves the presence of an App in the top chart three times, but a price discount increases the probability by 1.2 times from weekly ranking information.

Third, as noted previously a feature update encompasses both existing and new consumers while a price discount targets only new consumers. In conventional software markets, a feature update/upgrade is regarded as maintenance for the consumers who have already purchased (Krishnan et al. 2004). However, a quality improvement can also motivate additional consumer demand. Software products including mobile Apps can be also characterized as durable goods (Economides 2001). In general, Apps provide a stream of sustained consumption. In durable goods market, a seller tends to set price equal to marginal cost since strategic consumers have an incentive to delay purchasing if they anticipate that the seller of a durable good will lower prices in the future (Coase 1972; Orbach 2004). In the App market context, however, a developer has capabilities to prevent such delayed consumer demand by utilizing a quality update strategy instead of lowering price.

Finally, price and quality-based updates can be strategically adopted according to the dynamic consumer demands. Unlike other information products, hardware (e.g., mobile devices) and firmware (e.g., iOS and Android) running Apps influence consumer demands for Apps. There might be high demand for quality-based updates when a new firmware or hardware is introduced in the market. For example, an annual major update for Apple iOS and a new version of iPhones make consumers consider to download Apps compatible with new firmware and hardware. In this regard, it seems that there is a strong case for a developer to make quality-update to improve Apps sales. Meanwhile, a promotional price approach can be effective when there is an increase in smartphone sales and consumers want to have more Apps to use on them. For instance, during holiday seasons most hardware retailers offer a huge discount for mobile phones and tablets, and it usually boosts the sales of new devices and in turn Apps for them. Therefore, the decision on price-/feature-based updates should be made based on dynamic consumer demand in the market.

To summarize, the key aspects of a quality-based update differencing those of pricing strategy in mobile App markets call attention for researchers to theorize the value of quality in hyper-competitive long-tail markets.

5.3. Data and Research Design

Data Description

Our empirical analyses are conducted on the individual mobile Apps appearing in U.S. Apple App Store. Paid games Apps in the Top Paid 300 Charts were collected from July 1, 2013 to January 31, 2014 on a daily basis. The history of ranks, price discounts, and feature updates for 1,259 unique Apps over 215 days (180,445 observations) were recorded in the datasets. The use of paid Apps allows us to investigate the effects of both price discounts and feature updates on App sales. Moreover, games Apps accounted for over 40% of store downloads and covered 70% of App store revenue in the study period, so it enables us to incorporate heterogeneous consumers purchase decisions in the study. The definitions and summary statistics of research variables are presented in Table 22.

Variables	Description	Mean	S.D.	Min. (Max.)
	App Market Information			
Rank	An App's rank during the study period	150.486	86.595	1 (300)
Days_Top25	Number of days the App listed in the Top 25 chart	3.217	16.049	0 (215)
Days_Top100	Number of days the App listed in the Top 100 chart	12.868	33.118	0 (215)
Days_Top200	Number of days the App listed in the Top 200 chart	25.737	44.489	0 (215)
Days_Top300	Number of days the App listed in the Top 300 chart	38.601	50.891	1 (215)
Price	Price of an App	2.165	1.863	0.99 (19.99)
# Feature Update	Number of Feature Updates made in an App during study period	0.982	2.003	0 (27)
# Price Change	Number of price changes (discount only) made in an App during study period	0.280	0.834	0 (17)
	Research Variables			
$Top25_{it}$	1 if an App was listed in the Top 25 chart at time *t* 0 otherwise	0.019	0.135	0 (1)
$Top100_{it}$	1 if an App was listed in the Top 100 chart at time *t* 0 otherwise	0.075	0.263	0 (1)
$Top200_{it}$	1 if an App was listed in the Top 200 chart at time *t* 0 otherwise	0.149	0.357	0 (1)
$Top300_{it}$	1 if an App was listed in the Top 300 chart at time *t* 0 otherwise	0.224	0.417	0 (1)
$Price\_Discount_{it}$	1 if an App's price was discounted at time *t* 0 otherwise	0.002	0.443	0 (1)
$Feature\_Update_{it}$	1 if there was a feature update at time *t* 0 otherwise	0.007	0.084	0 (1)
$Price\_Discount\_size_{it}$	Discount percent of an App's price if a price discount was made at time *t*	16.701	27.934	0.0 (90.090)
$Feature\_Update\_size_{it}$	A change in version numbers (e.g., 4.2.3) at time *t* 3 if a change was made in the first digit (a major update) 2 if a change was made in the second digit (a medium update) 1 if a change was made in the third digit (a minor update) 0 if any changes were not made in the version numbers *The cube of values was used to weight the levels of updates. (i.e., Major (27), Medium (8) , Minor (1), and No (0) updates)	0.076	1.179	0 (27)
$Age\_of\_App_{it}$	Number of days elapsed from a release day to time *t*	549.362	511.559	1 (2,031)
	Observations			
Duration (T)	Number of days in the study period	215 Days		
#Unique Apps (N)	Number of observations in the study period	1,259 Apps		

Table 22. Summary Statistics of Research Variables

The first set of variables describes the dynamics of Apple's App Store during the study period, but is not used for analyses. The basic statistics were calculated for individual Apps in a cross-sectional manner at the end day of study. In terms of the popularity (rankings) of Apps, the chance/duration of being listed in the top charts becomes significantly lower in the higher charts. For example, Apps appeared in the top

25 chart for an average of 3.2 days, but 38.6 days in the top 300 chart. When it comes to the effort-related numbers, more feature updates were made than price discounts. On average, Apps in the sample updated features/content 0.98 times and had price discount 0.28 times during the study period.

The second set of variables is our interest for the study and is used for empirical analyses. Since Apple does not reveal actual App sales figures, our measure for the success of App sales is based on ranking information. Recent studies have shown that the consumer demand can be estimated from publicly available ranking information (Brynjolffsson et al 2010; Chevalier and Mayzlin 2006). In the mobile App market setting, Lee and Raghu (2014) and Garg and Telang (2012) used the rank in the chart to measure an App's sales performance. Since the rank of an App is made through App consumers' accumulated evaluations on the App, the presence of an App in the top charts is a necessary condition ensuring the success of its sales. Consequently, the success of App sales is measured by dichotomous variables indicating whether an App was listed in a specific top chart (i.e., $Top25_{it}$, $Top100_{it}$, $Top200_{it}$, and $Top300_{it}$). In line with this, we recorded Apps appearing at least once in the charts during the study period even when the Apps exited the charts. A few Apps that discounted to free (i.e., seven Apps) were dropped out of the sample since they were not available in the paid charts during the free-priced periods. The indicator variables of $Price\_Dicount_{it}$ and $Feature\_Update_{it}$ record the events of price/feature changes. A decrease in price at t was only considered as a price discount event and any changes in version numbers (e.g., 4.2.3) of an App at t were recorded as a feature update event. To evaluate the magnitudes of a price discount and a feature improvement, $Price\_Dicount\_Size_{it}$ and $Feature\_Update\_size_{it}$ are introduced.

The amount of price reduction was computed to a discount percentage from the original price to the discounted one. An average of 16.7% was discounted from the original price. Due to the difficulties in evaluating improvements in App features after an update, a change in the digits of version numbers (e.g., 4.2.3) was regarded as an update magnitude. In the sample, 93.7% Apps used a three-digit format for numbering version information. A change made in the first/second/third digit were considered as a major/medium/minor update with the value of 1, 2, and 3 respectively. We used the cube of values to weight the levels of values. The original and squared values were also used for analyses, but we did not find any remarkable differences in the estimation outcomes. Finally, $Age\_of\_App_{it}$ indicates the number of days elapsed from a release day to time t.

In addition, the same variables were collected for Apps in the free games charts (2,186 Apps) and paid productivity charts (1,261 Apps) during the study period to evaluate the direct effects of feature updates on App success. The estimation outcomes are presented in the Robustness Checks section.

Research Design

Next, we take account the different consumer demands driven by external events but relevant to the mobile App markets into the research setting in order to evaluate the dynamic consumers' responses to the changes in Apps' rankings, price, and features. The three distinctive periods are drawn toward the key events potentially affecting consumer demand in the market as depicted in Figure 9.

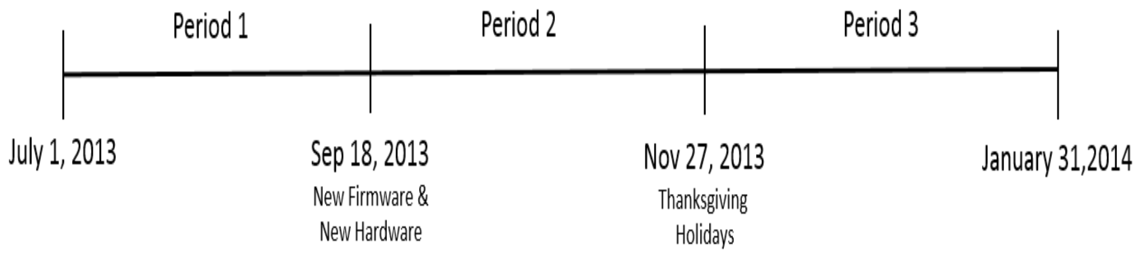
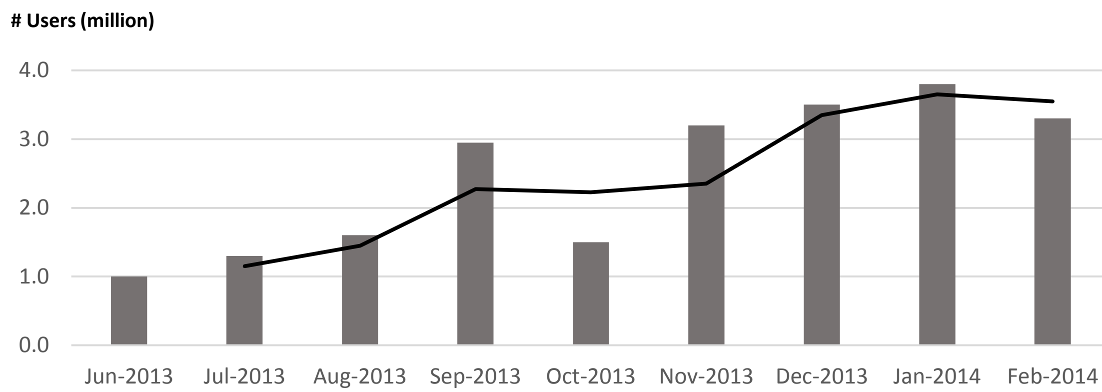


Figure 9. Dynamic Consumer Demand upon External Events

Period 1 is a baseline period and we assumed that any significant events influencing App sales did not occur in this period. Period 2 is characterized as high (new) consumer demand driven by changes to the platform features. A new firmware (iOS 7 on September 18, 2013) was released and a new hardware (iPhone 5S on September 20, 2013) was introduced in this period. Therefore, there might be high demands for improvements in features and content of Apps along with the introduction of new firmware and hardware. As a result, developers are likely to make more feature updates to resolve compatibility issues and accommodate increased consumer needs for the improvement in Apps. Period 3 represents high consumer demand driven by markets. Shopping seasons of Thanksgiving days (November 27-29, 2013), Christmas (December 24-25, 2013), and New Year's Day (January1, 2014) were included in the period. As such, consumer demand for Apps from newly purchased/activated devices are expected to be higher than those in any other periods. Consequently, developers are likely to promote Apps corresponding to holiday demand in the market. The number of new smartphone users during the study period is presented in Figure 10. Overall, a large volume of smartphone sales was observed in Periods 2 and 3 as compared with Period 1.



