Diversification and performance in the mobile app market: The role of the platform ecosystem

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Abstract

We examine the effect of app developers' product line diversification decision on their performance and shed light on whether the type of platform ecosystem (open versus closed) where they commercialize apps influences this effect. We compare the revenue performance of diversified and specialized developers in Apple's App Store and Google Play. We show that in the Apple's App Store (closed platform) diversified developers always display lower performance than their specialized counterparts. In Google Play (open platform) diversification is beneficial in categories where diversified developers have predominant market share, whereas it is detrimental in categories dominated by specialists. Hence, platform supply side users, such as app developers, should factor in the platform ecosystem where they operate when making diversification decisions.

Keywords: Diversification; Platform Ecosystem; Mobile App Market; Information Technology.

1. Introduction

The relationship between diversification and firm performance has been extensively examined by researchers in a number of disciplines including economics, finance and strategic management (Palich, 2000; Santalo and Becerra, 2008; Erdorf et al., 2013; Shin et al., 2015; Kim et al., 2017; Mackey et al., 2017). Nevertheless, there exists considerable disagreement about the true nature of the effect of diversification on firm performance, and how and when this strategy can be used to build competitive advantage (Markides and Williamson, 1994; Palich et al., 2000, Rajan et al., 2000, Chang et al., 2016; Mackey et al., 2017). It is noteworthy that the lack of consensus pertains to the effects of both corporate and product line diversification as the driving forces and the relative arguments usually invoked by the extant literature tend to be the same for both levels of firm diversification.

On the one hand, diversification can deliver a number of benefits to firms that may improve their performance. For instance, economists have suggested that, in the long-term, diversified firms could benefit from the adoption of predatory pricing strategy for certain products as, in comparison with their specialized counterparts, they can more easily sustain short-term losses through product cross-subsidization (Saloner 1987; Berger and Ofek, 1995; Palich, 2000; Aribarg and Arora, 2008). Even in the absence of predatory pricing intents, cross-subsidization can be particularly salutary to diversified firms as the large cash flows generated by certain divisions or product lines are the source of capital for new promising divisions or product lines. When managed efficiently, internally generated funds are less costly and can yield better performance than external sources of capital such as debt and equity (often the only sources at disposal of specialized firms), also by virtue of the superior information internal decision makers possess as compared with external investors when allocating capital and other resources among different businesses (Williamson, 1986; Kuppuswamy and Villalonga, 2015). Diversified firms are also better positioned than their specialized counterparts to take advantage of economies of scope by exploiting the excess productive capacity of certain resources, i.e., brand, customer loyalty, focused technologies and other specific assets, that cannot be sold externally due to high transaction costs and other market imperfections (Markides, 1992; Markides and Williamson, 1994).

On the other hand, a number of drawbacks are also associated with diversification, which may result in decreased firm performance. First, the hypothesized higher efficiency of the internal capital market has been questioned by a number of researchers (George and Kabir, 2012). This is because diversified firms are more exposed to agency problems, such as information asymmetry between corporate headquarters and division (or product line) managers, incentive problems, internal power conflicts, that can generate significant allocation inefficiencies as well as other organizational diseconomies, thus resulting in diminished performance (Williamson, 1967; Meyer et al., 1992; Rajan et al., 2000). In line with these views, a copious body of the financial literature believes that corporate diversification will result in a reduction in value for shareholders (Lang and Stulz, 1994; Berger and Ofek, 1995). Finally, by adopting the arguments of the stream of the organization theory literature that focuses on category spanning (Hannan and Freeman, 1977; Hsu, 2006; Hsu et al., 2009; Negro et al., 2010), in comparison to their specialized counterparts, diversified firms may fail to develop and consolidate the same level of expertise and specific capabilities enabling the creation of superior products able to fit customers' needs effectively. In turn, this would have potentially negative consequences in terms of performance.

