MOBILE APP PORTFOLIO MANAGEMENT AND DEVELOPERS’ PERFORMANCE: AN EMPIRICAL STUDY OF THE APPLE iOS PLATFORM

Research-in-Progress

Mei Li
Department of Information Systems
National University of Singapore
15 Computing Drive, Singapore 117418
limei@comp.nus.edu.sg

Khim Yong Goh
Department of Information Systems
National University of Singapore
15 Computing Drive, Singapore 117418
gohky@comp.nus.edu.sg

Huseyin Cavusoglu
The School of Management
University of Texas at Dallas
Richardson, Texas 75083
huseyin@utdallas.edu

Abstract

A critical challenge faced by mobile app developers today is to effectively manage their app portfolio, but this issue has rarely been addressed in the IS academic literature. To address this gap, we empirically examine the relationship between the size and diversity of mobile developers’ app portfolio and their performance in a mobile platform. Using a data set from the Apple App Store, and based on panel-level linear model estimation, we find a negative impact of app portfolio diversity on developers’ performance. However, this impact decreases with portfolio size. This result implies that a diversified app portfolio hinders developers from fostering core competency, whereas their increasing development experience could mitigate this negative effect. Our results provide mobile app developers with a strategic growth trajectory recommendation, i.e., focus on product specialization during the early growth phases but adopt a diversification strategy after the accumulation of substantial development experience.

Keywords: mobile app industry, mobile app developers, app portfolio management, competitive strategy
**Introduction**

The introduction of smartphones has radically altered the way people communicate. As a complementary product to these devices, mobile apps have attracted much attention from users and firms. According to 148Apps.Biz (2013), the number of active developers in the US Apple App Store has already exceeded 220,000. The revenue of mobile apps globally is estimated to soar to US$46 billion by 2016 (CNET 2012). Contrary to the purported lucrative sales in the mobile app industry, a majority of app developers are hit with poor profitability, due to fierce competition in the app market. A more sobering fact is that most developers lack effective marketing plans and seldom manage their app portfolio strategically (Bergvall-Kärebom and Howcroft 2011).

Product portfolio management plays a critical role in firms’ strategic management, including mobile app developers. These developers have broad flexibilities in choosing the size (i.e., how many apps they want to publish) and the diversity (i.e., what type of apps they want to design) of their app portfolio. However, most developers, in reality, rarely plan or execute their app portfolio strategically with a proper market research. Oftentimes, they build apps they like, assuming this “like” applies to the users or consumers being targeted, but end up with poor market responses or sales (VisionMobile 2013).

Although there are many prior studies on product portfolio management, the existing ones can hardly provide references for mobile app developers. The mobile app industry greatly differs from the traditional manufacturing industry which is the major research subject in the product portfolio management literature (e.g., Berry 1971; Shankar 2006). Single individual developers are barely able to gain market power in this highly competitive and rapidly evolving environment. Due to the service-oriented nature of the mobile app industry, human capital plays a more influential role than the fixed or capital assets (e.g., the plants and machines in factories) in the app production process (Boh et al. 2007; Gallivan et al. 2004). Yet, few scholars have noticed these disparities. Our study thus bridges this gap by examining the relationship between the size and diversity of mobile developers’ app portfolio and their performance in a mobile platform. We focus on the size and diversity of app portfolio, since these reflect the developer’s production scope and production concentration, respectively. Our research question is the following: How do the size and diversity of mobile app developers’ app portfolio influence their performance in a mobile platform?

To answer this question, we collected data from the Apple App Store. The data set contains the complete app release history of 11,579 developers from January 2011 to March 2012. We observe the monthly app portfolio for each developer. To measure a developer's performance, we use the monthly average user rating valence of apps published by the developer. Based on the estimation of a panel-level linear model, our results show that app portfolio diversity negatively influences developers’ performance. This effect, however, decreases with app portfolio size. This finding implies that while an app portfolio without appropriate specialization is detrimental to developers’ performance, an increasing app development experience could mitigate this impact.