Source: Number of new US smartphone users, Asymco.com, May 8. 2014

Figure 10. Number of New Smartphone Users

In Period 2, around 3 million smartphones were sold and activated after new iPhone 5S releases in September 2013. In Period 3, almost 10 million new smartphones were purchased during the shopping season. The increases in smartphone users in both periods indicate growing needs for purchasing Apps and in turn require developers' strategic market positioning for their Apps. To investigate the developer-side response to the increased App demands, we separated the datasets into the three distinctive periods based on the above classification. Table 23 summaries the key variables in each period.

Overall, the probability/duration of staying in the top charts are similar across the periods. As expected, however, the frequencies of feature updates and price discounts are disparate among the periods. Slightly more price discounts were made in Period 3 (0.139 times) than those in Period 2 (0.1 times) and Period 2 (0.114 times). Meanwhile, feature updates were made most frequently in Period 2 (0.536 times). To validate the differences in price and feature changes across the periods, a two-sample t-test was conducted for each pair of periods. Table 24 indicates the comparisons of feature and price changes between the periods.

Variables	Period 1			Period 2			Period 3		
	Mean	S.D.	Min. (Max.)	Mean	S.D.	Min. (Max.)	Mean	S.D.	Min. (Max.)
App Market Information									
Rank	150.487	86.597	1 (300)	150.493	86.600	1 (300)	150.477	86.591	1 (300)
Days_Top25	1.842	8.177	0 (79)	1.518	7.178	0 (70)	1.501	6.370	0 (65)
Days_Top100	7.371	16.044	0 (79)	6.072	13.362	0 (70)	12.011	12.914	0 (65)
Days_Top200	14.741	20.238	0 (79)	12.14	17.093	0 (70)	18.014	16.573	0 (65)
Days_Top300	22.112	21.885	1 (79)	18.21	18.414	1 (70)	17.391	17.391	1 (65)
Price	2.189	1.947	0.99 (19.99)	2.335	2.035	.99 (19.99)	2.302	2.039	0.99 (19.99)
#Price Discount	0.100	0.345	0 (3)	0.114	0.475	0 (8)	0.139	0.432	0 (6)
#Feature Update	0.477	0.939	0 (8)	0.536	1.070	0 (10)	0.394	0.810	0 (8)
Research Variables									
$Top25_{it}$	0.046	0.209	0 (1)	0.428	0.202	0 (1)	0.046	0.208	0 (1)
$Top100_{it}$	0.184	0.388	0 (1)	0.171	0.377	0 (1)	0.182	0.386	0 (1)
$Top200_{it}$	0.369	0.482	0 (1)	0.342	0.474	0 (1)	0.364	0.481	0 (1)
$Top300_{it}$	0.553	0.497	0 (1)	0.513	0.499	0 (1)	0.546	0.498	0 (1)
$Price\_Discount_{t}$	0.002	0.042	0 (1)	0.002	0.047	0 (1)	0.003	0.053	0 (1)
$Feature\_Update_{it}$	0.008	0.090	0 (1)	0.010	0.101	0 (1)	0.008	0.090	0 (1)
$Price\_Discount\_size_{it}$	14.129	27.208	0.0 (90.090)	13.674	26.653	0.0 (90.090)	17.043	28.880	20.040 (90.090)
$Feature\_Update\_size_{it}$	0.099	1.405	0 (27)	0.091	1.222	0 (27)	0.087	1.306	1 (3)
$Age\_of\_App_{it}$	579.830	514.084	1 (1,895)	570.475	529.866	1 (1,965)	653.339	557.927	1 (2,031)
Observations									
Duration (t)	79 Days			70 Days			65 Days		
# Unique Apps (n)	707 Apps			787 Apps			721 Apps		

Table 23. Summary Statistics of Research Variables across Periods

	P1 (n=707) vs. P2 (n=787)	P1 (n=707) vs. P3 (n=721)	P2 (n=707) vs. P3 (n=721)
# Price Discounts	$t(1492) = -0.642$, $p = 0.521$	$t(1426) = -1.850$, $p = 0.065$	$t(1506) = -1.038$, $p = 0.300$
# Feature Updates	$t(1492) = -10.091$, $p = 0.000$	$t(1496) = -8.526$, $p = 0.000$	$t(1506) = 2.89$, $p = 0.004$

Table 24. Two Sample t-Test for the Frequencies of Price Discounts and Feature Updates

Regarding the frequency of price discounts, developers in Period 3 lowered Apps' prices more often than those in Period 1 and Period 2 at 10% significance level. Moreover, developers made more improvements in App quality during Period 2 than other periods at 0.1% significance level. Consequently, the classification of sub-sample periods based on dynamic consumer demand and its corresponding developer efforts in price and feature updates is validated for further analyses.

5.4. Empirical Approach

To investigate the dynamic interdependencies among Apps' rankings, price discounts, and feature updates, the panel vector autoregressive (PVAR) model is adopted for empirical analyses. PVAR is built with the same logic of traditional VAR in a time-series manner where all variables are assumed to be influenced by each other (i.e., interdependency among variables) and endogenous. Additionally, PVAR allows to account for a cross-sectional dimension into the model specifications (Canova and Ciccarelli 2013). A few recent IS studies have adopted PVAR and its variations to evaluate the dynamic relationships among in a time-series manner such as the impacts of musicians' activities in social media on music sales (Chen et al. 2014) and the effects of location-based mobile promotion (Luo et al. 2013). We construct the following model evaluating interactions between popularity shaped by consumers (i.e., Rankings) and efforts exerted by developers (i.e., price discounts and feature updates) in mobile App markets:

$$\begin{bmatrix} Top\_Chart_{it} \\ Price\_Discount_{it} \\ Feature\_Update_{it} \end{bmatrix} = \Gamma_0 + \sum_{s=1}^{S} \Gamma_1 \begin{bmatrix} Top\_Chart_{it-s} \\ Price\_Discount_{it-s} \\ Feature\_Update_{it-s} \end{bmatrix} + \beta \cdot Age\_of\_App_{it-1} + \alpha_i + \tau_t + \mu_{it}, \quad \mu_{it} \sim iid(0, \Sigma_\mu)$$

The dependent variables of Top_Charts_{it}, $Price\_Discount_{it}$, and $Feature\_Update_{it}$ are endogenous, and therefore are influenced by their past realizations on the left hand side of the equation. $Age\_of\_App_{it-1}$ is an exogenous variable to control for unobserved factors that can affect the endogenous variables. α_i and τ_t are App-specific and time (days)-specific fixed effects terms respectively. Finally, μ_{it} is the unobservable shocks assumed to be independently and identically distributed.

To estimate the presented model, we use a standard generalized method of moment (GMM) where the lags of endogenous and exogenous variables are used as instruments. The fixed effects in the model were incorporated to the GMM estimation procedure by using forward mean-differencing for App-specific fixed effects (i.e., the Helmert procedure, Arellano and Bover 1995) and by mean-differencing the variables for day-specific (time) fixed effects (Love and Zicchino 2006).

We conducted *Fisher-type* unit-root test for unbalanced panel data (Choi 2001) to check the stationarity of endogenous variables during the study period. The statistics from Phillip-Perron test and augmented Dickey-Fuller (ADF) test with 5-day lags of variables rejected the null hypothesis of a unit root at 0.1% significance level presented in Table 25, and thus we conclude the endogenous variables are stationary.

Variables	Phillips-Perron Test Lags: 5 days, Statistic: Inverse Normal (z)	Augmented Dickey-Fuller (ADF) Test Lags: 5 days ,Statistic: Inverse Normal (z)
$Top25_{it}$	$z = -74.659$, $p < 0.000$	$z = -63.776$, $p < 0.000$
$Top100_{it}$	$z = -45.140$, $p < 0.000$	$z = -24.744$, $p < 0.000$
$Top200_{it}$	$z = -64.723$, $p < 0.000$	$z = -32.079$, $p < 0.000$
$Top300_{it}$	$z = -76.812$, $p < 0.000$	$z = -35.578$, $p < 0.000$
$Price\_Update_{it}$	$z = -55.834$, $p < 0.000$	$z = -22.936$, $p < 0.000$
$Feature\_Update_{it}$	$z = -89.783$, $p < 0.000$	$z = -39.566$, $p < 0.000$
$Price\_Update\_size_{it}$	$z= -6.641$, $p < 0.000$	$z= -2.960$, $p < 0.000$
$Feature\_Update\_size_{it}$	$z= -42.991$, $p < 0.000$	$z= -99.550$, $p < 0.000$

Note*: All statistics from different distributions (Inv. chi-squared, Inv. Logit t, and Modified Inv. Chi-squared) have the same significance levels ($p < 0.000$).*

Table 25. Stationarity Checks for Research Variables

Then, the lag order for PVAR was selected based on moment selection criteria (Andrews and Lu 2001; Ng and Perron 2001). The lowest statistics of Hansen's *J* (1982) and M-AIC, M-BIC, and M-QIC across one-to-five day lags indicate the best lag order for model estimation. An exemplar lag selection procedure with $Top100_{it}$, $Price\_Discount_{it}$, $Feature\_Update_{it}$, and $Age\_of\_App_{it}$ is presented in Table 26. A one-day lag of endogenous variables ensures the best model fit. We found the same outcomes with different combinations of variables for the three periods. The selection of one-day lag implies App consumers' immediate responses to the changes in ranks, prices, and features of an App.

