Determinants of Mobile Apps Success: Evidence from App Store Market

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Abstract

Mobile applications 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. This research examines key seller- and App-level characteristics that impact success in an App store market. We tracked individual Apps and their presence in the top grossing 300 charts in Apple App Store and examined how factors at different levels affect the Apps' survival in the top 300 *charts. We used a generalized hierarchical modeling approach to measure sales performance, and confirmed the results with the use of a hazard model and a count regression model. We find that broadening App offerings across multiple categories is a key determinant that contributes to a higher probability of survival in the top charts. App-level attributes such as free App offers, high initial ranks, investment in less popular (less competitive) categories, continuous quality updates, and high volume and high user review scores have positive impacts on Apps' sustainability. In general, each diversification decision across a category results in approximately a 15% increase in the presence of an App in the top charts. Survival rates for free Apps are up to two times more than that for paid Apps. Quality (feature) updates to Apps can contribute up to a three-fold improvement in survival rate as well. A key implication of the results is that sellers must utilize the natural segmentation in consumer tastes offered by the different categories to improve sales performance.*

Keywords: App store market, mobile software sustainability, product portfolio management, survival analysis.

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Introduction

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

- William Cowper, 1785

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 (henceforth, AppStore) launched with only 500 Apps and a dozen developers in July 2008, the market has increased to over 845,900 Apps and 226,500 unique sellers in April 2013[1]. This rapidly growing market has in turn led to over 500 million AppStore users downloading around 40 billion Apps in 155 countries and the platform had paid out over 7 billion dollars to App developers in 2012[2].

Mobile App store markets exhibit key characteristics of "long tail market" [3] 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 [13], music [29], and movies [26, 36]. First, sellers in mobile App markets have a single channel for selling their product (especially in case of Apple's App market) and terms of access to the market are uniformly determined for all

[1] Apple's App Store Report (April, 15th, 2013), 148Apps, available at http://148apps.biz/app-store-metrics/
[2] App Store Tops 40 Billion Downloads with Almost Half in 2012 (January 17th , 2013), Apple, available at http://www.apple.com/pr/library/2013/01/07App-Store-Tops-40-Billion-Downloads-with-Almost-Half-in-2012.html

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 [53], specialization within categories can allow sellers to develop distinct competencies and benefit from scope economies through reduced product development costs [9]. 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.

The key contributions of this research to the extant literature are as follows. First, we show that specific portfolio properties affect sales performance sustainability in high velocity software markets such as the Apple's App Store. Using the rich data context of the App store market, we overcome key methodological barriers to understanding portfolio impacts on sustained sales performance. By utilizing three different types of models (a generalized hierarchical linear model, a hazard model, and a count regression model), we provide empirical evidence to show how sellers' App portfolio management influences success in App markets. In general, we find that each diversification decision across a category results in approximately a 15 % increase in survival probability. Moreover, we find that free offering, higher debut rank, investment in less popular categories, continuous feature updates, and higher user review scores on Apps have positive impacts on Apps' sustainability.

Theoretical Foundation

Product Portfolio Management

Day [25] 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 [4, 49] and meet customer need in a manner superior to competitor's product offerings [53]. 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 [21]. Many studies applying financial portfolio theory to product portfolio management [17, 28] 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 [13, 46]. Although Brynjolffson [14] 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 [14] 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 [39, 48]. A firm's ability to leverage investment experience and knowledge from one setting to another can confer significant performance benefits. Bailey and Friedlaender [8] 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 [22] 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 [5]. 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 [20, 35]. 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 [40] 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.

In summary, 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. In the following section, we outline our research approach by describing the empirical models and data collection.

Empirical Approach and Data Descriptions

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 [22, 56]. 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 [54].

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 [26]. 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.Sustainability of App Sales: 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

[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.

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 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 [45]. 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

Definition of Measures

Dependent Variables

Since Apple does not release actual sales figures to the public, our measures for sales performance and App's sustainability are based on rank information. Many recent studies show that the demand (or sales amount) can be estimated from publicly available rank information [15, 19]. Consistent with these findings, we measure an App's ranking as a proxy for an Apps' actual sales performance.

App_survival: An App's survival in the top charts (a dichotomous variable).

*Seller(App)_survival_time_top 300***:** A dependent variable indicating the elapsed time since the first appearance of the seller/App on the top 300 chart. On average, seller/Apps have a survival time of 30.4/19.7 weeks.

