# Does diversification pay in the app market? Evidence from the Apple App Store and Google Play

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## Abstract

In this paper we address the study of the effects of product line diversification on firm performance in the mobile application market. Specifically, we shed light on whether the distribution platform ecosystem where developers commercialize their apps influence the effect of product line diversification, i.e., diversification across different app categories, on developer sales performance. To these purposes, we compare the sales performance of diversified developers with that of category-specialized developers in the two major app stores (namely, Apple's App Store and Google Play). Our results show that the diversification strategy has a positive impact on developer sales in Google Play, while no significant impact emerges in the Apple's App Store. The cross-platform differences in consumer willingness to pay are the rationale behind the different effect of diversification on sales performance across platform ecosystems. Our results have an important implication for developers as they suggest that developers should factor in the app ecosystem where they operate when making the decision on whether to diversify or not.

**Keywords:** Diversification, Mobile App Market, Distribution Platforms, Ecosystems, Empirical analysis.

## 1. Introduction

There is considerable disagreement about the effects of corporate diversification on the firm financial performance, and how and when this strategy can be used to build competitive advantage (Markides and Williamson, 1994; Palich et al., 2000). For instance, a copious body of the financial literature believes that corporate diversification will result in a reduction in value for shareholders (Berger and Ofek, 1995; Lang and Stulz, 1994). In contrast, other studies in the same literature provide evidence that numerous diversified firms are traded at a premium, and not at a discount (Villalonga, 2004). In line with the existence of opposing views, some studies document notable heterogeneity of price reactions following the announcement of diversification processes (Rajan, Servaes, and Zingales, 2000; Santalo and Becerra, 2008).

Divergent views also exist about the impact of product line diversification on firm performance. In spite of the rise of organizational diseconomies and internal capital market inefficiencies (Grant et al., 1988; Markides, 1992; Palich et al., 2000), firm could gain a number of benefits from product line diversification. Firms can take advantage of economies of scope by increasing the utilization of certain resources, i.e., brand, focused technologies, that cannot be sold externally due to high transaction costs and other market imperfections (Markides, 1992; Markides and Williamson, 1994). By means of diversification, firms also become more able to reduce the firm's overall risk (Berger and Ofek, 1995). Economic theory also suggests that diversification can deliver benefits related to enhanced market power. For instance, in the long-term diversified firms could benefit from the adoption of predatory pricing strategy for certain products as they can more easily sustain short-term losses through product cross-subsidization (Saloner 1987; Berger and Ofek, 1995; Aribarg and Arora, 2008). Moreover, by diversifying their product offering, firms can better exploit the opportunity to serve consumers with different preferences and needs (Quelch and Kenny, 1994) and, in turn, the ability to reduce the risk associated with the uncertainty of future preferences and demand for each line. Despite the existence of numerous benefits associated with product line diversification, some firms may feel more advantageous to focus on narrow product lines in order to achieve economies through reductions in production, design and inventory costs, and especially to favor the development and the consolidation of specific skills enabling the creation of superior products (Argote and Miron-Spektor, 2011; Boh et al., 2007; Mukhopadhyay et al., 2011).

While there exists consolidated literature on both corporate and product line types of diversification, some recent studies (e.g., Santalo and Becerra, 2008) point out that whether the diversification strategy has a positive or negative impact on firm performance depends on the industry where the firm operates. This implies that the competitive environment where firms compete plays an important role in shaping the relationship between diversification and firm performance. Therefore, from a practical viewpoint, the study of specific industries is important to deliver information that can be utilized by practitioners in their strategic decisions. Also, from a theoretical viewpoint, the argument that the competitive environment where firms operate can influence the performance-diversification relationship opens up room for enhancing the understanding of which environment features are likely to play a role in such relationship. In this paper we address the study of the effects of product line diversification on firm performance in a peculiar (and novel) industry, namely the mobile application (hereafter, app) market. To the best of our knowledge, there are only very few studies examining the impact on performance of a product line diversification strategy in the app market. For example, Lee and Raghu (2014) find that broadening app offerings across multiple categories is a key determinant that contributes to a higher probability of survival in the top charts. This finding hints at the existence of a positive relationship between inter-category diversification and developer sales performance. We further examine the impact of diversification on developer performance. Specifically, we endeavor to shed light on whether an important environment feature, i.e., the distribution platform ecosystem where developers commercialize their apps influence the effect of product line diversification (intended to be as diversification across different app categories) on developer sales performance. An app store can be indeed viewed as an online platform ecosystem where multiple parties (app users, developers, OS/device makers, platform owners) can interact. As a matter of fact, in an app store, users can download and rate apps developed by third parties (i.e., developers) for mobile devices and operating systems (OS) supported by the platform. In particular, the unique relationship between the mobile OS/device market and the app market creates significant differences in the type of consumers accessing different platforms. Indeed, once consumers choose their favorite OS/mobile device (e.g., Apple or Android), they are locked in by this decision, as they rely exclusively on the sponsored platform to source their apps. This implies that the customer base in a given platform strictly depends on the customer base of the associated product, i.e., the mobile device and the relative OS. Different mobile device makers and/or OS providers naturally target different segments based on their product quality and marketing capabilities. As a result, developers are likely to face significantly different consumer segments in different distribution platform ecosystems. For instance, Apple targets exclusively the (loyal) high-end of the market, whereas the sales of Android devices are mostly fueled by low-end segments of the market (Hixon 2014; Ghose and Han 2014). As result of the emergence of these cross-platform differences, we posit that, the effect of product line diversification on developer sales performance should vary across different platform ecosystems. Therefore, we contribute to the extant literature on diversification by adding one important factor that can shape the relationship between diversification and firm performance, namely the distribution platform ecosystem.