Lag	Coefficient of Determination	Hansen's *J*	M-BIC	M-AIC	M-QIC
1	0.89204	1.17e-30	1.17e-30	1.17e-30	1.17e-30
2	0.89923	4.86e-29	4.86e-29	4.86e-29	4.86e-29
3	0.90124	1.22e-29	1.22e-29	1.22e-29	1.22e-29
4	0.90495	9.49e-30	9.49e-30	9.49e-30	9.49e-30
5	0.90688	2.59e-29	2.59e-29	2.59e-29	2.59e-29

Note: Since the model is just-identified, Hansen's J statistics are equal to M-AIC, M-BIC, and M-QIC

Table 26. A Lag Selection from Moment Criteria

Consequently, a set of PVAR models examining relationships among rankings, price discounts, and feature updates are estimated under different ranking charts for each period.

5.5. Results

We examine the direct effects of rankings, price discounts, and feature updates made in the prior day at *t-1* on the current rankings at *t*. Furthermore, the impulse response functions (IRFs) are used for evaluating the timing duration of effects of one variable on another. The estimation outcomes from PVAR for each period are presented in Table 27.

	Response of *Top_Chart* (*t*) to Changes (*t-1*)			
Changes (*t-1*)	$Top25_t$	$Top\ 100_t$	$Top\ 200_t$	$Top\ 300_t$
Period 1: Baseline (n=707, t=79)				
Top_Chart_{it-1}	0.790***	0.741***	0.685***	0.620***
	(0.018)	(0.011)	(0.009)	(0.011)
$Price\_Discount_{it-1}$	0.088**	0.210***	0.194***	0.103***
	(0.033)	(0.045)	(0.031)	(0.019)
$Feature\_Update_{it-1}$	0.014	0.026*	0.021	-0.002
	(0.008)	(0.011)	(0.014)	(0.015)
Period 2: Platform-driven (n =787, t=70)				
Top_Chart_{it-1}	0.768***	0.732***	0.692***	0.665***
	(0.020)	(0.011)	(0.009)	(0.010)
$Price\_Discount_{it-1}$	0.031	0.088*	0.186***	0.081***
	(0.029)	(0.041)	(0.031)	(0.023)
$Feature\_Update_{it-1}$	0.015*	0.029*	0.040**	0.003
	(0.006)	(0.011)	(0.013)	(0.015)
Period 3: Market-driven (n=721, t=65)				
Top_Chart_{it-1}	0.768***	0.786***	0.702***	0.646***
	(0.020)	(0.011)	(0.010)	(0.011)
$Price\_Change_{it-1}$	0.021	0.165***	0.170***	0.056**
	(0.014)	(0.033)	(0.033)	(0.019)
$Feature\_Update_{it-1}$	0.016	0.004	0.016	-0.010
	(0.009)	(0.014)	(0.015)	(0.018)

Table 27. Estimation Results from Panel Vector Autoregressive Models

Direct Effects of Popularity and Efforts on App Success

Ranking Effects: As expected, the effect of prior success in sales on current success is positive and significant. The estimates of prior rankings, *Top_Chart*$_{it-1}$, indicate the strong rankings effects across all study periods. The estimates are over 7 times (30 times) larger than those of *Price_Discount*$_{it-1}$ (*Feature_Update* $_{it-1}$) across the periods. Overall, the effects become stronger in the higher ranking charts. In Period 1, the effects of prior rank of an App (i.e., the presence of an App in the top 25 chart) on the current rank is 0.793 and the effects decrease to 0.745, 0.691, and 0.624 in the top 100, 200, and 300 charts respectively. This outcome empirically confirms the presence of strong ranking effects in the search-intensive markets argued in prior studies (Ghose et al. 2012; Lee et al., 2015).

Price Discount Effects: We find significant price discount effects on App sales throughout the periods. Overall, the effect size of *Price_Discount* $_{it-1}$ is much smaller than that of *Top_Chart*$_{it-1}$, but a reduction in App price has a significant and positive impact on App sales. High discount effects are presented when the market has a new consumer group for purchasing more Apps (i.e., Period 3) as compared with the market revealing increasing demand for App quality improvements corresponding to new platforms. Interestingly, the Apps in the Top 25 charts do not benefit from price discounts and it suggests dominant ranking effects for highly successful Apps.

Quality Update Effects*:* We observe the positive and significant estimates of *Feature_Update* $_{it-1}$ in Period 2 when there exist surge in demand for improvement in App features and functionalities. However, the impact becomes smaller for Apps listed in the higher charts and not significant for the Apps in the 300 chart. Therefore, a feature update decision seems crucial for developers who successfully listed Apps in the higher charts. Meanwhile, a quality update is not effective any more when consumers are more interested in downloading Apps for their new devices in Period 3.

Consequently, our findings suggest strategic price- and feature-based update decisions corresponding to dynamic consumer demands in the market.

Dynamic Effects of Efforts on App Success

To observe the reaction of an App's rank to the lagged price discount or feature update events while other shocks remain zero, we utilize the impulse responsive functions (IRFs). The coefficients estimated from PVAR were converted to a series of MA process and then we examined how a one-unit of price/feature update shock changes the ranks over time and how long the effect lasts (i.e., a decay time). Figures 11 and 12 presents the graphs of IRFs with 5% error bounds generated from Monte Carlo simulation with 500 repetitions.

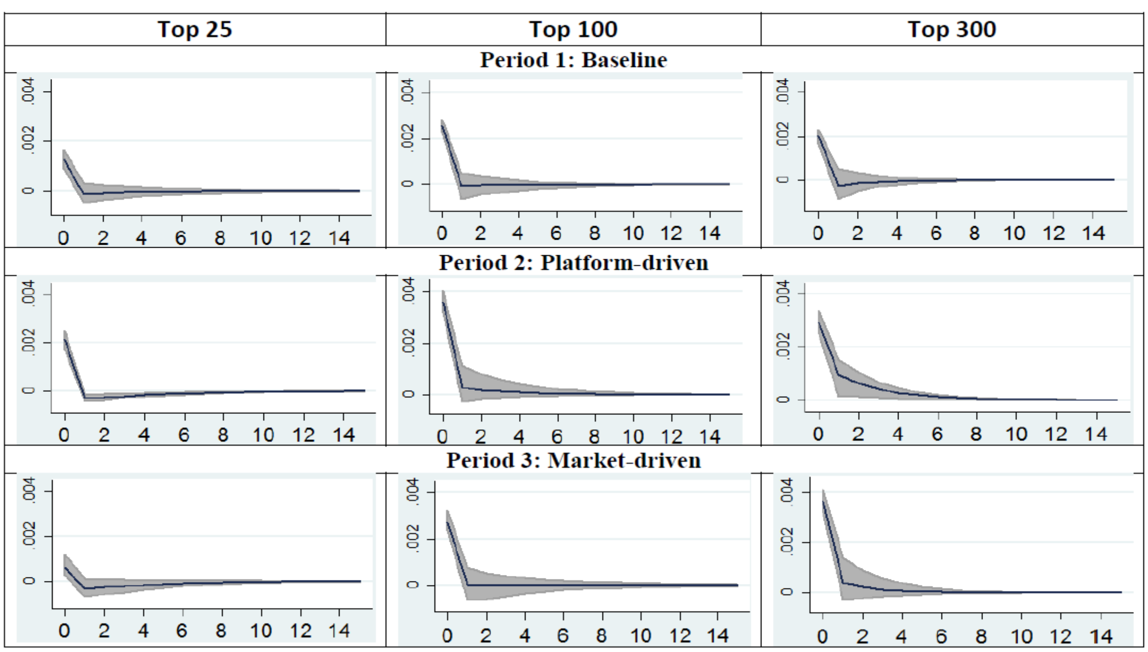


Figure 11. Impulse Responses of App Success (t) to Price Discounts (t-1)

When it comes to the response of App success to the lagged price discount, a reduction in price instantly improves the presence of an App in the top charts and the impact dramatically decreases in a short period of time. Overall, smaller impact size and instant drops (decay time to zero) are observed from Apps appearing in the higher charts: on average, one day in Top25, three days in Top100, and five days in Top300 charts. The impact becomes even negative for Apps in the Top25. Moreover, shorter decay times are shown in Period 3 when many developers offered discounted Apps than in Period 2. The finding suggests a promotional price strategy has an immediate but short-term impact on App sales, and is not helpful in hitting the higher top charts due to strong ranking effects.