In summary, this study makes several significant contributions. First, it fills the research gap on prior product portfolio management literature about human capital intensive industries. We provide some evidence that the accumulation of human capital entails the economies of scope. Second, our empirical analysis in this research captures the evolution of developers’ app portfolio with panel-level data, which controls for unobserved developer-specific characteristics to provide more rigorous causality inferences. Third, our work is among the first studies that provide mobile app developers with recommendations on competitive strategies. Specifically, we suggest specialization in early growth phases to foster core competency and diversification after the accumulation of app development experiences.

**Literature Review**

*Product Portfolio Management*

A product portfolio refers to an assortment of products or services offered by firms and a well-managed product portfolio could generate positive short-term and long-term returns. The major incentives for

---

1 A developer in this study refers to a publisher of mobile apps, either an individual person or software firm.
firms to expand their product portfolio come from two aspects, i.e., demand side and supply side. Consumers have long been recognized as possessing heterogeneous preferences (e.g., Berry et al. 1995; Hotelling 1929). Individuals may have discrepant tastes toward the same product. Moreover, some consumers seek varieties in their consumption. They gain larger utility from the trial of different products (McAlister and Pessemer 1982; Simonson 1990). These demand side effects incentivize firms to diversify their product portfolio. By producing multiple products, they could satisfy the demand of different consumer segments and prepare for future demand uncertainties. With a diversified product portfolio, firms may be able to differentiate their products from their competitors and obtain higher profits (Aribarg and Arora 2008). In addition, a diversified product portfolio could help firms to reduce risk and avoid market failure in particular industry sectors (Amihud and Lev 2007).

On supply side, the decision of product portfolio expansion is tightly related to firms’ cost structure. If economies of inter-product production exist, firms may choose to increase their product variety (Lancaster 1990). Economies of inter-product production could exist in various forms, such as spreading sunk cost (Bailey and Friedlaender 1982). If the resources required by existing products have not been fully utilized, and concurrent production of a new product can share these resources, firms may have incentives to add new products to their portfolio, which can also benefit them due to the demand side effects as stated earlier.

In spite of the various motivations for firms to diversify their product portfolio, previous literature has not reached a consensus on the impact of a diversified product portfolio. Many industrial organization studies (e.g., Gort 1962; Markham 1973) conclude that there are no significant effects of a diversified product portfolio on firms’ performance. In contrast, strategic management studies (e.g., Cottrell and Nault 2004; Rumelt 1982) find positive impacts of portfolio diversification. Besides, there are a few studies (Jaquemin and Berry 1979; Palepu 1985) taking a different approach by distinguishing the types of diversification (i.e., related diversification versus unrelated diversification). They find that related diversification positively influences firms’ performance whereas unrelated diversification does not.

Mobile App Industry

The mobile app industry has become more established only after the popularity of smartphones. Compared with the long history of mobile technology platforms, the mobile app industry is a newly emerging and evolving marketplace. Due to its infancy, existing studies have only investigated more about high-level business models rather than the detailed market dynamics (e.g., app supply and demand). Schlagwein et al. (2010) create a framework from the perspective of resource openness to analyze the business models used by the major platforms. Similarly, Anvaari and Jansen (2010) analyze the openness of each layer on the mobile platforms and conclude that unlike mobile phone manufacturers, app developers are more concerned about high-level openness of a platform. Based on the theory of industry architecture and technological platforms, Kenney and Pon (2011) analyze Apple, Google, Microsoft and Nokia’s key strategies in adapting themselves to the new environment. They find that Apple and Google have adopted unusual strategies departing from previous literature and hence call for a reconsideration of the classical platform theory.

Only a handful of studies focus their attention to a special group – mobile app developers. Interviewing typical mobile app developers from Sweden, Britain and USA, Bergvall-Kåreborn and Howcroft (2011) comprehensively describe these developers’ motivation to develop and publish apps in the app stores. Using the perspective of professional logic and market logic, Qiu et al. (2011), employ a qualitative approach to analyze how iOS independent app entrepreneurs solve the logic tension in the open mobile app marketplace. Hyrynsalmi et al. (2012) investigate multi-homing behavior of apps with descriptive statistics from iOS, Android and Windows Phone. They find that the owners of multi-homing apps are likely to be professional developers, who have a clear monetization plan. Idu et al. (2011) also study multi-homing behaviors but only focus on Apple Inc.’s three platforms – iPhone, iPad and Mac store. They find that obtaining a wider user base is the primary incentive for multi-homing. A common feature of these studies is that they are interpretive and descriptive in nature. To the best of our knowledge, the study of Lee and Raghu (2011) is the only quantitative research investigating mobile developers’ strategy.