We contribute from a practical perspective as well. Indeed, according to Venturebeat, the app market has shown an astonishing growth stepping from less than $10 billion annual revenue in 2011 up to estimated $70 billion by 2017 (Takahashi, 2014). Nowadays, apps are commercialized mostly in two app distribution platforms, namely Apple's App Store and Google Play, which account together for almost 90% of the market (Gartner, 2013) and offer business opportunities to a multitude of developers across the globe. In a highly dynamic and competitive environment, app developers need to make a number of decisions crucial for their profitability. One of them certainly relates to the choice of the type and the number of apps to market. Particularly, app developers face the strategic decision to specialize in a few (maybe one) app categories or diversify among a large number of app categories. Therefore, shedding light on how a diversification strategy impacts on their sales performance and how the diversification-performance relationship hinges upon the platform ecosystem where developers operate can provide useful guidelines to help them make better diversification (or specialization) decisions.

To our purposes, we compare the sales performance of diversified developers (i.e., a developers marketing apps in different categories) with that of category-specialized developers in the two major app stores (Apple's App Store and Google Play) and examine whether the app store ecosystem (Apple vs. Google) in which developers operate plays an important role in the relationship between diversification and sales performance. By way of anticipation, our results show that the diversification strategy has a positive impact on developer sales in Google Play, while no significant impact emerges in the Apple's App Store. Essentially, diversified developers are associated with a better sales performance than specialized developers in Google Play, whereas in the Apple's App Store, diversified developers do not seem to differ from specialized developers in terms of sales performance.

We connect these results to the cross-platform differences in consumer willingness to pay, which naturally influences the comparative advantages and disadvantages of diversification versus specialization.

The paper unfolds as follows. In § 2 we present the theoretical background behind our hypotheses. In § 3 we describe the dataset, the variables and the methods utilized in this paper. We present and discuss the results in § 4. Finally, § 5 concludes.

## 2. Theory and hypotheses

In line with some previous studies (e.g., Tanriverdi and Lee, 2008; Lee and Raghu, 2014), given the absence of cost information, we rely on sales as a measure of firm performance, and accordingly our arguments on the advantages and/or disadvantages of diversification need to reflect the implications of diversification on such measure of performance. In this regard, we argue that app development and commercialization across multiple categories may have some advantages from sales perspective. First, consistent with the theories of product line extensions (Rothaermel et al., 2006), serving heterogeneous consumer demands helps reduce the uncertainty associated with demand variability. That is, the demand reduction in a certain category can be compensated by an increase in another category. Second, enhanced market power via diversification can also have a positive influence on sales (Saloner 1987; Berger and Ofek, 1995; Aribarg and Arora, 2008). As explained, in the long-term diversified firm could benefit from the adoption of predatory pricing strategy for certain products as they can more easily sustain short-term losses through product cross-subsidization (Saloner 1987; Berger and Ofek, 1995; Aribarg and Arora, 2008). Moreover, by diversifying their product offering, developers can take advantage of the consumer base already installed for a certain product line when introducing a new product line. This helps fuel the "bandwagon effect", which is particularly relevant for the diffusion of information goods (Tanriverdi and Lee, 2008).

However, in spite of the benefits above and the additional cost-related advantages entailed for instance by the reuse of code components for some common functions (Haefliger et al., 2008), the specificity of each category in terms of content and functionality may require developers to develop a great variety of coding skills and other resources necessary for the development and commercialization of different apps. For instance, applications in the navigation category require frequent map updates, which calls for strong support from the server. In contrast, games app may not need a high-end server coding, but still they require sophisticated designs, user interface, and the creation of the game. This suggests that, in comparison with a specialized developer, a diversified developer may not be able to develop the same level of expertise necessary to create high-quality products able to succeed in the market. This is because the diversified developer has to distribute the efforts for the realization of very different applications (Montgomery and Wernerfelt, 2010).