In the attempt to reconcile the diverging views and the overwhelming mixed evidence with regard to the effect of diversification on firm performance, some studies in the strategic management literature have posited and tested curvilinear relationships between these variables, such as the inverted-U and the intermediate models (Palich et al., 2000). Other studies still consider the choice of diversifying as a dichotomous decision (i.e., diversification versus specialization). However, they explain the mixed evidence as the consequence of the effect of some characteristics of the competitive environment on the relationship diversification-performance (Santalo and Becerra, 2006, 2008; Erdorf et al., 2013; Kuppuswamy and Villalonga, 2015). For instance, Santalo and Becerra (2006, 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. Erdorf et al. (2013) and Kuppuswamy and Villalonga (2015) highlight that the relationship between diversification and performance may be influenced by economic conditions such as the business cycle, the financial constraint and the state of the capital market. These arguments nourish the view that the effect of diversification on firm performance is not immutable when some features characterizing the environment where firms compete change. However, little is still known on which (and how many) characteristics of the competitive environment are likely to play a role in the relationship between diversification and firm performance. This opens up room for a number of research paths aimed to identify these characteristics and understand their effect on the diversification-performance relationship.

In this paper we take one of these research paths and investigate the relationship between product line diversification and firm performance in the context of platform ecosystems. More specifically, we endeavor to shed light on whether and how the platform ecosystem where firms operate influence this relationship. In this respect, our study advances the theoretical understanding of firms' diversification-performance relationship introducing a new important element (the platform ecosystem) that may influence it.

Indeed, in recent years many businesses across the most disparate industries and applications (operating systems, video-game consoles, Internet retailing, financial services, hospitality, car transportation service, crowdfunding, etc.) have been (re-)organized as platform ecosystems, i.e., as multisided markets where two or more distinct groups of participating users interact with each other to create and exchange value, according to the rules designed for the specific type of platform (Cennamo and Santalo, 2013; Hagiu and Wright, 2015). In addition to its novelty and increasing importance for business, it is theoretically important to study the role of the platform ecosystem in the diversification-performance relationship because this factor is overarching the concept of industry (for instance considered in Santalo and Becerra, 2006, 2008) given that multiple industries, product categories and/or applications may co-exist and compete within a single platform ecosystem, as well as numerous industries, product categories and/or applications can be operated under a logic of platform ecosystem. As such, the characteristics and the rules set at the level of platform ecosystem may shape the behavior of the actors operating within the platform, in particular supply side and demand side users. Moreover, since a single platform ecosystem may encompass multiple industries or product categories, its characteristics and rules may not only directly shape how the diversification influences firm performance, but also they may affect how this relationship is moderated by the product category (industry) commercialized by the supply side of the platform.

It is important to point out that this paper does not examine the effect of diversification decisions at the platform level. That is, it does not study the decision of a platform ecosystem of diversifying across a variety of platform users and/or products. Rather, it focuses on understanding how the different platform ecosystem where firms operate influences the effect of firms' product line diversification decisions on firms' performance. The focus is therefore on the relationship between product line diversification and performance at the level of firms operating in the platform ecosystem and on unraveling whether and how such relationship is contingent upon the different platform where firms operate. In particular, we identify the openness of the platform ecosystem, i.e., the characteristic of opening or limiting the participation of different actors to the platform, as the element that may ultimately influence the dynamics around the diversification-performance relationship.

Specifically, in identifying such characteristic, we follow the classification of Eisenmann et al. (2009), who suggest that a platform ecosystem can be open or closed with respect to different roles, namely end-users (i.e., the demand side of the platform), complementors (i.e., the supply side of the platform), platform providers (i.e., actors who facilitate users' access to complements by providing them a point of contact with the platform), and platform sponsors (i.e., actors who develop platform technologies, exercise property rights and determine rules for participation). We argue that the platform characteristic of being more or less open to one or more of the above roles directly or indirectly affects the type of end users (i.e., demand side) who will populate the platform ecosystem. This in turn may determine a different effect of platform supply side players' diversification decisions on their performance, across different platform ecosystems.