Similar to our research, Lee and Raghu (2011) investigate the influence of app portfolio on developers’ performance and find that developers could improve their performance by diversifying their app portfolio. However, our study differs in the following ways. First, unlike a cross-sectional data used in their study,
our panel data captures both within- and between-developer variations. The time dimension of the within variation allows us to track the influence of the app portfolio change on a developer’s performance, through which we can gain better causality inferences. Second, their sample consists of developers who have at least one top-ranked app, while ours contains a larger cross-section of developers, including those individuals or small-scale developers who may not have been that successful. This helps to rule out self-selection bias that successful developers tend to publish apps in more app categories (Zhong and Michahelles 2013). Third, Lee and Raghu (2011) use standard deviation of the app numbers in each category to measure product portfolio diversity. In contrast, we measure that with entropy (Jacquemin and Berry 1979; Palepu 1985), which is frequently used in strategic management studies and is more sensitive to small changes in the app portfolio composition.

**Hypotheses Development**

In this study, we mainly investigate the impact of portfolio size and diversity on developers’ performance. Based on the literature review above, we formulate a research model shown in Figure 1. Our research hypotheses are elaborated in the subsequent paragraphs.

A major research subject of the product portfolio management literature is the traditional manufacturing industry, which is characterized by physical capital assets. The IT industry however has long been recognized as human capital intensive (Gallivan et al. 2004; Lee et al. 1995). Labor forces are soft assets of IT firms but the capabilities of the developers directly determine the firms’ performance. As the mobile app industry is a relatively new one, most stakeholders are still learning the ropes of the industry. The majority of experience gained by developers, whether on technical or managerial aspects, is accumulated in the process of learning by doing (Arrow 1962; Jovanovic and Nyarko 2010). Every mobile platform has its own software development kit (SDK). Developers need to familiarize themselves with the unique grammar, commands and libraries of the SDK in continuous development. They can learn from the apps they have published on various aspects, such as framework design, code reuse and bug detection. The increasing number of apps also provides developers with more opportunities to interact with customers and this helps them to better understand their customers’ preferences and needs. The accruing experience increases developers’ human capital (Boh et al. 2007), which, in return, improves the quality of their apps. Thus, we expect a positive impact of the app portfolio size on performance. Hence, we posit that:

**Hypothesis 1 (H1):** The size of a developer’s app portfolio is positively related to the developer’s performance.

The diversity of a developer’s app portfolio reflects the developer’s production concentration over app categories. A higher diversity indicates a more diverse app portfolio. The Apple App Store has 23 major categories, ranging from spare time killers to productivity improving tools. Each category distinguishes itself from others by its functionality and content. From developers’ perspective, the programming skills and other resources required by each category may vary. For example, apps in the category of Navigation & Map need a strong support from the server end since frequent changes in maps should be updated timely to the client end via the server. In contrast, apps in the category of Games may not need so much server
end programming, but probably require sophisticated designs in user interface and game play. Nevertheless, developers may reuse code components for some common functions, such as camera access and data storage. Compared to apps in different categories, apps in the same category may be able to share more common components due to their greater similarity. Thus, the choice of what kind of apps to publish is an important decision for developers.

Previous studies have dichotomous conclusions about the impact of a diversified product portfolio on firms’ performance. The advocators of diversification argue that the shared sunk cost could reduce the total cost of firms (Bailey and Friedlaender 1982) and diversification helps reduce risk (Cardozo and Smith Jr 1983). The opponents maintain that firms with a diversified product portfolio disperse their resources to multiple areas and can hardly foster firm-specific core competencies, consequently resulting in a poorer performance (Montgomery and Wernerfelt 1988). In the mobile app market, most developers are small entrepreneurs or startups, who do not have enough financial support and lack abundant resources (Qiu et al. 2011). Almost all of their production capacity is fully occupied. Thus, a sensible way for them to grow is to concentrate on a small set of app categories to develop their core competency step by step. Distributing efforts to multiple app categories drains their resources, leaving them little competitive advantage over their competitors. Therefore, we hypothesize that:

**Hypothesis 2 (H2): The diversity of a developer’s app portfolio is negatively related to the developer’s performance.**

A diverse portfolio hinders developers from developing core competency by focusing on a small set of app categories. There is a caveat that the apps in the same categories probably are close substitutes for each other. Since these apps strive for the same consumers, sales cannibalization may exist among a developer’s apps (Batra et al. 2010; Hamilton and Chernev 2010). As the app categories are differentiated from each other in terms of their functionality and content, consumers may need apps from different categories, but only choose a few from each category. Competition within a category is typically much larger than between categories. After developers have published certain number of apps in a few categories, it is thus sensible for them to expand their potential market by serving more categories. Otherwise, the cannibalization among their own apps decreases the positive returns to their efforts. In other words, a focused strategy of development at the beginning helps them cultivate core competency. Once they accumulate substantial experience or users, they could widen the markets served to improve their performance in the mobile platform. Hence, we hypothesize a moderating effect of the app portfolio size on the app portfolio diversity:

**Hypothesis 3 (H3): The negative effect of the diversity of a developer’s app portfolio on the developer’s performance decreases with the size of the app portfolio.**

**Methodology**

**Data Collection and Operationalization**

To empirically test our hypotheses, we use the developers’ information from the Apple App Store. The data set is obtained from Mobilewalla (Datta et al. 2012). It contains the basic information (e.g., name, developer, release date, category) of all apps that were released between January 2011 and March 2012. The information of user ratings is collected on a daily basis but the crawler only captures the changes detected. Previous research (Qiu et al. 2011) points out that many amateur developers publish apps on mobile platforms only for fun. This observation contradicts the objective of our study which is to provide insights for developers who view creating mobile apps as a career. Thus, we exclude the developers who have less than four apps at the end of our observation period. The reason is that developers with an app portfolio of a moderate to large size are likely to be professional developers. Another concern is that it is meaningless to analyze portfolio management if a developer only has very few apps. Finally, we exclude the developers who entered the Apple App Store before 2011 since we do not have complete information on them.

---

2 We also estimate our model with alternative cutoffs i.e., 3 and 5. Our results do not change qualitatively.

3 As a result, our sample contains developers who entered the Apple App Store between January 2011 and March 2012 and had no less than 4 apps in March 2012. Our observation period covers a whole year and is able to capture different segments of developers.
As our study aims to uncover the impact of app portfolio size and diversity on developers’ performance, the time granularity of one month is appropriate to capture the change of developers’ app portfolio. We cluster apps by their developer and aggregate each developer’s app release history to a monthly level. From the data, one can observe the developers’ monthly app portfolio composition as well as the user rating information of each app. Finally, we obtain a panel data of 11,579 developers, containing 92,018 observations. Since developers joined the Apple App Store at various time points, the panel is unbalanced. In our data set, each developer, on average, has 8 observations.

We do not observe developers’ actual performance in terms of sales revenue or downloads, since the Apple App Store does not publicize such information (Zhong and Michahelles 2013). We contend that consumers’ willingness to pay increases in the quality of an app and the valence of user ratings is a good indicator for the app quality (Liu 2006). Thus, the valence of user ratings is used to measure developers’ performance. In the Apple App Store, users are asked to evaluate an app by assigning a score from 0 to 5 stars, with an interval of 1 star. As there are multiple apps in a developer’s app portfolio, we average the values of user rating valence and use as our dependent variable (DV). Our DV, hence, is a real number between 0 and 5.