Because of the existence of counteracting forces, the ultimate effect of diversification on sales performance is unclear. Particularly, we argue that such effect may be significantly influenced by the ecosystem (Apple vs. Google) in which developers operate. Some recent studies in the financial literature (e.g., Santalo and Becerra, 2008) have shown that whether corporate diversification can create or destroy value strongly depends on the industry characteristics (specifically, the prevalence of diversified vs. specialized firms). By following this argument, we advance that in the app market whether product line diversification yields a better sales performance than product line specialization depends on the distribution platform ecosystem where developers operate. Specifically, we posit that, in Google Play ecosystem, developers who have chosen to diversify across multiple app categories should display a higher sales performance than specialized developers. In contrast, we argue that this should not be the case in the Apple ecosystem.

The rationale is that in Google Play, consumers have lower average willingness to pay (Ghose and Han, 2014). Therefore, to increase sales, developers operating in this store need to capture a large market base (comparatively speaking). According to Tanriverdi and Lee (2008), diversified developers can "exploit" the consumer base already installed for a certain app category also for other app categories, fueling the "bandwagon effect" in the diffusion of apps across categories. This advantage is, of course, precluded to specialized developers. In addition, in Google Play specialized developers cannot counterbalance much this disadvantage with the specialization-related benefit of commercializing higher quality (and thus higher prices) apps because consumers in this ecosystem are less receptive to highly priced apps as compared to the Apple's App Store. This implies that a diversification strategy should be preferred to a specialization strategy in this store. In contrast, in the Apple's App Store, the presence of higher consumer willingness to pay provides higher incentive to develop higher quality (and thus higher price) apps (Ghose and Han, 2014), and thus monetize on margins. Through specialization, developers operating in this store can build expertise that will allow them to develop and commercialize high quality apps more effectively. In contrast, this is more difficult to obtain through product line diversification as in this case development and commercialization efforts are distributed across a number of different applications. Therefore, in the Apple's App Store, the advantages of specialization (i.e., higher quality products) are likely to compensate the advantages of diversification (i.e., higher user base). Accordingly, we formulate the following hypotheses:

*Hypothesis 1: Diversified developers do not display higher sales performance than specialized developers in the Apple App Store.*

*Hypothesis 2: Diversified developers display higher sales performance than specialized developers in Google Play.*

## 3. Data & Methods

### *3.1 Data*

To test our hypotheses, we use data preliminarily collected in a period between March 9th, 2013 and June 7th, 2014 from the two major app stores, namely Apple App Store and Google Play. Specifically, we consider all apps of developers ranked (with at least one app) in the top 1000 grossing app ranking (i.e., the ranking of 1000 apps generating the highest revenue) in the above time span. As revenues are not publicly available, to compute them for each developer in our sample we use the procedure suggested by Garg and Telang (2013). Essentially, this procedure allows to infer daily app sales from daily app ranks by means of the well-known power law function relationship estimation (Brynjolfsson et al., 2003, Chevalier and Goolsbee, 2003). This procedure differs from previous approaches in that it does not need real sales data to estimate the parameters of the power law function. Indeed, Garg and Telang (2013) take advantage from the fact that several (inter-related) top app rankings are provided by app stores. Specifically, laying out a system of power law relationships between daily sales and daily ranks for top grossing, top paid and top free apps rankings allows to estimate the parameters necessary to compute the sales (with no need of retrieving data on real sales). The procedure can be easily extended to incorporate revenue from free apps (e.g., advertising revenue streams) and in-app purchase, thus allowing the estimation of all revenue streams that an app can generate. For more details on the procedure, the reader can refer to Garg and Telang (2013). In this paper we strictly follow this procedure to estimate the daily app revenue, obtaining results quite similar to those obtained by Garg and Telang (2013). The outcome of this procedure, i.e., the estimates of daily app sales for each developer in both stores, is the starting point of our analysis.[1]

Note that the apps considered in our sample are not only those appearing in the top 1000 grossing app rankings of the two stores, but they include also those not featured in these rankings, but still developed by a developer able to bring at least one app in one of the two top grossing rankings. The reason is clearly due to the fact that we need to consider all revenue components for each developer to properly examine the role of diversification on the sales performance. Excluding some apps for a developer would lead to inaccurate revenue estimates. Essentially, monitoring the top 1000 grossing app rankings allows us to identify successful developers, to be intended as those able to bring at least one app in one the two top grossing rankings. All apps commercialized by these developers are considered in our sample.

The choice of relying on top app rankings is consistent with prior research analyzing the app market (e.g., Carare 2012; Garg and Telang 2013). There are several important reasons for why all studies consider top app rankings. First, these rankings are easily available from the app stores. Second, the insights obtained from studying successful apps and developers, rather than average apps and developers, can be certainly more useful to developers that are planning the development and marketing of new apps. Third and most important, although both App Store and Google Play count more than one million applications available for download, the actual number of apps that are displayed to consumers is much more limited. In both stores consumers have access only to web pages displaying top rankings (e.g., top free, top paid, top grossing) for all apps, top rankings within each app category or top new entries and sponsored apps. Essentially only the very top portion of the app market is actually visible to consumers. This implies that top rankings are arguably the primary source of information not only for researchers to study this novel market, but also for consumers to make their purchase decisions, as highlighted also by Carare (2012). Finally, our choice of observing apps and developers in a time span of about four months is in line with previous studies on the app market (Carare 2012; Garg and Telang 2013). In particular, it is in line with Lee and Raghu (2014), who first study the performance implications of diversification in the app market.