Seller(App)_censor_top300: A dummy variable representing whether an App is considered in the survival analysis. In the top 300 chart, Apps having unknown initial times (31%), exit times (43%), and exited and reappeared (19%)-discontinuous survival times-were considered censored (these properties overlapped). As a result, 55% of sellers (66.3% of Apps) in the charts were censored.

Seller_num_apps_top: A variable measuring a seller's sales performance. We evaluate a seller's sales performance (or sales success) by counting the total number of Apps in the top grossing 100, 200, and 300 charts across all 20 categories.

Explanatory Variables of Product Portfolio Management

Several seller-level attributes related to App portfolio management were utilized to examine the marginal impact of increasing one more App and category on sales performance.

Seller_num_app: The total number of Apps offered by a seller on AppStore.

Seller_num_cate: The total number of categories that include a seller's Apps. This is computed by the sum of categories that contain at least one App. This measure is used as a proxy for measuring the diversification of Apps over multiple categories (i.e., categories scope).

*Seller_ num_app*num_cate:* An interaction term between *Seller_num_app* and *Seller_num_cate*. It was used for examining the marginal impact of adding one more App/category on App success. Since the creation of a new App (i.e., increase in the number of Apps) entails a decision on whether to stick with existing category(ies) or expand to a new category, the model includes the interaction term of *Seller_num_app* and *Seller_num_cate* to address how this decision on App portfolio is associated with App sales.

App-Specific Control Variables

Presumably, the sales performance of a seller/App can be affected by App-specific attributes in addition to seller's App portfolio. Therefore, we include App-level properties that are potentially associated with the survival time of a seller/App.

App_free_price: A dummy variable representing whether an App is offered for free. While 34.5% of all Apps in the AppStore are free Apps, around 80% of free Apps include in-app-payments. In our sample 12% of Apps are completely free of charge, but we do not separate purely free Apps from those having in-app-purchase options.

App_Minus_initial_rank: The popularity achieved on the first appearance on the top 300 (i.e., reversed rank). This measures the initial popularity of an App (i.e., the amount of downloads in the first week).

App_popular_cate and *App_unpopular_cate*: A dummy variable revealing whether an App is in the most (least) three popular categories. According to 148 apps.biz, three popular categories take around 40% of all Apps in AppStore: 17.26% Apps for games, 10.97% Apps for books, and 10.32% Apps for entertainment. The three least popular categories take only 4%: 1.85% for medical, 1.64% for navigation, and 0.42% for weather.

App_price_promotion: A dummy variable representing whether an App had a promotional offer over its survival time. Generally, the App has three price update processes. First, a seller lowers the App's price for a short time period. Second, the seller keeps the same price as in the previous week. Third, the seller returns it to the original price. These price update processes for all Apps in the dataset were recorded, and we considered the first case of price update as a price promotion.

App_quality_update: A dummy variable indicating whether an App had at least one update. Any change in Apps was defined as a quality update (with a version number change). App users can observe the update of an App without downloading. For example, AppStore provides an updated date of every App. If the update date is different from the released date, the App was updated at least once. Furthermore, each App's description includes the update information (sometimes even including a lengthy description of what new updates/features have been added). Therefore, the latest update can be a signal reflecting quality of App and a seller's effort.

App_review_avr and *App_review_num*: Those two variables indicate the weekly averaged review scores (on a scale of 1-5) and the cumulative number of user reviews respectively.

App_age_of_app: the number of days elapsed after an App was released. This variable controls the endogenous time effects on an App's survival.

Empirical Models

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

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 [31].

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:

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

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 predictors at $t\text{-}1$, 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:

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

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 $t\text{-}1$ 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.

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

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:

$$
\begin{aligned}
logit(App\_survival_{ijt}) = {} & \gamma_{000} \\
& + \gamma_{001}(Seller\_num\_app)_{jt-1} + \gamma_{002}(Seller\_num\_cate)_{jt-1} + \gamma_{003}(Seller\_num\_apps * num\_cate)_{jt-1} \\
& + \gamma_{010}(App\_free\_price)_{ijt} + \gamma_{020}(App\_minus\_initial\_rank)_{ijt} + \gamma_{030}(App\_price\_promotion)_{ijt-1} \\
& + \gamma_{040}(App\_quality\_update)_{ijt-1} + \gamma_{050}(App\_popular\_cate)_{ijt} + \gamma_{060}(App\_unpopular\_cate)_{ijt} \\
& + \gamma_{070}(App\_review\_avr)_{ijt-1} + \gamma_{080}(App\_review\_num)_{ijt-1} + \gamma_{090}(App\_age\_of\_app)_{ijt-1} \\
& + \tau_{0ij} \\
& + u_{01j}(App\_free\_price)_{ijt} + u_{02j}(App\_minus\_initial\_rank)_{ijt} + u_{03j}(App\_price\_promotion)_{ijt-1} \\
& + u_{04j}(App\_quality\_update)_{ijt-1} + u_{05j}(App\_popular\_cate)_{ijt} + u_{06j}(App\_unpopular\_cate)_{ijt} \\
& + u_{07j}(App\_review\_avr)_{ijt-1} + u_{08j}(App\_log\_review\_avr)_{ijt-1} + u_{090j}(App\_age\_of\_app)_{ijt-1} \\
& + u_{00j}
\end{aligned}
\tag{4}
$$