The key independent variables (IVs) are the size and diversity of an app portfolio. The size of an app portfolio is measured as the total number of apps owned by a developer in a certain month. To measure the diversity of an app portfolio, we use entropy, which is more sensitive to small changes than other alternative measurements and recommended by previous literature (Jacquemin and Berry 1979). The calculation of the entropy is shown in Equation (1) and Equation (2). The Apple App Store allows an app to be attached to multiple categories. We define a distinct pair of category and app as a combination. \( P_s \) captures the ratio of the number of combinations that belongs to category \( s \) to all the combinations in the developer’s app portfolio. The entropy is the sum of \((-P_s \times \ln P_s)\) over the non-empty categories.

\[
\text{CategoryEntropy} = - \sum_{s \in Z} (P_s \times \ln P_s) \quad (1)
\]

\[
P_s = \frac{\sum_{j \in AP} \mathbb{1}(s \in C_j)}{\sum_{j \in AP} \text{count}(C_j)} \quad (2)
\]

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

**Model Specification**

To measure the moderating effect, we use an interaction term between app portfolio diversity and portfolio size. Besides the size and diversity of the developers’ app portfolio, many other factors may influence the developers’ performance. We categorize these factors into two groups, developer-level heterogeneities (e.g., developers’ tenure, the average price of apps) and platform-level competition factors (e.g., the numbers of existing apps and new apps on the platform). We incorporate these factors in our empirical model as control variables. Since not all factors that influence developers’ performance are observed by us, the impact of unobservable factors is captured by developer fixed-effects. We include a company indicator to control for the difference between company developers and individual developers. As this indicator is time invariant, its main effect will be absorbed by the fixed-effects. Thus, we add an interaction term between company indicator and portfolio diversity, to capture potential differences between company developers’ portfolio diversity and individual developers’ portfolio diversity.

The changes in app portfolio may take time to affect developers’ performance. Hence, all IVs are lagged by one month\(^4\). Our econometric model is shown in Equation (3), where subscripts \( i \) denotes developer and \( t \) denotes month. Variable definitions and operationalizations are listed in Table 1. \( \beta s \) are the model

---

\(^4\) We estimate the model with current value of the IVs, which generate similar results. We also try models with other lags (i.e., two months and three months), but most coefficients in the models are insignificant, indicating that developers in our sample likely reacted to the market changes in previous month.
coefficients, $\alpha$ captures the developer’s unobserved heterogeneity and $\epsilon_{i,t}$ is the residual error term.

$$\text{AvgRatingValence}_{i,t} = \alpha + \beta_1 \text{APSize}_{i,t} + \beta_2 \text{APDiversity}_{i,t} + \beta_3 \text{APVersion}_{i,t} \times \text{APSize}_{i,t} + \beta_4 \text{APDiversity}_{i,t} \times \text{Company}_{i,t}$$
$$+ \beta_5 \text{FreeRatio}_{i,t} + \beta_6 \text{AvgPrice}_{i,t} + \beta_7 \text{StdPrice}_{i,t} + \beta_8 \text{PromotionApps}_{i,t} + \beta_9 \text{AvgVersionNum}_{i,t}$$
$$+ \beta_{10} \text{Tenure}_{i,t} + \beta_{11} \text{iOSNewApps}_{i,t} + \beta_{12} \text{iOSPromotionApps}_{i,t} + \beta_{13} \text{iOSAppName}_{i,t} + \epsilon_{i,t}$$