[1] The details of this preliminary estimation analysis are available from the authors.

Naturally, given that we examine the effect of developers' diversification on their sales performance, the developer is our unit of analysis, and some characteristics are observed for each developer on daily basis during the period of observation. This implies that the daily app sales related to the same developer are aggregated on a daily basis for each developer. In a time span of 120 days, our initial sample encompasses more that 3,500 apps developed by 416 developers in the two stores. To properly compare diversified developers with specialized developers, we are forced to remove from the analysis some developers. Therefore, our final sample includes 45,444 observations related to 386 developers. Specifically, in our final sample we count 24,886 observations related to 209 developers commercializing apps in the Apple's App Store and 20,558 observations related to 177 developers in Google Play. Since we are interested in the performance implications of product line diversification, it is useful to point out that the above observations are related to 20 categories, namely Books & Consulting, Customization, Education, Entertainment, Finance, Games, Healthcare & Fitness, Lifestyle, Medicine, Music, Navigation, News, Photo & Video, Productivity, Social Networking, Sports, Tools, Travel, Utilities, and Weather. In our study, developers commercializing apps in more than one of these categories are considered diversified, whereas those focusing on apps belonging only to one of these categories are considered specialized. This is consistent with the definition of product line diversification as apps belonging to different categories satisfy different sets of consumer needs. Finally, our sample is an unbalanced panel dataset as some developers were able to bring at least one app in the top 1000 app ranking of the given store only during the period of observation. Thus, we count a lower number of observations for these developers as compared with those developers able to bring at least one app in the top 1000 app ranking of the given store since the beginning of our period of observation.

### *3.2 Variables*

*Dependent variable*

To properly compare the sales performance of diversified developers with that of specialized developers we need to identify a measure of sales performance that rules out the trivial differences between diversified and specialized developers. To do so, we adopt the standard chop-shop approach (Lang and Schulz, 1994; Berger and Ofek, 1995; Santalo and Becerra, 2008). In our setting, this consists of adjusting the revenues of diversified developers in order to ensure a correct comparison with nondiversified developers. Specifically, for each diversified developer we compute the ratio between the actual daily revenue generated by the developer (estimated by using Garg and Telang (2013) procedure) and a "what would be" daily revenue of the same developer. The latter is computed as the weighted average of the daily revenue the developer would generate if he were a specialized developer in each category in which he develops apps. The daily revenue in each category is simply the average revenue of all specialized developers in the category in the given day. The weights are given by the ratio between the daily revenue of the diversified developer in the given category and the developer's total daily revenue. For specialized developers, the computation is similar except for the fact that only one category is naturally considered. The ratio between the actual daily revenue and the "what would be" daily revenue is essentially a category-adjusted measure of performance. Our dependent variable for each developer is the logarithm of this ratio (i.e., *Category-adjusted Developer Sales Performance Ratio*) computed above for diversified and specialized developers, respectively. In Table 1, we report the descriptive statistics of this ratio (with no logarithmic transformation). It can be noted that this ratio is on average equal to 5.495, thus implying that the actual revenue is more than five times higher than the "what would be" revenue. Given that by construction this ratio is on average equal to one for specialized developers, there could be an overall positive effect of diversification on sales performance. However, it is interesting that, while being higher than one for both stores, this ratio is much higher in Google Play than in the Apple's App Store (7.855 vs. 3.547), thus hinting at the existence of an effect of the distribution platform ecosystem on the relationship between diversification and sales performance. We will unravel these aspects by using more appropriate instruments than simple descriptive statistics.

*Main independent variables*

*Diversification:* in line with the prior literature (e.g., Santalo and Becerra, 2008) we introduce a dummy variable (*Diversification*) equal to one if the given developer is diversified in the given day, and equal to zero if specialized. As discussed earlier, developers commercializing apps in more than one category are considered diversified, whereas those focusing on apps belonging only to one category are considered specialized. Table 1 shows that approximately twenty percent of the observations are related to diversified developers and there are no differences between the two major stores. This suggests that during our period of observation the inter-category diversification strategy was actually chosen by a minority of developers in both stores. To test whether the effect of diversification on sales performance is influenced by the store where the developer operates, one approach we undertake is to introduce in the regression model the interaction between the diversification dummy and a variable (namely, *Store*) equal to one if the given developer in the given day is observed in Apple's App Store, zero if observed in Google Play.