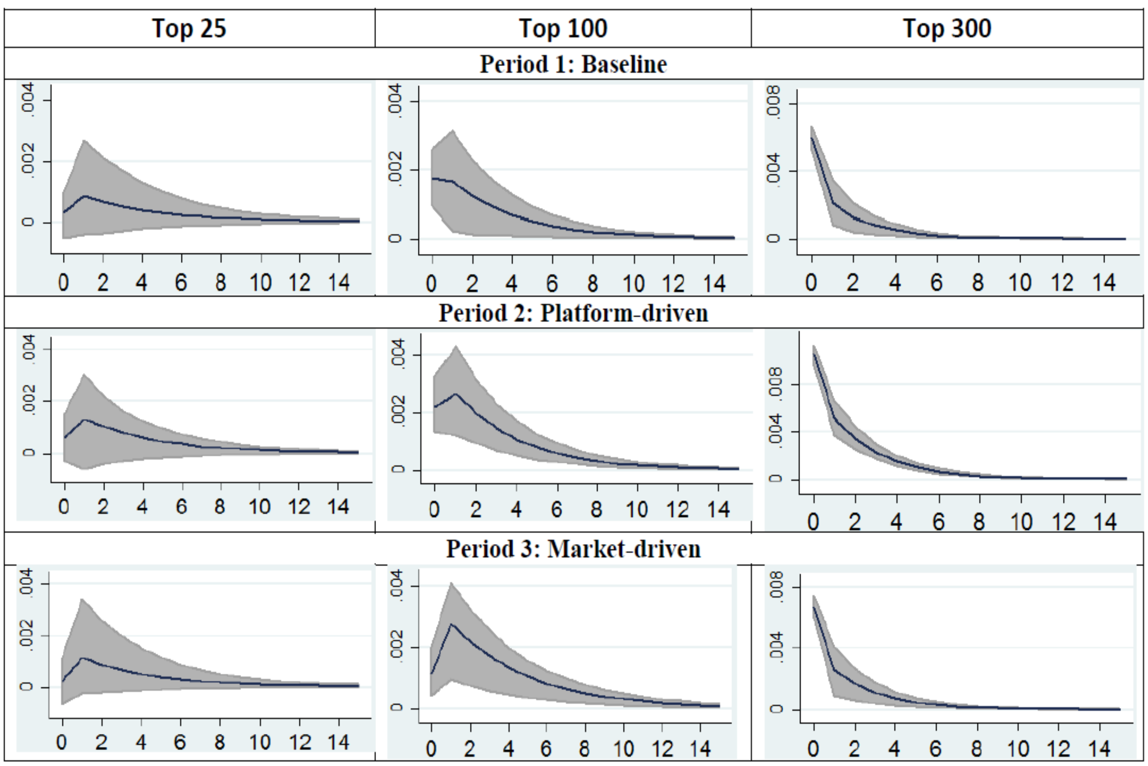


Figure 12. Impulse Responses of App Success (t) to Feature Updates (t-1)

The impulse responses of App success to one-day lagged feature updates show delayed but longer impacts as compared with those to price discounts. A shock of quality update to the presence in the charts increases and peaks at the second day, and the impact gradually fades away and lasts until 14th day for the Apps in the Top25 and Top100 charts. In the Top300 chart, meanwhile, we find a huge drop after an immediate increase in the presence of App in the chart as featured in the impact of a price discount on App success. Consequently, we find the long-lasting impact of quality updates on App success, and it has a higher and longer impact even for very highly ranked Apps (in Top25) than a price discount has. As expected, in addition, the value of quality updates become less significant when consumers are less concerned with quality improvements (i.e., Period 3).

5.6. Robustness Analysis

The main findings are restricted to the associations between App success and price/feature-based update strategies using unbalanced panel data including only paid games Apps listed in the top 300 charts. We conducted a set of robustness analyses with PVAR to test the validity and sensitivity of main findings. First of all, the magnitude of a price discount and a feature update is introduced in the model estimation. Besides an update event, the level of an update decision may be important when consumers make App purchase decisions. However, we do not expect a positive relationship between a consumer purchase decision and price/quality update size due to small variation among App prices and unobservable quality improvement before downloading Apps. Most Apps in our sample were offered the price of $0.99 (84.2%), and the discount prices converged to $0.99 in most cases of price promotions (92.7%). Therefore, consumer purchase decisions are likely to be indifferent for any Apps. Moreover, the characteristics of Apps as experience goods make consumers unable to assess the value of Apps prior to actual use (Nelson 1970), and thus it is difficult for consumers to realize what components were added or updated. The estimation results from the variables of *Top_Chart*, *Price_Discount_Size*, and *Feature_Update_Size* are presented in Table 28.

	Response of *Top_Chart* (*t*) to Changes (*t-1*)			
Changes (*t-1*)	$Top25_t$	$Top\ 100_t$	$Top\ 200_t$	$Top\ 300_t$
Period 1: Baseline (n=707, t=79)				
Top_Chart_{it-1}	0.793*** (0.019)	0.745*** (0.012)	0.691*** (0.009)	0.624*** (0.011)
$Price\_Discount\_Size_{it-1}$	-0.001 (0.000)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.002)
$Feature\_Update\_Size_{it-1}$	0.000 (0.000)	0.002*** (0.001)	0.001 (0.001)	-0.003 (0.002)
Period 2: Platform-driven (n =787, t=70)				
Top_Chart_{it-1}	0.764*** (0.021)	0.734*** (0.011)	0.703*** (0.010)	0.666*** (0.011)
$Price\_Discount\_Size_{it-1}$	0.001* (0.000)	0.001 (0.000)	0.002* (0.001)	0.000 (0.001)
$Feature\_Update\_Size_{it-1}$	0.001* (0.000)	0.001* (0.000)	0.002* (0.001)	-0.004 (0.002)
Period 3: Market-driven (n=721, t=65)				
Top_Chart_{it-1}	0.769*** (0.020)	0.786*** (0.012)	0.708*** (0.011)	0.660*** (0.012)
$Price\_Discount\_Size_{it-1}$	0.001** (0.000)	0.003*** (0.001)	0.003** (0.001)	0.004*** (0.001)
$Feature\_Update\_Size_{it-1}$	0.001* (0.001)	0.002* (0.001)	0.000 (0.001)	-0.002 (0.002)

Table 28. Estimation Results from PVAR models on Update Level

Overall, the estimation outcomes support our main findings. While more positive and significant estimates of $Price\_Discount\_Size_{it-1}$ are appeared in Period 3, those of $Feature\_Update\_Size_{it-1}$ are observed in Period 2. As expected, however, we find the minimal impacts of feature update and price discount sizes on App success. The impact size (coefficients) of estimates are much smaller than those in the main model, and hence the level of updates does not have practical implications. As a result, we do not consider the magnitude of updates in the other robustness analyses.

Next, we estimate the models including different datasets. The comparisons between the original outcomes (in the second column) and a new set of outcomes with different datasets for Apps in Top25 (higher charts) and Top300 charts (lower charts) over Period 2 and Period 3 are summarized in Table 29. The detailed estimation results are presented in APPENDIX C.

	Paid Games with Unbalanced Panel (N=1,259)		Paid Games with Balanced Panel (N=396)		Free Games (N=2,186)		Paid Productivity (N=1,262)	
	$Top25_{it}$	*$Top300_{it}$*	*$Top25_{it}$*	*$-ln(Rank)_{it}$*	*$Top25_{it}$*	*$Top300_{it}$*	*$Top25_{it}$*	*$Top300_{it}$*
Top_Chart_{it-1}	+***	+***	+***	+***	+***	+***	+***	+***
$Price\_Discount_{it-1}$	+**	+***	+	+**	.	.	+**	+**
$Feature\_Update_{it-1}$	+	+	+	+	+*	-	-	+
Period 2								
Top_Chart_{it-1}	+***	+***	+***	+*	+***	+***	+***	+***
$Price\_Discount_{it-1}$	+	+***	+	+**	.	.	+	+***
$Feature\_Update_{it-1}$	+*	+	+*	+*	-	-	+	+*
Period 3								
Top_Chart_{it-1}	+***	+***	+***	+*	+***	+***	+***	+***
$Price\_Discount_{it-1}$	+	+***	+	+***	.	.	+***	+*
$Feature\_Update_{it-1}$	+	+	+*	+	-	-	+	+*

Table 29. Estimation Outcomes from Robustness Checks

We confirm positive and highly significant impacts of prior rankings on the current rankings across different datasets. However, we find the distinctive role of price/feature updates in each market context.

First, we test a potential endogeneity concern that can arise from the repeated entries and exits of Apps in the top charts. The same analysis was conducted with a balanced panel including only Apps that continuously appeared in the top charts over each period. The outcomes from the balanced panel in the second column indicate qualitatively the same outcomes as compared to the original analysis. We further find significant and positive impacts of quality updates on success in the higher top charts regardless of periods. This emphasizes the pivotal role of quality improvements in sustaining Apps' success.

Second, we evaluate the direct impact of quality updates using free Apps. Interestingly, the event of a feature update does not have an impact for free Apps. This outcome may be attributed to strong zero-price effects among App consumers, where free Apps are more likely to be consumed for hedonic reasons or trial purposes by the virtue of zero costs. Therefore, a consumer's quality assessment on an App is less important. Moreover, severe competition among free Apps may discourage developers to make quality improvements. Although more Apps (double that of paid Apps) were listed in top charts, less number of feature updates (0.65 times per an App) was made during the same study period. That is, this finding suggests developers take a different approach for competition with many free Apps. Under this circumstance a seller's best strategy seems to enlarge installed base in a short period of time and to make users consume in-app-purchases. For example, while many free mobile Apps are being advertised through media as well as via other free Apps to attract more new customers, paid Apps seem to hardly benefit from mass media.

Finally, we investigate how price/feature updates influence the sales of Apps consumed for utilitarian purposes. Paid productivity Apps were used for evaluating differential role of update decisions for a consumer group who uses Apps for personal tasks such as a task organizer, a file manager, and PDF viewer. Overall, we have similar results. A feature update (price discount) has a positive relationship with App success in Period 2 (Period3). Even though we expected a strong impact of quality update for productivity Apps in the higher charts, the outcomes present a significant quality update impact only for the Apps in the lower charts. In addition, a price discount helps the Apps hit the higher chart in Period 3, which is not observed in game Apps. This is expected as consumers having utilitarian purposes know better about the feature and functionalities of Apps than those who have hedonic purposes. As a result, productivity App users are likely to purchase high-quality Apps, and so additional quality improvements may not be the main driver for a new purchase. Since the price of a productivity App (an average of $3.39) is generally higher than that of game Apps (an average of $2.19), moreover, a temporary price reduction might be attractive to new users especially when they are willing to download new Apps (in Period 3)

Consequently, we conclude that price-based and quality-based updates have significant impacts on App success in the presence of strong ranking effects and suggest App developers should make strategic update decisions according to the dynamic consumer demand in the market.

5.7. Concluding Remarks

This research highlights the importance of App developer's continuous endeavor in stimulating and responding to dynamic consumer demands. We empirically substantiate the presence of predominant ranking effects in mobile App market and suggest a set of strategic update approaches under different consumer demands. Specifically, while a quality update has a positive impact on App success when consumers look for Apps compatible with new firmware and hardware, a promotional price is important when there is growing demand for Apps along with the increased device sales. We further find a positive and longer-term relationship between quality update and App sales. This establishes the quality of App as the key driver for success in hyper-competitive mobile App markets.