Table 1 Variable Definitions and Operationalizations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition and Operationalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>AvgRatingValence</td>
<td>Average user rating score of the apps in developer $i$’s portfolio in month $t$, which was calculated based on the rating information on the last day of month $t$.</td>
</tr>
<tr>
<td>APSize</td>
<td>Total number of apps in developer $i$’s portfolio in month $t$, which was calculated based on the rating information on the last day of month $t$.</td>
</tr>
<tr>
<td>APDiversity</td>
<td>Category entropy of developer $i$’s portfolio, which was calculated according to Equation (1) and Equation (2). Its variation came from developer $i$’s newly released apps in month $t$.</td>
</tr>
<tr>
<td>Company</td>
<td>Indicator of a company developer (=1, company developer; =0, non-company developer) Company developers were recognized by the last word of developers’ names. We clustered developers based on the last word of their names since most company developers ended their name with words such as “Ltd.”, “Inc.”, etc. Developers, who belong to clusters with size equal or larger than two$^5$, are considered as company developers, otherwise, individual developers.</td>
</tr>
<tr>
<td>FreeRatio</td>
<td>Number of free apps divided by the total number of apps in developer $i$’s portfolio in month $t$. Free apps are apps with zero average price in month $t$.</td>
</tr>
<tr>
<td>AvgPrice</td>
<td>Average price of all the apps in developer $i$’s portfolio in month $t$. We first acquired the average price of each app in month $t$ (since we had apps’ daily price information), then took the mean value of the average prices of apps in developer $i$’s portfolio.</td>
</tr>
<tr>
<td>StdPrice</td>
<td>Standard deviation of prices of all the apps in developer $i$’s portfolio in month $t$. We first acquired the average price of each app in month $t$ (since we had apps’ daily price information), then took the standard deviation of the average prices of apps in developer $i$’s portfolio.</td>
</tr>
<tr>
<td>PromotionApps</td>
<td>Number of apps that have been promoted in developer $i$’s portfolio in month $t$. We first acquired price standard deviation of each app in month $t$ (since we had apps’ daily price information). Apps with non-zero price standard deviation were considered being promoted.</td>
</tr>
<tr>
<td>AvgVersionNum</td>
<td>Average number of versions an app has in developer $i$’s portfolio in month $t$. We first counted the total versions that each app had on the last day of month $t$, then calculated the average version number owned by developer $i$’s apps.</td>
</tr>
<tr>
<td>Tenure</td>
<td>Count of months that have passed since developer $i$ released the first app till month $t$.</td>
</tr>
<tr>
<td>iOSNewApps</td>
<td>Number of new apps released in the Apple App Store in month $t$ (in thousands).</td>
</tr>
<tr>
<td>iOSPromotionApps</td>
<td>Number of apps that have been promoted in the Apple App Store in month $t$ (in thousands). The operationalization of promoted apps is the same as that of PromotionApps.</td>
</tr>
<tr>
<td>iOSAppName</td>
<td>Total number of apps available in the Apple App Store in month $t$, excluding the new apps (in hundred thousands).</td>
</tr>
</tbody>
</table>

Preliminary Results

Our DV AvgRatingValence is a real number between 0 and 5, with a mean of 0.96, a median of 0.25 and a standard deviation of 1.29. A linear panel data model is thus appropriate for our empirical analysis. Since many explanatory variables in our model are cumulative measures, the error term in our model may be serially correlated. In order to test serial correlation, we follow the approach proposed by Wooldridge (2002) and Drukker (2003). The test rejects the null hypothesis of no serial correlation at the significance level of 0.05. A panel-level ordinary least square estimator with a first-order autoregressive disturbance structure, therefore, is used to estimate our econometric model. The correlation matrix (omitted due to space limits) shows that all pairwise correlations are less than 0.6, indicating that multicollinearity is not a problem in this study. We first estimate the model without the interaction term. Both fixed-effects (FE) model and random-effects (RE) model are estimated. The Hausman test rejects the null hypothesis, thus

$^5$ The size of a cluster refers to the number of developers in this cluster and these developers share a common end word. Developers in a cluster with larger size are more likely to be company developers since the end word is shared by more developers. We define company developers in our data set as developers whose name with an end word that is shared by no less than two developers. To examine whether our results are sensitive to this cutoff, we also tested alternative size cutoffs, i.e., 3, 4, 10, 20, 60. All results are qualitatively similar to the main results reported in the section of Preliminary Results.
we focus on the results of FE model. As both $APSize$ and $APDiversity$ are significant, we further investigate their moderating effect by incorporating the interaction term. Columns (1) and (2) in Table 2 are the results of the FE model and RE model, respectively. The Hausman test again rejects the null hypothesis. Hence, we interpret the results based on column (1).