*Control variables*

*Developer concentration in an app category:* in line with previous studies (Santalo and Becerra, 2008; Tanriverdi and Lee, 2008) we control for the level of developer concentration within each app category in the given store by computing and introducing a daily measure of the Herfindahl-Hirschman Index (HHI), namely *Category HHI*. The level of developer concentration (and thus the level of developer competition) within a category is indeed an important category characteristic that can affect the sales performance of both diversified and specialized firms, thus needs to be controlled for. In our study, this measure is obtained by computing the market shares as the daily revenue of each developer appearing, with at least one app, in the top 1000 grossing apps of the given store on the given day divided by the total revenue of all the developers featured in the top 1000 grossing app ranking of the same store on the same day. We recognize that this measure does not take into account all developers commercializing apps in the given category in the given store on a given day. However, as explained earlier, the vast majority of apps and developers are never displayed on the pages of the two stores. Therefore, it is not possible to retrieve time-varying information on the sales of all developers in a category and a platform. With a multitude of apps "invisible" to consumers, the majority of developers of such apps are never a threat to developers of top apps. Therefore, our measure of developer concentration is likely to be an accurate measure of the level of competition with a category in a given store as the major threats for a developer are likely to come from successful developers, i.e., from developers able to feature their apps in the top 1000 grossing rankings. From Table 1, we observe that the level of developer concentration within category is not high (the average is overall 0.141), thus confirming that, at least among successful developers, the competition within category tends to be fierce, with no relevant differences between the two platforms.

*Store sales growth rate*: in line with Tanriverdi and Lee (2008), we also control for the daily growth rate of the total sales generated in the app store where the given developer competes (namely, *Store Sales Growth Rate*) to account for the intuitive fact that a growing (shrinking) market can result in a better (worse) firm sales performance. From Table 1, we observe that the store sales level is relatively stable with an average growth rate almost equal to zero in both stores, and a slightly more pronounced standard deviation.

Developer prior sales*:* we control for the prior sales performance of a developer as in a relatively short period of observation the sales performance is likely to be persistent. That is, the previous sales performance of a developer can influence its subsequent sales performance (Tanriverdi and Lee, 2008). Given that we have estimates on developer sales at our disposal for the entire period of observation, we compute the prior sales of each developer in the given store by simply lagging the developer sales. In particular, we introduce the revenue generated in the previous seven days as our measure of developer prior sales (namely, *Developer Prior Sales*).[2]

Developer age: we control for the developer age in the given store by computing and introducing a variable, namely *Developer Age*, which indicates the number of days a developer has been marketing apps in the given store since its first app commercialization. Firm age is naturally associated with firm performance as it reflects the experience and the knowledge maturated by the firm in the given market (Stern and Henderson, 2004; Tanriverdi and Lee, 2008). In fact, developers mature most of their experience from both technical and managerial perspectives by means of a learning by doing process (Argote e Miron-Spektor 2011; Boh et al. 2007; Mukhopadhyay et al. 2011; Singh et al. 2011). Developers need indeed to become familiar with the software development kit provided by the platform in order to develop good apps that can succeed in the market. For these reasons, it appears clear that, *ceteris paribus*, a developer that has marketed apps in the given store for longer time is more likely to be successful. Therefore, controlling for the developer age helps capture the possible effect of experience on the measure sales performance. From Table 1, we observe that developer age is almost two years (687 days) on average. In this case, there are notable differences between Apple's App Store and Google Play as developer age in the latter store tends to be (almost) half of that in the former store, consistent with the argument that developers usually target the Apple's App Store first.

Brand notoriety*:* we take into account the extent of developer notoriety by including a dummy (namely, Brand notoriety), which is equal to one if the brand/developer of the given app is worldwide established, zero otherwise. We identify a list of 36 top developers in our sample based on corporate revenue information and worldwide brand recognition. For instance, this

[2] Note that our results are fully robust when lagging developer sales differently.

list includes mobile app divisions of Adobe Systems, Apple, Disney, Electronic Arts, Gameloft, Marvel Entertainment, Sega, TomTom International, Zynga, among others.

Temporal dummies: to control for any daily factor common to all developers that could affect their sales performance we introduce in the model one dummy for each day of observation.

Table 2 reports the correlation matrix, which suggests no serious degree of correlation between the variables employed in this study. Moreover, our results are not influenced by the presence of multi-collinearity, in spite of the fact that the (uncentered) Variance Inflation Factor (VIF) computed after performing our regression model is high for certain variables (but never of our variable(s) of interest).

### *3.2 Methods*

The results of the Hausman test (as well as a generalization of it, which compares the appropriateness of the random effects versus the fixed effects model and produces the Sargan-Hansen statistic) strongly support the use of fixed effects over random effects regression models ($p<0.001$). Therefore, we use this model to test our hypothesis. However, this implies that time-invariant variables will be automatically removed when performing this regression model. In our sample, the brand notoriety variable does not vary over time, thus it is removed from the analysis when the fixed effects model is used. At any rate, we will consider it when checking robustness of our results by performing standard OLS regression models for each day of observation.