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 [58]. Thus, the standard errors may become too small, and may subsequently lead to misleading significance of estimates and high p-values [1]. 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 [23].

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:

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

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

$h_0(t)$ 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 [2, 30, 34]. The penalized partial likelihood approach was used for fitting the frailty model [50]. 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 [43] and the normal distribution [1] respectively. For a hazard model, the inclusion of time-varying variables can introduce endogeneity [10, 11, 37]. Endogenous time-varying covariates cause bias in coefficient estimates [33]. 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 [33] 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 [6]; (3) jointly model the duration and the time varying covariate [24]; (4) use the ideas of simultaneous equations to duration models [7]; (5) include the covariate, but drop the time-varying portion [33]. 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” [33]. 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*, $Seller\_num\_apps\_top_{jt}$.

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

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 [51]. 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 [1].

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.

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 [44]. Improvements in predictability were determined by the proportional reduction of deviance compared with the null (baseline) model [16].

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 [44].

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 [55]. 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. However, a user's unobservable self-selection for buying an App, which is not controlled in this research setting, is also likely to affect the success of App sales. For example, a user may purchase a paid App after trying its free version [41]. In addition, strong ranking effects in the App markets could form a bias among users to predominantly fixate on hit products [32], and subsequently, users may download the Apps in the top charts.

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 [59]. 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)**	**Model II (1)**	**Model II (2)**	**Model II (3)**	**Model II (4)**
	Cox Main Effect (Survival of Sellers)	Cox Main Effect (Survival of Apps)	Cox with Gamma Frailty (Survival of Apps)	Weibull with Gamma Frailty (Survival of Apps)	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 [58]. 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 [1]. 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

* *Note: 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 Performance 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 $\left(\frac{Number\ of\ Apps\ in\ the\ Top\ Charts}{Total\ Number\ of\ Published\ Apps}\right)$
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 [12] and increased demand in a complementary premium good [47].

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 [52, 57, 60]. Thus, there is limited evidence for returns to efforts on App advertising and promotion before release [26].

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 [13, 29], 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. As evidenced in prior literature, positive user reviews have the potential to increase product demand [27, 42]   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.

Sensitivity and 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.

[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.

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 1 in Appendix I shows that seller-level predictors are 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 a Seller 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 2 in Appendix I. 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 3 in Appendix I). 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

[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

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.

Conclusion

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.

Contribution and Managerial Implications

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 [18] and the expected time to perform major upgrade to software systems [38]. 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.

Limitations and Future Research Directions

The findings of this study are based on the survival of Apps only over 39 weeks in the top 300 chart. We continue to track and monitor the Apps to examine if there are reasons to expect different results over a longer duration. The analytic approach used in the study does not allow us to make causal predictions. Future research can examine the causal linkage between product portfolio decisions and App performance. 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. Furthermore, we estimated the sales amount of an App (or a seller) with survival in the top charts and total number of Apps in the chart. However, there may exist several alternatives to estimate actual sales amount instead of ranking. We also did not specifically examine App specific features or seller specific characteristics. Further examination of these attributes will be necessary in developing deep insights into mobile App markets.
While this study only considers a seller (or 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 mobiles 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.

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) and a different proportion of free Apps (Apple: 25 percent; Google: 57 percent). As a result, future studies exploring sellers' portfolio management in different mobile App markets and potential for platform competition among the markets are necessary.

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Appendix I: Sensitivity Analysis

1. GHLM with 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 ($\sigma^2\tau$)	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 ($\sigma^2_{u09.}$)	.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 1. Analysis Results from Different Ranking Charts

2. GHLM with Two 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 ($\sigma^2_{u09.}$)	.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 2. Analysis Results from Different Periods

3. GHLM with a Hedonic / Utilitarian Variable

	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 ($\sigma^2_{u08.}$)	.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 3. Analysis Results from Hedonic Use