### Table 2 Estimation Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) FE</th>
<th>(2) RE</th>
<th>(3) FE-CategoryHHI</th>
<th>(4) FE-CategoryCount</th>
</tr>
</thead>
<tbody>
<tr>
<td>$APSize$</td>
<td>0.0001</td>
<td>-0.0084***</td>
<td>-0.0010</td>
<td>0.0012*</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0007)</td>
<td>(0.0012)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>$APDiversity$</td>
<td>-0.0291***</td>
<td>-0.0930***</td>
<td>-0.0556***</td>
<td>-0.0046**</td>
</tr>
<tr>
<td></td>
<td>(0.0079)</td>
<td>(0.0071)</td>
<td>(0.0143)</td>
<td>(0.0019)</td>
</tr>
<tr>
<td>$APDiversity^{*}APSize$</td>
<td>0.0016***</td>
<td>0.0034***</td>
<td>0.0047***</td>
<td>0.0001*</td>
</tr>
<tr>
<td></td>
<td>(0.0006)</td>
<td>(0.0005)</td>
<td>(0.0018)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>$APDiversity^{*}Company$</td>
<td>0.0033</td>
<td>0.0183**</td>
<td>-0.0087</td>
<td>-0.0014</td>
</tr>
<tr>
<td></td>
<td>(0.0096)</td>
<td>(0.0080)</td>
<td>(0.0214)</td>
<td>(0.0027)</td>
</tr>
<tr>
<td>$FreeRatio$</td>
<td>0.0189**</td>
<td>0.0308***</td>
<td>0.0189**</td>
<td>0.0198**</td>
</tr>
<tr>
<td></td>
<td>(0.0081)</td>
<td>(0.0075)</td>
<td>(0.0081)</td>
<td>(0.0081)</td>
</tr>
<tr>
<td>$AvgPrice$</td>
<td>0.0000</td>
<td>-0.0003</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>$StdPrice$</td>
<td>-0.0002</td>
<td>-0.0005**</td>
<td>-0.0002</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>$PromotionApps$</td>
<td>-0.0128</td>
<td>0.0288</td>
<td>-0.0127</td>
<td>-0.0129</td>
</tr>
<tr>
<td></td>
<td>(0.0180)</td>
<td>(0.0183)</td>
<td>(0.0180)</td>
<td>(0.0180)</td>
</tr>
<tr>
<td>$AvgVersionNum$</td>
<td>-0.0009</td>
<td>0.1196***</td>
<td>-0.0008</td>
<td>-0.0007</td>
</tr>
<tr>
<td></td>
<td>(0.0031)</td>
<td>(0.0028)</td>
<td>(0.0031)</td>
<td>(0.0031)</td>
</tr>
<tr>
<td>$Tenure$</td>
<td>0.0256**</td>
<td>0.0253***</td>
<td>0.0255**</td>
<td>0.0258**</td>
</tr>
<tr>
<td></td>
<td>(0.0107)</td>
<td>(0.0025)</td>
<td>(0.0107)</td>
<td>(0.0107)</td>
</tr>
<tr>
<td>$iOSNewApps$</td>
<td>-0.0002</td>
<td>-0.0010***</td>
<td>-0.0002</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>$iOSPromotionApps$</td>
<td>-0.0000</td>
<td>0.0002</td>
<td>-0.0000</td>
<td>-0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>$iOSAppNum$</td>
<td>-0.1916***</td>
<td>-0.2572***</td>
<td>-0.1911***</td>
<td>-0.1915***</td>
</tr>
<tr>
<td></td>
<td>(0.0447)</td>
<td>(0.0104)</td>
<td>(0.0448)</td>
<td>(0.0447)</td>
</tr>
<tr>
<td>$Constant$</td>
<td>1.7608***</td>
<td>2.1557***</td>
<td>1.7645***</td>
<td>1.7488***</td>
</tr>
<tr>
<td></td>
<td>(0.0473)</td>
<td>(0.0476)</td>
<td>(0.0472)</td>
<td>(0.0474)</td>
</tr>
</tbody>
</table>

1. Standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.
2. Number of observations = 92,018, number of developers = 11,579.

$APSize$ has a positive coefficient in column (1) but is insignificant. It indicates that, statistically, app portfolio size does not influence developers’ performance. $H1$ is thus not supported. The coefficient of $APDiversity$ is negative and significant, which suggests that app portfolio diversity negatively affects developers’ performance. This supports $H2$. The interaction term between $APDiversity$ and $APSize$ is significantly positive. It implies that the negative impact of app portfolio diversity on developers’ performance decreases with app portfolio size. $H3$ thus gains support. Combining the coefficients of $APDiversity$ and $APDiversity^{*}APSize$, we know that the net marginal effect of $APDiversity$ on developers’ performance is (-0.0291+0.0016*APSize). There is a critical point of about 18 (i.e., 0.0291/0.0016) in $APSize$. On average, when $APSize$ is smaller than 18, an app portfolio with a higher diversity brings about poorer performance for developers. However, when $APSize$ is equal to or greater than 18, developers could benefit from a more diversified app portfolio. Our findings with regard to the control variables are: (1) Portfolio diversity has same impact on company developers and individual developers. (2) Price composition of an app portfolio also influences developers’ performance. Developers who have a portfolio with a larger proportion of free apps perform better. (3) Developers with longer tenure have a better performance. (4) The competition intensity in the Apple App Store negatively associates with developers’
performance.