As largely discussed in the extant literature (Campa and Kedia, 2002; Villalonga, 2004; Santalo and Becerra, 2008), potential endogeneity concerns may arise with regard to the relationship between the diversification decision and the sales performance ratio. Various authors have tried to address this problem by resorting to the instrumental variables (IVs) approach. For instance, Campa and Kedia (2002) utilize two sets of instruments, one related to industry characteristics such as industry attractiveness, and the other one capturing firm characteristics such as the presence in major exchange listings and the country of incorporation. However, more recently, Santalo and Becerra (2008) have questioned the exogeneity of this type of instruments, by showing that especially industry characteristics strongly influence the relationship between diversification and firm performance. As a result, the use of the IVs approach in this stream of study is limited by the difficulty to find completely exogenous instruments. We recognize the existence of potential endogeneity concerns, but leave this issue for future improvements of the present study.

## 4. Results and discussion

Table 3 shows our major results of our empirical analysis based on the fixed effects regression model. In the first column, we check the impact of the only control variables alone. It is shown that past sales performance, developer concentration within category, and store sales growth rate are major factors influencing the category-adjusted developer sales performance ratio and they all have positive influence on it. In particular, the previous sales performance is strongly significant. In the second column, we add the diversification dummy and find that, while the significance and the sign of the above control variables remain unchanged, the effect of the diversification decision is largely not significant. Given that this result is derived under the full sample (which includes observations from both Apple's App Store and Google Play), we cannot simply conclude that (at least based on our sample) there is no evidence to claim that diversified developers obtain a superior or inferior perfomance as compared with specialized developer. Indeed, as we have theorized, the effect of diversification on sales performance may be different between the two mobile app ecosystems. Failing to capture the diversity of the two major ecosystems might result in insignificant effects. Therefore to examine the effect of diversification on sales performance more accurately and capture the role of the platform ecosystem, we utilize two approaches. First, as anticipated earlier, we add to the model presented in the second column the interaction term between the diversification dummy and the store dummy. Second, we analyze the subsamples of developers in the Apple's App Store and in Google Play separately. The results obtained under the first approach are reported in the third column of Table 3. After adding the interaction, we find that the coefficient of the diversification dummy, which now reflects the marginal change in the category-adjusted developer sales performance ratio due to diversification in Google Play, is largely significant ($p<0.001$). On the opposite, the coefficient of the interaction term, which instead reflects the marginal change in the category-adjusted developer sales performance ratio due to diversification in the Apple's App Store, is largely insignificant. The regression analysis performed under the separate subsamples further confirms and strengthens this evidence. As a matter of fact, in the fourth column of Table 3, it is shown that the diversification dummy is positive and significant for the subsample drawn from Google Play. On the other hand, in the fifth column of the same table, which reports the results for the subsample drawn from the Apple's App Store, the coefficient of this dummy is once again largely insignificant. Overall, these results suggests that in Google Play diversified developers are associated with a better sales performance than specialized developers, whereas in the Apple's App Store, there is no statistical evidence to claim that diversified developers differs from specialized developers in terms of sales performance. In turn, this suggests that the ecosystem where developers choose to commercialize their apps plays an important role in the sales performance implications of diversification. As we have argued, the two major ecosystems are characterized by large differences in average consumer willingness to pay (Ghose and Han, 2014). In Google Play, consumers have lower average willingness to pay. This implies that, in comparative terms, consumer are not willing to spend much on apps, thus discouraging developers from marketing high quality, which would require high prices. Therefore, to raise their sales developers operating in this store cannot count much on high margins. Rather they need to rely on capturing a large user base. In this environment, by diversifying their product offering and thus serving a multitude of consumer needs, developers can exploit the consumer base already installed for a certain app category also for other app categories, fueling the "bandwagon effect" in the diffusion of apps of the latter categories (Tanriverdi and Lee, 2008). In contrast, specialized developers cannot take advantage of their installed consumer base, thus failing to activate this virtuous circle that propels sales. In addition, in Google Play they cannot counterbalance much this disadvantage with higher quality (and thus higher margin) apps due to specialization because consumers in this ecosystem are less inclined to pay high prices, as compared to the Apple's App Store. As a result, as demonstrated by our results, in Google Play diversified developers perform better than specialized developers. In contrast, in the Apple's App Store, specialization generates returns in terms of sales performance. Indeed, by means of specialization developers can build expertise that will allow them to develop and commercialize high quality apps. Given that consumers have relatively high willingness to pay in this store, they are more likely to recognize a price premium to high quality apps. As a result, the sales disadvantage of lower user base is likely to be compensated by the higher margins their apps can generate. Therefore, it is possible that in this platform ecosystem the sales performance of diversified developers does not differ from that of specialized developers significantly, as also suggested by our results. Overall, our results have an important implication for developers as they suggest that developers should factor in the app ecosystem where they operate when making the decision on whether to diversify or not.

We check the robustness of our results by performing OLS regression models for each day of observation. In particular, Table 4 reports the results of some representative models (when the days of observation are 9, 60, and 120). Once again, the results support the arguments above on the role of the platform ecosystem in the relationship between the sales performance and diversification. It is interesting that, in some circumstances, the effect of diversification on sales performance in the Apple's App Store becomes negative and significant (though at the 10% level of significance), suggesting the benefits of specialization dominates in these cases.