We believe the findings of the study will set off theoretical insights to extant literature on information goods management and to managerial implications in understanding the key determinants of success in mobile App markets. From an academic perspective, this research presents a deeper understanding of content creators' strategic quality update decisions and the ensuing impacts on success in the market. The outcomes also provide solid theoretical and empirical frameworks that allow researchers to investigate more interesting issues in this domain. Form a practical perspective, this research will provide valuable managerial implications not only for mobile App developers, but also for platform providers. First of all, the findings provide a set of guidelines helping developers respond dynamic and heterogeneous consumer needs by utilizing effective price/feature update strategies in a timely manner. Moreover, platform providers can apply the key outcomes of the study to their App management. For example, downloads for a new update can be reflected to decide an App's ranks. It will promote developers to make better/more updates, and in turn the efforts will increase consumers' satisfaction from Apps in the market.

CHAPTER 6

6. CONCLUSION

6.1. Summary of Findings and Implications

In the three studies in this dissertation, I have examined the key characteristics of mobile App store markets and filled gaps in the existing literature, and finally identified the key determinants for the sustainability of mobile Apps. The empirical results suggest that long-term success is dependent on prudent approach to developing and offering Apps in marketplaces. Specifically, diversification across selling categories is a key determinant of high survival probability in the top charts and contributes to sales performance. Regarding App-specific attributes, the findings suggest that offering free Apps, investment in less popular categories, continuous updates on App features and price, and higher user feedbacks on Apps are positively associated with sales performance. Therefore, these App attributes lead to further potential user demand and increase App sales. Furthermore, I find that while product cues in App product descriptions solely do not have impacts on App sales, the extrinsic cues in the descriptions are complementary to product cues offered from markets and are significantly associated with App sales. Finally, this result establishes a positive relationship between quality improvement and App success in the long run.

The findings of the studies will have several significant implications to extant literature on digital product management and business practice. From an academic perspective, this research creates new knowledge about mobile App seller’s strategic decisions on product portfolio management, product description, and long-term App product management, and their impacts on success in mobile App markets. This research is a first step to investigate evidence for the significant associations of product portfolio strategy, product description formulation, and price/feature update strategies with sales performance. From a practitioner perspective, this research will inform App sellers in formulating strategic App assortment across categories, successful keyword presentation strategies, and long-term App product management. Moreover, the findings will provide guidelines to new market entrants and enable them to have a better understanding of the strategic importance of pricing, updates, and reputation building through user reviews and other channels.

6.2.Future Research Directions

In this section, limitations of the three dissertation studies are addressed and opportunities for future research are explored.

First, the findings of the studies are based on an App's ranking information. However, there may exist several alternatives to estimate actual sales amount instead of ranking. In addition, appearing in the top charts itself may have a potential to facilitate purchase decision making at the point users initially search for Apps. However, data availability restrictions prevent us from such App users' potential preferential attachment mechanisms. In this regard, I continue to track and monitor the Apps to examine if there are reasons to expect different results over a longer duration. Moreover, the analytic approach used in the study does not allow us to make causal predictions. Future research can examine the causal linkage between the presented App developer strategies and App performance.

Second, while this study only considers a developer as a decision maker for App portfolio management, many individual sellers provide Apps through big mobile software publishers such as Gameloft or Chillingo. Thus, for such big publishers, the management of various developers and much larger selections of mobile Apps could be crucial for successful sales performance. In the regard, it is important to investigate how publisher-level properties affect App-/seller-level variables.

Third, the results in this study are based on sellers in a single mobile App market. A seller's mobile App portfolio management and its impact on sales performance can vary under distinct App market structures. For example, each market has a different number of categories (e.g., Apple: 20 categories; Blackberry: 18 categories; Google: 34 categories), a different proportion of free Apps (Apple: 25 percent; Google: 57 percent) and a different presentation of product cues in the App product pages. As a result, future studies exploring developers' App positioning approaches in different mobile App markets and potential for platform competition among the markets are necessary.

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APPENDIX A

A. ROBUSTNESS CHECKS OF APP PORTFOLIO MANAGEMENT

Results from Different Ranking Charts

	Model 1 (Top 300)	Model 2 (Top 200)	Model 3 (Top 100)
Fixed Effects			
Intercept (r_{000})	-.404(.041)***	-.479(.040)***	-1.632(.050)***
Seller_num_app (r_{001})	.002(.000)***	.003(.000)***	.004(.000)***
Seller_num_cate(r_{002})	.152(.006)***	.153(.006)***	.175(.008)***
*Seller_num_app*num_cate* (r_{003})	-.0002(.000)***	-.0002(.000)***	-.0004(.000)***
App_free_price (r_{010})	.536(.067)***	.601(.067)***	.761(.093)***
App_minus_initial_rank(r_{020})	.004(.000)***	.009(.000)***	.016(.000)***
App_price_promotion (r_{030})	.321(.104)*	.357(.091)*	.282(.089)
App_quality_update(r_{040})	1.077(.023)***	1.077(.022)***	.922(.031)***
App_popular_cate(r_{050})	-.504(.075)***	-.652(.075)***	-.774 (.099)***
App_unpopular_cate(r_{060})	.365(.069)**	.236(.071)	.057(.085)
App_review_avr (r_{070})	.046(.012)*	.166 (.014)***	.238(.019)***
App_review_num (r_{080})	.328(.009)***	.445(.010)***	.511 (.013)***
App_age_of_app(r_{090})	-.006(.000)***	-.004(.000)***	-.003(.000)***
Random Effects			
Intercept-1 ($\sigma^2 r$)	1.876(.050)***	1.987(.078)***	1.920(.094)***
Intercept-2 (σ^2_{u00})	2.397(.091)***	2.330(.041)***	2.184(.034)***
App_free_price (σ^2_{u01})	1.979(.179)***	1.72(.070)***	2.623(.277)***
App_minus_initial_rank (σ^2_{u05})	.000(.000)	.000(.000)	.000(.000)
App_price_promotion (σ^2_{u03})	.334(.293)	.366(.211)	.223(.173)
App_quality_update (σ^2_{u02})	.842(.038)***	.865(.040)***	1.189 (.064)***
App_popular_cate (σ^2_{u06})	1.706(.192)***	1.440(.174)***	1.665(.250)***
App_unpopular_cate (σ^2_{u07})	1.867(.189)***	1.800 (.185)***	1.195(.202)***
App_review_avr (σ^2_{u08})	.048(.004)***	. 074(.006)***	.122(.009)***
App_log_review_num (σ^2_{u09})	.034(.002)***	.044 (.003)***	.054(.004)***
App_age_of_app(σ^2_{u10})	.000(.000)	.000(.000)	.000(.000)
Deviance	387891.27	391771.08	388409.86

*= p <.005, **=p <.001, ***=p <.0001

Table A1. Estimation Results from Different Ranking Charts

Results from Different Periods

	Period 1 (Week 1 ~ 19) N=231,968	Period 2 (Week 20 ~ 39) N=356,535
Fixed Effects		
Intercept (r_{000})	-1.307(.045)***	-1.619(.033)***
Seller_num_app (r_{001})	.001(.000)***	.007(.000)**
Seller_num_cate(r_{002})	.145(.008)***	. 168(.005)***
*Seller_num_app*num_cate* (r_{003})	-.00006 (.000)**	-.00009(.000)***
App_free_price (r_{010})	.175(.065)	.344(.078)**
App_minus_initial_rank(r_{050})	.011(.000)***	. 004(.000)***
App_price_promotion (r_{030})	.028(.128)	.695(.182)*
App_quality_update(r_{020})	.759(.023)***	1.917(.323)***
App_popular_cate(r_{060})	-.339(.069)**	-.529(.057)***
App_unpopular_cate(r_{070})	.296(.059)**	.294(.049)***
App_review_avr (r_{080})	.017(.014)	.026(.014)
App_review_num (r_{090})	.204(.009)***	.261(.010)***
App_age_of_app(r_{0100})	-.001(.000)***	-.001(.000)***
Random Effects		
Intercept-1 ($\sigma^2\tau$)	1.274(.052)***	.890(.042)***
Intercept-2 (σ^2_{u00})	2.003(.014)***	1.388(.021)***
App_free_price (σ^2_{u01})	1.005(.141)***	.648(.093)***
App_minus_initial_rank (σ^2_{u05})	.000(.000)	.000(.000)
App_price_promotion (σ^2_{u03})	.000(.000)	1.418(.571)
App_quality_update (σ^2_{u02})	.000(.000)	1.698(.076)***
App_popular_cate (σ^2_{u06})	.184(.155)	.907(.132)***
App_unpopular_cate (σ^2_{u07})	.944(.124)***	.851(.106)***
App_review_avr (σ^2_{u08})	.037(.004)***	.024(.004)***
App_review_num (σ^2_{u09})	.013(.002)***	.016(.002)***
App_age_of_app(σ^2_{u10})	.000(.000)	.000(.000)
Deviance	152411.88	207329.54