As a robustness check, column (3) and column (4) use alternative measurements, i.e., the adapted Herfindal-index (Jacquemin and Berry 1979) and category count, to measure the diversity of an app portfolio. The calculation of the adapted Herfindal-index is shown in Equation (4). The model with Herfindal-index supports H2 and H3 as well. Category count is the total number of categories that a developer's apps are relevant to. The corresponding results are shown in column (4). The results support not only H2 and H3, but also H1.

\[
\text{CategoryHHI} = 1 - \sum_{s \in S} \frac{P_s * P_s}{P_s}
\]  

(4)

Discussion and Future Research

In this study, we investigate the impact of app portfolio, particularly portfolio size and diversity, on developers' performance. We find that the diversity of an app portfolio is negatively associated with developers' performance, but the strength of this relationship decreases with app portfolio size. It implies that when the size of the app portfolio is small, increasing app portfolio diversity is detrimental to developers' performance. After app portfolio size crosses a critical point, diversifying app portfolio benefits developers. Different from our results, the study by Lee and Raghu (2011) finds a positive return in the diversity of an app portfolio. A possible explanation is that they only focus on developers who have at least one top-ranked app. These developers may have already crossed the critical point that is found in our study, hence resulting in a positive marginal effect of the diversity.

Our study does not come without limitations. The first problem originates from the measurement of developers' performance. We use app rating valence to proxy developers' performance, but the best choice is to use developers' financial performance. As the Apple App Store keeps app downloads and revenue data confidential, the general public is unable to access these information, which is acknowledged by many relevant studies (e.g., Garg and Telang 2012; Zhong and Michailhes 2013). Due to the relatively low entry barrier in app stores, a large proportion of mobile app developers are individuals or part-time teams rather than registered or listed companies. Though some financial databases do provide information about small to medium enterprises, this information hardly covers most of the developers in mobile app stores. Thus, user ratings are the most complete and directly observable metrics to measure developers' performance. Moreover, we use the category classification system predefined by the app store to quantify the diversity of developers' app portfolio. The category relatedness of each app is reported by developers. It may reflect developers' perception of category relatedness of their apps or it may be developers' deliberate marketing tricks. Some developers may categorize their apps to popular categories (e.g., Games, Entertainment) rather than the most relevant categories so as to reach a wide market. A potential method to overcome this effect is to assess the category relatedness of each app by ourselves. However, because of the large number of apps in our dataset (214,608 apps released by developers who entered the Apple App Store since 2011), manual coding is infeasible. A possible solution is to analyze apps' description or permission list and compute the similarity or dissimilarity of apps in developers' portfolio. In addition, developers' performance is greatly influenced by supply side factors, such as the size of development team, working experience of team members and funding conditions. However, while we do not have information on such developers' characteristics, such attributes can be partially controlled by developer time-invariant fixed-effects. Detailed developer-level information in the future, if any, will greatly benefit our empirical analysis.

Though we have estimated the impact of app portfolio size and diversity on developers' performance, the underlying mechanisms are not yet clear. We do not know the details of how developers' performance changes with each new app added or how the new apps interplay with the existing apps in a portfolio. Additionally, the dissimilarity between two categories may vary and a single dimensional measurement of app portfolio diversity may not capture this variation sufficiently. Hence, we plan to do further analysis in the future study: (1) Use a different approach to capture the similarity or dissimilarity between apps rather than depending on the predefined category scheme in the Apple App Store. (2) Incorporate the introduction of new apps to the analysis. We will add variables that capture the relatedness or unrelatedness of the new apps to the existing app portfolio, such as category similarity, price difference. (3) Account for developer-level heterogeneity by incorporating more factors, such as the dummy variables for multi-homing developers and publicly listed developers.
References