## 5. Conclusion

In this paper, we have contributed to the vast literature on the effects of diversification on firm performance by addressing this issue in the app market, where developers can diversify by marketing apps belonging to different categories (i.e., satisfying different sets of consumer needs), but still in the same competitive arena, i.e., the app store. More importantly, we have contributed to the extant literature by investigating the role of the platform ecosystem in the performance-diversification relationship. Applying the argument of Santalo and Becerra (2008) to the context of platform ecosystems, we have indeed argued that the effect diversification on sales performance hinges upon the distribution platform where the developer operates. In particular, the cross-platform differences in consumer willingness to pay provide the rationale behind the different effect of diversification on sales performance across different platform ecosystems.

Our results show indeed that the diversification strategy has a positive impact on developer sales in Google Play, while no significant impact emerges in the Apple's App Store. That is, diversified developers are associated with a better sales performance than specialized developers, whereas in the Apple's App Store, diversified developers do not differ from specialized developers in terms of sales performance. We have explained that in the Apple's App Store the benefits derived from specialization are sufficiently high because consumer have relatively high willingness to pay and they can afford to pay high prices, giving the incentive to developers to specialize in order to develop and market high quality apps. In contrast, in Google Play, because of the lower consumer willingness to pay, the benefits of specialization cannot counterbalance the benefits derived from diversification, such as the greater ability to capture a large user base by exploiting the installed user base for one app category also for other app categories served by the diversified developer. As a result, we find that the inter-category diversification strategy raises developer sales performance in Google Play, but it does not yield different sales performance from a specialization strategy in the Apple's App Store.

This study has important implications for developers and platform owners. First, we inform developers that they should carefully assess the platform ecosystem where they operate before making diversification decisions as their decision to diversify across app categories is likely to have different consequences in terms of sales performance in different platforms. Second, our findings help increase distribution platform owners' awareness on the role of the platform ecosystem factors in the relationship diversification-performance and rethink their strategies to attract both users and developers in order to improve platform profitability.

There are of course some limitations in our study, which may however offer opportunities for improvements. First, similarly to recent studies focusing on information goods (Tanriverdi and Lee, 2008; Lee and Raghu, 2014), given the absence of cost information, we use sales as a measure of firm performance. Accordingly our arguments on the advantages and/or disadvantages of diversification reflect the implications of diversification on such measure of performance. However, to fully evaluate the effects of diversification on firm profitability, we should rely on a large survey to obtain cost information estimates. At any rate, the current study still allows us to make some further useful considerations. It is indeed well known that diversification comes at a cost. Therefore, if no benefits of diversification emerge in terms of sales performance (and this is the case of developers in the Apple's App Store), we should expect a negative effect of diversification on firm profitability. When there are significant benefits of diversification (i.e., the case of developers in Google Play), then the knowledge of costs will tell us whether the diversification has a positive effect on firm profitability as well. At any rate, the different effect (in magnitude or in sign and magnitude) of diversification on firm performance across different ecosystems still remains. Second, as we have already pointed out, endogeneity concerns may arise with regard to the relationship between sales performance and diversification. While we have discussed the issues associated with the identification of appropriate IVs in this context, the present study would certainly benefit from resorting to this approach to mitigate the emergence of endogeneity, if any. Third, in spite of the laborious procedure to retrieve data and estimate developer revenue, the extension of our sample to a longer period of observation (e.g., several years) would improve the reliability of our findings. Finally, we draw some line for future research. For instance, in line with Santalo and Becerra (2008), the investigation of how the effect of diversification on firm performance depends not only on the platform ecosystem but also on the app category is undoubtedly worthwhile.

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## Table 1. Variable descriptive statistics

| | Full sample | | Apple's App Store sample | | Google Play sample | |
|---|---|---|---|---|---|---|
| | Mean | Std. Deviation | Mean | Std. Deviations | Mean | Std. Deviations |
| **Category-adjusted Developer Sales Performance Ratio** | 5.495 | 17.489 | 3.547 | 7.843 | 7.855 | 24.321 |
| **Diversification** | 0.204 | 0.403 | 0.204 | 0.403 | 0.205 | 0.404 |
| **Developer Sales (Euros)** | 27,443.94 | 61,523.42 | 37,598.81 | 76,299.09 | 15,151.2 | 32,314.04 |
| **Store Sales (Euros)** | 5,722,023 | 2,778,037 | 8,242,415 | 222,457.5 | 2,671,021 | 33,227.34 |
| **Store Sales Growth Rate** | 0.0006 | 0.014 | 0.0008 | 0.019 | 0.0004 | 0.003 |
| **Developer Age (days)** | 687 | 451 | 867 | 500 | 469 | 247 |
| **Brand Notoriety** | 0.167 | 0.373 | 0.157 | 0.364 | 0.178 | 0.382 |
| **Category HHI** | 0.141 | 0.169 | 0.157 | 0.184 | 0.127 | 0.153 |