*= p <.005, **=p <.001, ***=p <.0001

Table A2. Estimation Results from Different Periods

Results from Hedonic Use

	Model 1 (Hedonic Dummy only) N=530,503	Model 2 (+ Hedonic Dummy) N=530,503
Fixed Effects		
Intercept (r_{000})	-.442 (.017)***	-.385(.047)***
Seller_num_app (r_{001})	.003(.000)***	.003(.000)***
Seller_num_cate(r_{002})	.148(.006)***	.152(.006)***
*Seller_num_app*num_cate* (r_{003})	-.0002(.000)***	-.0002(.000)***
App_free_price (r_{010})	.579(.0682)***	.536(.068)***
App_minus_initial_rank(r_{020})	.004(.000)***	.004 (.000)***
App_price_promotion (r_{030})	.306(.104)	.312(.104)
App_quality_update(r_{040})	1.074(.021)***	1.069(.0208)***
App_popular_cate(r_{050})	.	-.541(.047)**
App_unpopular_cate(r_{060})	.	.372(.071)***
App_review_avr (r_{070})	-.046(.012)*	.047(.012)*
App_review_num (r_{080})	.325(.009)***	.326(009)***
App_age_of_app(r_{090})	-.006(.000)***	-.003(.000)***
App_hedonic_cate(r_{0100})	.033(.044)	.111(.045)
Random Effects		
Intercept-1 ($\sigma^2\tau$)	2.438(.104)***	2.229(.102)***
Intercept-2 (σ^2_{u00})	2.732(.034)***	3.363(.058)***
App_free_price (σ^2_{u01})	2.101(.187)***	2.017(.184)***
App_minus_initial_rank (σ^2_{u02})	.000(.000)	.000(.000)
App_price_promotion (σ^2_{u03})	.332(.294)	.323(.292)
App_quality_update (σ^2_{u04})	.853(.038)***	.831(.038)***
App_popular_cate (σ^2_{u05})	.	1.678(.201)***
App_unpopular_cate (σ^2_{u06})	.	1.782(.197)***
App_review_avr (σ^2_{u07})	.047(.004)***	.047(.004)***
App_log_review_num (σ^2_{u08})	.034(.002)***	.034(.002)***
App_age_of_app(σ^2_{u09})	.000(.000)	.000(.000)
App_hedonic_cate(σ^2_{u10})	1.518(.106)***	1.318(.104)***
Deviance	396976.95	385245.89
*= p <.005, ** = p <.001, ***= p <.0001		

Table A3. Estimation Results from Hedonic Use

APPENDIX B

B. ROBUSTNESS CHECKS OF APP PRODUCT DESCRIPTION

The Selection of Keywords Clusters

We evaluated whether the four clusters with the 30 terms used in our analyses presents the key product-related information in the head of App descriptions. First, the optimal number of key terms in the descriptions was identified based on sparsity of terms across the descriptions. Figure A1 presents the changes in sparsity according to the number of key terms.

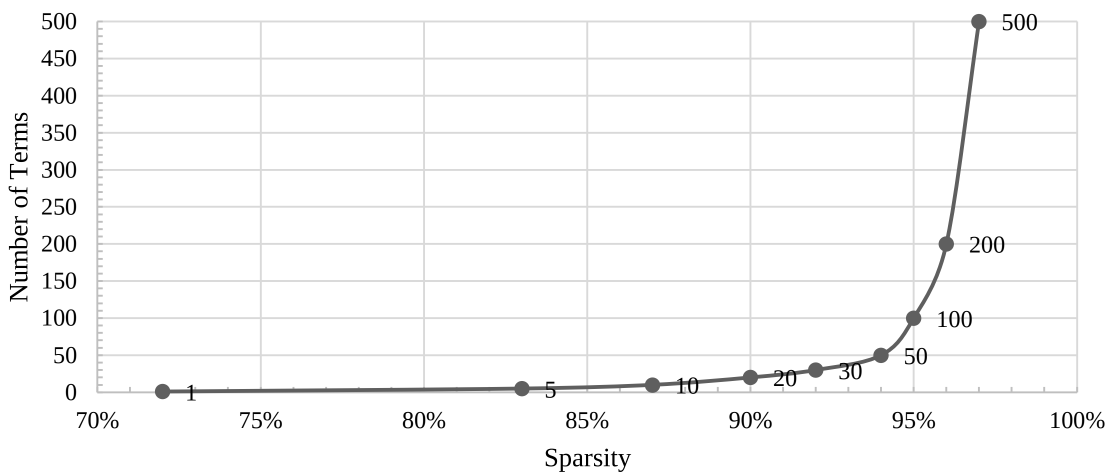

Figure A1. Number of Terms and Sparsity

The sparsity increased dramatically when 30 or more key terms were selected. Hence, the selection of 30 key terms presents the optimal number of keywords without losing meaningful App product information in the descriptions.

Second, we varied the number of clusters to check if the choice of four clusters identifies the distinctive dimensions of App product cues from the selected keywords. Figures A2 and A3 illustrate the three clusters and five clusters of the 30 terms respectively.

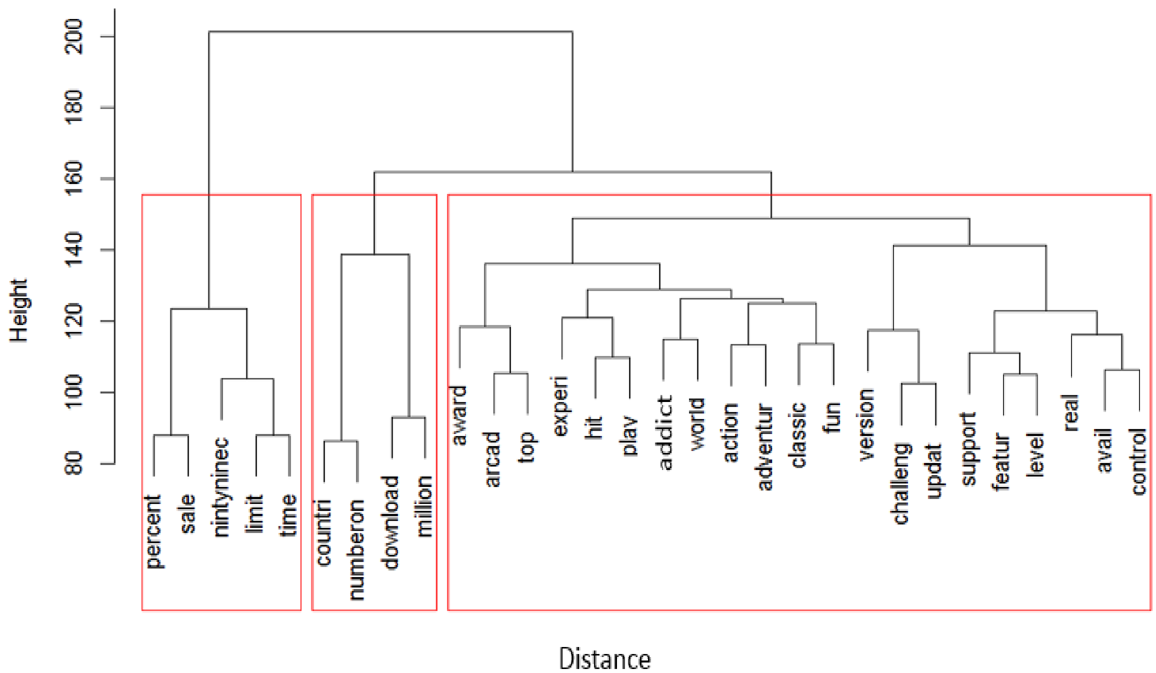

Figure A2. Three Clusters of Keywords

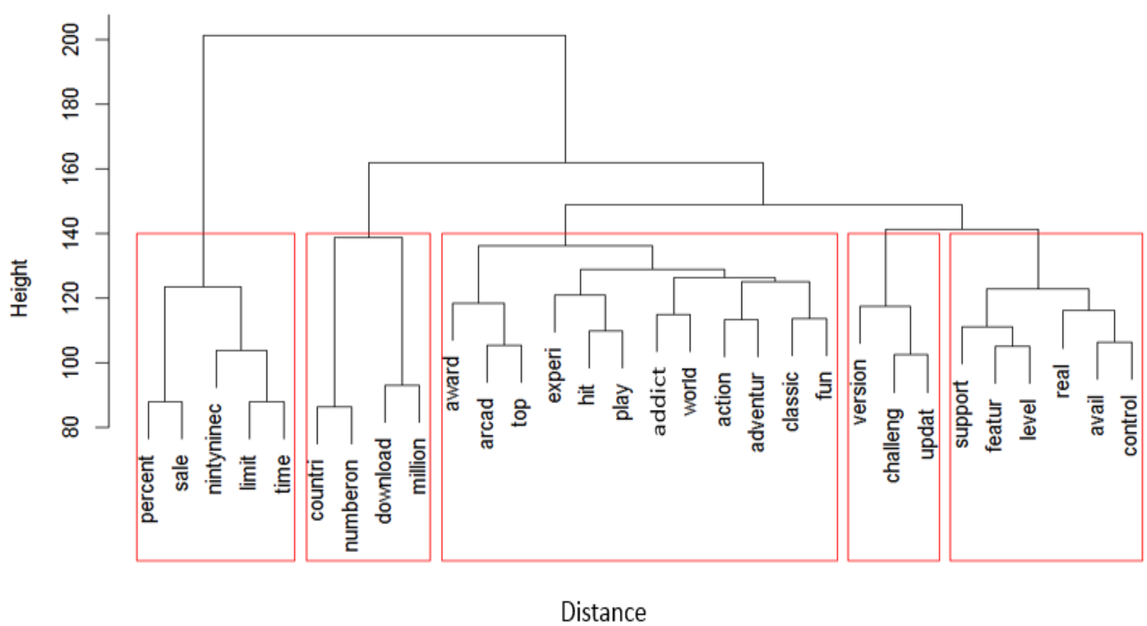

Figure A3. Five Clusters of Keywords

While the three clusters cause an information reduction from the key terms (i.e.., the collapse of ‘Review’ and ‘Update’ clusters), the five clusters include redundant information from the terms (i.e., the separation of 'Update' cluster). As such, the four clusters ensure the distinctive App product cues from the keywords.

In addition, a principal component analysis (PCA) on the selected key terms was conducted for determining the principal components (i.e., groups/clusters of the terms) and appropriate number of components. We had very similar composition of keywords in the components to the terms in the clusters gaining from a hierarchical cluster analysis. The scree plot in Figure A4 shows an elbow (a big gap) between the fourth and fifth eigenvalues. Subsequently, this outcome supports the selection of four clusters.