## Table 2. Correlation matrix

| | Developer Prior Sales (Ln) | Category HHI | Stores Sales Growth Rate | Developer Age (Ln) | Diversification |
|---|---|---|---|---|---|
| **Category HHI** | -0.219* | | | | |
| **Stores Sales Growth Rate** | -0.002 | 0.001 | | | |
| **Developer Age (Ln)** | 0.229* | 0.065* | 0.000 | | |
| **Diversification** | 0.182* | 0.194* | -0.000 | 0.259* | |
| **Brand notoriety** | 0.411* | 0.004 | -0.000 | 0.158* | 0.107* |

The symbol * indicates that the Pearson correlation coefficient is significant at $p<0.05$

## Table 2. Fixed effects regression models

| | Full Sample only controls | Full Sample with no Diversification - Store interaction | Full Sample with Diversification - Store interaction | Only Google Play sample | Only Apple's App Store sample |
|---|---|---|---|---|---|
| **Developer Prior Sales (Ln)** | 0.096*** | 0.096*** | 0.096*** | 0.214*** | 0.078*** |
| | (0.022) | (0.022) | (0.022) | (0.024) | (0.075) |
| **Category HHI** | 0.790* | 0.784* | 0.784* | 0.417** | 0.944* |
| | (0.405) | (0.409) | (0.411) | (0.191) | (0.556) |

| | | | | | |
|---|---|---|---|---|---|
| **Store Sales Growth Rate** | 0.150* | 0.150* | 0.150* | 2.644 | 1.119* |
| | (0.081) | (0.081) | (0.081) | (4.207) | (0.620) |
| **Developer Age (Ln)** | 0.038 | 0.038 | 0.038 | -0.013 | 0.033 |
| | (0.042) | (0.042) | (0.042) | (0.048) | (0.051) |
| **Diversification** | | 0.054 | 0.033*** | 0.032*** | 0.084 |
| | | (0.048) | (0.010) | (0.008) | (0.075) |
| **Diversification X Store** | | | 0.028 | | |
| | | | (0.056) | | |
| **Temporal Dummies** | Included | Included | Included | Included | Included |
| **Constant** | -1.161*** | -1.171*** | -1.170*** | -1.576*** | -1.202*** |
| | (0.335) | (0.333) | (0.333) | (0.352) | (0.432) |
| *N of observations* | 42745 | 42745 | 42745 | 19322 | 23423 |
| *N of developers-store pairs* | 385 | 385 | 385 | 176 | 209 |
| $R^2$ *within* | 0.080 | 0.080 | 0.080 | 0.281 | 0.097 |
| $R^2$ *between* | 0.694 | 0.689 | 0.680 | 0.816 | 0.690 |
| $R^2$ *overall* | 0.617 | 0.616 | 0.601 | 0.787 | 0.570 |

Robust standard errors in parentheses - * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## Table 2. Representative OLS regression models for cross-sectional samples

| | Only Google Play Day 9 | Only Apple's App Store Day 9 | Only Google Play Day 60 | Only Apple's App Store Day 60 | Only Google Play Day 120 | Only Apple's App Store Day 120 |
|---|---|---|---|---|---|---|
| **Developer Prior Sales (Ln)** | 0.365*** | 0.391*** | 0.372*** | 0.384*** | 0.375*** | 0.337*** |
| | (0.092) | (0.016) | (0.019) | (0.015) | (0.017) | (0.021) |
| **Category HHI** | 0.866*** | 2.136*** | 1.090*** | 2.281*** | 1.238*** | 2.172*** |
| | (0.092) | (0.312) | (0.193) | (0.209) | (0.192) | (0.422) |
| **Developer Age (Ln)** | 0.048* | 0.033 | 0.072*** | -0.053* | 0.025 | -0.011 |
| | (0.025) | (0.030) | (0.021) | (0.029) | (0.032) | (0.060) |
| **Brand Notoriety** | 0.077 | 0.047 | 0.073 | 0.041 | 0.076 | 0.076 |
| | (0.057) | (0.089) | (0.066) | (0.071) | (0.056) | (0.075) |
| **Diversification** | 0.362*** | -0.155* | 0.310*** | -0.003 | 0.283*** | -0.138* |
| | (0.090) | (0.085) | (0.096) | (0.071) | (0.092) | (0.072) |
| **Constant** | -3.3666*** | -4.004*** | -3.617*** | -3.441*** | -3.375*** | -3.314*** |
| | (0.191) | (0.196) | (0.185) | (0.227) | (0.233) | (0.400) |
| *N of observations* | 167 | 201 | 171 | 208 | 176 | 209 |
| $R^2$ | 0.839 | 0.803 | 0.832 | 0.832 | 0.833 | 0.702 |

Robust standard errors in parentheses - * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$