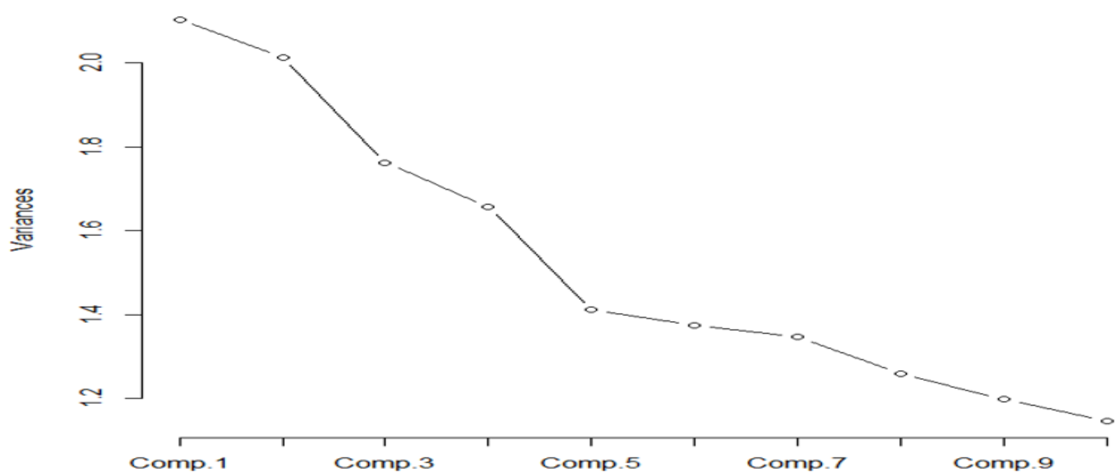

Figure A4. Scree Plot in a Principal Component Analysis

Results from Full Descriptions

Cue	Variable	Main Effects			Complementary Effects		
		P	M	P+M	P * ME	P * MI	P * M
	$Constant_{it}$	-1.873*** (0.155)	-2.715*** (0.381)	-1.301*** (0.391)	-3.056** (1.022)	-1.296** (0.398)	-3.029** (1.059)
	Variables from Product Descriptions (Producer Cues: P)						
PI	$Intrinsic1_{it}$	-0.043 (0.145)	.	0.082 (0.121)	-0.196 (0.485)	0.082 (0.121)	-0.194 (0.492)
	$Intrinsic2_{it}$	-0.049 (0.124)	.	-0.110 (0.107)	0.096 (0.388)	-0.115 (0.107)	0.063 (0.386)
	$Intrinsic3_{it}$	0.302 (0.198)	.	-0.027 (0.142)	0.617 (0.440)	-0.022 (0.142)	0.640 (0.445)
	$Intrinsic4_{it}$	0.310* (0.141)	.	-0.041 (0.096)	0.474 (0.441)	-0.044 (0.096)	0.461 (0.449)
	Variables from Market Formats (Market Cues: M)						
ME	$ln(Price)_{it}$	.	-0.879*** (0.060)	-0.882*** (0.060)	-0.891*** (0.234)	-0.883*** (0.060)	-0.890*** (0.234)
	$Review\_score_{it}$	.	0.109* (0.049)	0.117* (0.051)	0.444** (0.168)	0.116* (0.051)	0.435* (0.173)
	$Age\_of\_app_{it}$	.	-0.012*** (0.002)	-0.011*** (0.003)	-0.009 (0.005)	-0.011*** (0.003)	-0.009 (0.005)
	Hit_app_{it-1}	.	-0.005 (0.058)	-0.006 (0.058)	0.220 (0.254)	-0.004 (0.059)	0.223 (0.254)
MI	$Feature\_update_{it}$	.	0.191*** (0.042)	0.194*** (0.043)	0.194*** (0.043)	0.151 (0.147)	0.186 (0.146)
	$ln(Size)_{it}$	.	0.030* (0.013)	0.028* (0.012)	0.014 (0.015)	0.029* (0.013)	0.015 (0.016)
	$In\text{-}App\text{-}Purchase_{it}$	.	-0.141 (0.110)	-0.149 (0.111)	-0.121 (0.132)	-0.146 (0.111)	-0.118 (0.133)
	Interactions with $ln(Price)_{it}$ (ME)						
PI	$Intrinsic1_{it}$	.	.	.	0.109 (0.134)	.	0.108 (0.133)
	$Intrinsic2_{it}$	.	.	.	-0.022 (0.073)	.	-0.023 (0.073)
	$Intrinsic3_{it}$	.	.	.	0.022 (0.080)	.	0.022 (0.080)
	$Intrinsic4_{it}$	.	.	.	-0.069 (0.093)	.	-0.068 (0.093)
	Interactions with $Review\_score_{it}$ (ME)						
PI	$Intrinsic1_{it}$	.	.	.	0.112 (0.101)	.	0.112 (0.102)
	$Intrinsic2_{it}$	.	.	.	-0.088 (0.079)	.	-0.083 (0.079)
	$Intrinsic3_{it}$	.	.	.	-0.091 (0.086)	.	-0.094 (0.087)
	$Intrinsic4_{it}$	.	.	.	-0.106 (0.085)	.	-0.104 (0.087)
	Interactions with $App\_of\_age_{it}$ (ME)						
PI	$Intrinsic1_{it}$	.	.	.	-0.005** (0.002)	.	-0.005** (0.002)
	$Intrinsic2_{it}$	.	.	.	0.005** (0.002)	.	0.005** (0.002)
	$Intrinsic3_{it}$	.	.	.	-0.002 (0.002)	.	-0.002 (0.002)
	$Intrinsic4_{it}$	.	.	.	-0.001 (0.002)	.	-0.001 (0.002)
	Interactions with Hit_app_{it-1} (ME)						
PI	$Intrinsic1_{it}$	.	.	.	-0.145 (0.089)	.	-0.147 (0.089)
	$Intrinsic2_{it}$	.	.	.	0.029 (0.099)	.	0.029 (0.100)
	$Intrinsic3_{it}$	.	.	.	0.042 (0.118)	.	0.040 (0.118)
	$Intrinsic4_{it}$	.	.	.	-0.101 (0.087)	.	-0.098 (0.088)
	Interactions with $Update_{it}$ (MI)						
PI	$Intrinsic1_{it}$	.	.	.	.	-0.039 (0.080)	-0.035 (0.077)
	$Intrinsic2_{it}$	.	.	.	.	0.057 (0.078)	0.055 (0.076)
	$Intrinsic3_{it}$	.	.	.	.	-0.002 (0.054)	-0.015 (0.053)
	$Intrinsic4_{it}$	.	.	.	.	0.014 (0.054)	0.003 (0.055)
	Control Variable						
	$-ln(Rank)_{it-1}$	0.533*** (0.036)	0.508*** (0.033)	0.508*** (0.033)	0.502*** (0.033)	0.508*** (0.033)	0.502*** (0.033)
	R^2(adj. R^2)	0.375 (0.370)	0.540 (0.536)	0.540 (0.536)	0.548 (0.541)	0.541 (0.536)	0.548 (0.541)

Note: $\sum Time_{it}$ *variable was included in the analysis, but not reported here.*

Table A4. Estimation Results from Full Descriptions

Results of Main Effects from Productivity Apps

Cue	Variable	Null	Model I(1) (Producer Cues)			Model I(2) (Market Cues)			Model I(3) (Producer + Market Cues)		
			Extrinsic (PE)	Intrinsic (PI)	Overall (P=PE+PI)	Extrinsic (ME)	Intrinsic (MI)	Overall (M=ME+MI)	Extrinsic (M=PE+ME)	Intrinsic (I=PI+MI)	Overall (E+I or P+M)
	$Constant_{it}$	-1.863***	-2.061***	-1.801***	-1.836***	109.991	-1.627***	108.594	108.129	-1.334***	107.070
		(0.247)	(0.203)	(0.290)	(0.352)	(71.749)	(0.297)	(72.286)	(71.343)	(0.379)	(70.693)
	Variables from Product Descriptions (Producer Cues: P)										
PE	$Extrinsic_{it}$	.	0.477***	.	0.500***	.	.	.	0.089*	.	0.078*
			(0.125)		(0.131)				(0.45)		(0.37)
PI	$Intrinsic1_{it}$	.	.	0.200	-0.118	.	.	.	.	0.198	-0.306
				(0.183)	(0.185)					(0.186)	(0.195)
	$Intrinsic2_{it}$	.	.	-0.106	-0.022	.	.	.	.	-0.215	0.250
				(0.169)	(0.178)					(0.192)	(0.197)
	$Intrinsic3_{it}$	.	.	0.042	0.130	.	.	.	.	0.116	0.100
				(0.128)	(0.127)					(0.140)	(0.157)
	$Intrinsic4_{it}$	.	.	-0.051	-0.116	.	.	.	.	-0.123	-0.271
				(0.069)	(0.100)					(0.086)	(0.142)
	Variables from Market Formats (Market Cues: M)										
ME	$ln(Price)_{it}$	.	.	.	.	-0.794***	.	-0.811***	-0.752***	.	-0.844***
						(0.173)		(0.162)	(0.188)		(0.151)
	$Review\_score_{it}$	.	.	.	.	0.263***	.	0.261***	0.262***	.	0.255***
						(0.046)		(0.047)	(0.046)		(0.045)
	$Age\_of\_app_{it}$	.	.	.	.	-8.944	.	-8.826	-8.801	.	-8.643
						(5.693)		(5.735)	(5.662)		(5.610)
	Hit_app_{it-1}	.	.	.	.	-0.032	.	-0.038	-0.032	.	-0.018
						(0.070)		(0.070)	(0.070)		(0.069)
MI	$Feature\_update_{it}$	.	.	.	.	.	0.060	0.022	.	0.060	0.021
							(0.039)	(0.036)		(0.039)	(0.036)
	$ln(Size)_{it}$	.	.	.	.	.	-0.122	0.000	.	-0.171*	-0.069
							(0.071)	(0.100)		(0.074)	(0.087)
	$In\text{-}App\text{-}Purchase_{it}$	.	.	.	.	.	-0.271***	-0.494***	.	-0.237***	-0.354*
							(0.030)	(0.060)		(0.060)	(0.139)
	Control Variable										
	$-ln(Rank)_{it-1}$	0.481***	0.459***	0.479***	0.457***	0.429***	0.474***	0.428***	0.427***	0.471***	0.418***
		(0.067)	(0.055)	(0.067)	(0.054)	(0.075)	(0.066)	(0.075)	(0.074)	(0.067)	(0.072)
	R^2(adj. R^2)	0.240	0.270	0.242	0.272	0.361	0.244	0.366	0.362	0.247	0.375
		(0.231)	(0.261)	(0.231)	(0.262)	(0.352)	(0.234)	(0.355)	(0.353)	(0.235)	(0.363)

*= p <0.05, **= p <0.01, ***= p <0.001

Note: $\sum Time_{it}$ variable and app specific fixed effects were included in the analysis, but not reported here

Table A5. Estimation Results of Main Effects from Productivity Apps

Results of Complementary Effects from Productivity Apps

Cue	Variable	Model II(1) (PE * M)	Model II(2) (PI * M)	Model II(3) (P * M)
	$Constant_{it}$	-1.794*** (0.406)	-1.102 (0.587)	-1.374* (0.638)
	Variables from Product Descriptions (Producer Cues: P)			
PE	$Extrinsic_{it}$	-0.807** (0.251)	0.092 (0.111)	-1.010** (0.313)
PI	$Intrinsic1_{it}$	-0.317 (0.210)	0.431 (0.459)	0.612 (0.380)
	$Intrinsic2_{it}$	0.225 (0.179)	0.351 (0.507)	0.438 (0.475)
	$Intrinsic3_{it}$	0.175 (0.156)	0.008 (0.313)	-0.260 (0.240)
	$Intrinsic4_{it}$	-0.265 (0.138)	0.158 (0.301)	0.246 (0.262)
	Variables from Market Formats (Market Cues: M)			
ME	$ln(Price)_{it}$	-0.943*** (0.164)	-0.594 (0.387)	-0.749 (0.403)
	$Review\_score_{it}$	0.212*** (0.041)	0.495* (0.198)	0.419* (0.167)
	$Age\_of\_app_{it}$	-8.932 (5.140)	-8.285 (5.716)	-8.079 (5.155)
	Hit_app_{it-1}	-0.054 (0.076)	0.261 (0.173)	0.180 (0.172)
MI	$Feature\_update_{it}$	0.043 (0.042)	0.138 (0.141)	0.140 (0.140)
	$ln(Size)_{it}$	-0.200* (0.100)	-0.027 (0.087)	-0.159 (0.090)
	$In\text{-}App\text{-}Purchase_{it}$	-0.361** (0.131)	-0.300** (0.112)	-0.332** (0.113)
	Interactions with $ln(Price)_{it}$ (ME)			
PE	$Extrinsic_{it}$	0.311* (0.130)	-	0.237 (0.121)
PI	$Intrinsic1_{it}$	-	-0.282 (0.199)	-0.268 (0.183)
	$Intrinsic2_{it}$	-	0.087 (0.303)	0.199 (0.290)
	$Intrinsic3_{it}$	-	0.154 (0.194)	0.144 (0.184)
	$Intrinsic4_{it}$	-	-0.127 (0.152)	-0.091 (0.148)
	Interactions with $Review\_score_{it}$ (ME)			
PE	$Extrinsic_{it}$	0.205** (0.064)	-	0.254** (0.078)
PI	$Intrinsic1_{it}$	-	-0.104 (0.113)	-0.147 (0.084)
	$Intrinsic2_{it}$	-	0.011 (0.122)	-0.027 (0.105)
	$Intrinsic3_{it}$	-	-0.019 (0.066)	0.050 (0.052)
	$Intrinsic4_{it}$	-	-0.079 (0.073)	-0.090 (0.061)
	Interactions with $Age\_of\_app_{it}$ (ME)			
PE	$Extrinsic_{it}$	-0.010 (0.011)	-	-0.006 (0.010)
PI	$Intrinsic1_{it}$	-	-0.004 (0.015)	-0.009 (0.016)
	$Intrinsic2_{it}$	-	-0.035 (0.025)	-0.035 (0.024)
	$Intrinsic3_{it}$	-	0.016 (0.015)	0.018 (0.015)
	$Intrinsic4_{it}$	-	0.001 (0.014)	-0.005 (0.013)
	Interactions with Hit_app_{it-1} (ME)			
PE	$Extrinsic_{it}$	0.106 (0.106)	-	0.126 (0.104)
PI	$Intrinsic1_{it}$	-	0.223 (0.136)	0.188 (0.134)
	$Intrinsic2_{it}$	-	0.012 (0.100)	-0.048 (0.109)
	$Intrinsic3_{it}$	-	-0.039 (0.063)	0.011 (0.069)
	$Intrinsic4_{it}$	-	-0.109 (0.056)	-0.105 (0.070)
	Interactions with $Update_{it}$ (MI)			
PE	$Extrinsic_{it}$	-0.098 (0.063)	-	-0.073 (0.061)
PI	$Intrinsic1_{it}$	-	-0.133* (0.065)	-0.154* (0.073)
	$Intrinsic2_{it}$	-	0.054 (0.109)	0.051 (0.106)
	$Intrinsic3_{it}$	-	-0.038 (0.042)	-0.037 (0.043)
	$Intrinsic4_{it}$	-	-0.018 (0.053)	-0.012 (0.054)
	Control Variable			
	$-ln(Rank)_{it-1}$	0.407*** (0.070)	0.406*** (0.072)	0.390*** (0.071)
	R^2(adj. R^2)	0.389 (0.375)	0.401 (0.382)	0.414 (0.393)

*= $p < 0.05$, **= $p < 0.01$, ***= $p < 0.001$

Note: $\sum Time_{it}$ variable was included in the analysis, but not reported here.

Table A6. Estimation Results of Complementary Effects from Productivity Apps

APPENDIX C

C. ROBUSTNESS CHECKS OF APP QUALITY UPDATE DECISION

Results from Paid Game Apps with Balanced Panel

	Response of *Top_Chart* (*t*) to Changes (*t-1*)			
Changes (*t-1*)	$Top25_t$	$Top\ 100_t$	$Top\ 200_t$	$Top\ 300_t$
Period 1: Baseline (n=127, t=79)				
Top_Chart_{it-1}	0.785***	0.670***	0.500***	0.921***
	(0.024)	(0.023)	(0.041)	(0.043)
$Price\_Discount_{it-1}$	0.023	0.145*	0.060	0.207**
	(0.017)	(0.066)	(0.036)	(0.074)
$Feature\_Update_{it-1}$	0.023	0.007	0.005	0.039
	(0.017)	(0.014)	(0.016)	(0.020)
Period 2: Platform-driven (n =125, t=70)				
Top_Chart_{it-1}	0.782***	0.654***	0.386***	0.690*
	(0.024)	(0.022)	(0.061)	(0.338)
$Price\_Discount_{it-1}$	0.044	0.046	0.012	0.360**
	(0.061)	(0.047)	(0.010)	(0.130)
$Feature\_Update_{it-1}$	0.031*	0.001	0.000	0.076*
	(0.015)	(0.019)	(0.010)	(0.032)
Period 3: Market-driven (n=144, t=65)				
Top_Chart_{it-1}	0.768***	0.756***	0.493***	0.798*
	(0.023)	(0.019)	(0.056)	(0.340)
$Price\_Change_{it-1}$	0.048	0.216***	0.061	0.358***
	(0.038)	(0.063)	(0.046)	(0.054)
$Feature\_Update_{it-1}$	0.045*	-0.001	0.012	0.065
	(0.022)	(0.022)	(0.012)	(0.037)

Table A7. Estimation Results from Paid Games Apps with Balanced Panel

Results from Free Game Apps

	Response of *Top_Chart* (*t*) to Changes (*t-1*)			
Changes (*t-1*)	$Top25_t$	$Top\ 100_t$	$Top\ 200_t$	$Top\ 300_t$
Period 1: Baseline (n=1,100, t=79)				
Top_Chart_{it-1}	0.820***	0.803***	0.787***	0.782***
	(0.013)	(0.008)	(0.007)	(0.008)
$Feature\_Update_{it-1}$	0.013*	0.024**	0.021	-0.033
	(0.005)	(0.009)	(0.011)	(0.022)
Period 2: Platform-driven (n =1,034, t=70)				
Top_Chart_{it-1}	0.782***	0.744***	0.708***	0.695***
	(0.015)	(0.010)	(0.009)	(0.010)
$Feature\_Update_{it-1}$	-0.002	0.004	0.017	-0.018
	(0.006)	(0.008)	(0.011)	(0.011)
Period 3: Market-driven (n=949, t=65)				
Top_Chart_{it-1}	0.819***	0.800***	0.769***	0.766***
	(0.015)	(0.010)	(0.008)	(0.009)
$Feature\_Update_{it-1}$	-0.006	0.001	0.014	-0.014
	(0.006)	(0.011)	(0.012)	(0.013)

Table A8. Estimation Results from Free Games Apps

Results from Effects from Paid Productivity Apps

	Response of *Top_Chart* (*t*) to Changes (*t-1*)			
Changes (*t-1*)	$Top25_t$	$Top\ 100_t$	$Top\ 200_t$	$Top\ 300_t$
Period 1: Baseline (n=867, t=79)				
Top_Chart_{it-1}	0.674***	0.559***	0.470***	0.373***
	(0.019)	(0.011)	(0.008)	(0.008)
$Price\_Discount_{it-1}$	0.074**	0.096***	0.080**	0.082**
	(0.024)	(0.023)	(0.025)	(0.025)
$Feature\_Update_{it-1}$	-0.003	0.019	0.032*	0.002
	(0.006)	(0.011)	(0.013)	(0.014)
Period 2: Platform-driven (n =951, t=70)				
Top_Chart_{it-1}	0.689***	0.568***	0.442***	0.364***
	(0.019)	(0.011)	(0.008)	(0.007)
$Price\_Discount_{it-1}$	0.031	0.094***	0.065**	0.102***
	(0.017)	(0.024)	(0.024)	(0.027)
$Feature\_Update_{it-1}$	0.003	0.013	0.032**	0.024*
	(0.005)	(0.009)	(0.011)	(0.012)
Period 3: Market-driven (n=970, t=65)				
Top_Chart_{it-1}	0.640***	0.548***	0.445***	0.347***
	(0.019)	(0.010)	(0.008)	(0.007)
$Price\_Change_{it-1}$	0.069***	0.088***	0.090***	0.065*
	(0.019)	(0.024)	(0.025)	(0.026)
$Feature\_Update_{it-1}$	0.002	0.020	0.007	0.041*
	(0.007)	(0.010)	(0.014)	(0.016)

Table A9. Estimation Results from Paid Productivity Apps