To understand the role of the platform ecosystem in the above diversification-performance relationship, we focus on mobile apps platform ecosystems, and study whether and how the openness of the platform ecosystem where developers commercialize their apps influences the effect of developers' product line diversification (intended to be as diversification across different app categories) on their performance. App stores can be indeed viewed as online platform ecosystems where multiple parties (app users, developers, OS/device makers, platform owners) can interact. In an app store, users can download and rate apps developed by third parties (i.e., developers), which are the supply side of platform, for mobile devices and operating systems (OS) sponsored by the platform. The platform openness or closure to different type of users (developers, app users, device makers, etc.) may create significant differences in the type of demand side users accessing the platform. For instance, according to the classification provided by Eisenmann et al. (2009), Apple's mobile app platform ecosystem is closed with regard to the platform provider in the sense that the iOS operating system can run exclusively on proprietary Apple's mobile devices (iPhone and iPad), whereas Android platform ecosystem is open with regard to the platform provider because the Android operating system can run on multiple mobile devices, such as Samsuing, Huawei, Xiaomi, etc. In turn, this influences the demand side (app users) since, in this case, the supply side of this type of platform ecosystems (i.e., app developers) essentially inherits the customer base of the mobile device makers in terms of size and characteristics. In this paper, we advance that the cross-platform differences in terms of openness, and thus also in terms of demand side users' characteristics, crucially influence the relationship between developers' product line diversification and their performance. In this regard, we contribute to the growing body of literature examining diversification decisions in the context of platform ecosystems (Tanriverdi and Lee, 2008; Boudreau, 2012; Cennamo and Santalo, 2013; Inoue and Tsujimoto, 2018; Cennamo et al., 2018), by shedding light on how the effect of product line diversification platform of supply side players (i.e., platform complementors) on their performance varies across different type of platform ecosystems in light of the different openness of such ecosystems.

By examining the performance implications of diversification decisions across platform ecosystems, we also contribute to the growing strand of the information technology management literature that has started studying the intriguing dynamics of the app market (Garg and Telang, 2013; Ghose and Han, 2014; Lee and Raghu, 2014; Roma et al., 2016). Indeed, initial studies have mostly concentrated on app demand estimation (Carare, 2012; Garg and Telang, 2013; Ghose and Han, 2014), pricing decisions (Roma et al., 2016), the determinants of app success (Lee and Raghu, 2014; Liu et al., 2014; Roma and Ragaglia, 2016), consumers' purchase intentions and mobile app adoption (Gurtner et al., 2014; Hsu and Lin, 2015; Hsu and Lin, 2016), or the role of the platform ecosystem in content diversity (Lee and Hwang, 2018). However, to the best of our knowledge, the study of the relationship between product line diversification and performance in the app market has been mostly disregarded. A notable exception is Lee and Raghu (2014) who find that broadening app offerings across multiple categories in the Apple's App Store is a key determinant that contributes to a higher probability of survival in the top charts. By taking an approach similar to the cited studies in corporate finance literature (e.g., Santalo and Becerra, 2008), we depart significantly from Lee and Raghu (2014) as we compare the revenue performance of diversified and specialized developers and study how the effect of inter-category diversification hinges upon the distribution platform ecosystem, which has never been studied.

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 face the strategic decision to specialize in a few (or even one) app categories or diversify among a large number of app categories. Therefore, shedding light on how a diversification strategy impacts on their performance and how the diversification-performance relationship depends on 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 revenue performance (including all major revenue streams, e.g., sales, in-app purchase, advertising) 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 and how the effect of the diversification on developer performance varies across these two platform ecosystems, also depending on the different product categories. By way of anticipation, we argue and find that the type of platform ecosystem (open versus closed) where developers operate plays an important role in shaping the diversification-performance relationship, influencing the comparative advantages and disadvantages of diversification versus specialization in the app market. In the Apple's App Store (i.e., the closed platform), diversified developers display lower revenue performance than their specialized counterparts, irrespective of the level of the total within-category market share held by diversified developers. In contrast, in Google Play (i.e., the open platform), diversification is beneficial in categories where diversified developers have predominant market share on the whole, whereas it is detrimental in categories dominated by specialists.

The paper unfolds as follows. In § 2 we present the theoretical background and arguments behind our hypotheses. In § 3 we describe the dataset and the variables utilized in this paper. We present and discuss the results in § 4. We provide a robustness check of our results in § 5. Finally, in § 6 we provide managerial implications and conclude.

2. Theory and hypotheses

2.1. Platform ecosystem background

A platform ecosystem can be defined as a multisided market that enables two or more distinct groups of users to interact each other, generating and exchanging value for themselves and the platform (Cennamo and Santalo, 2013; Hagiu and Wright, 2015). Alternatively, it has been defined as a semi-regulated marketplace that promotes entrepreneurial activities through the coordination and guidance of the platform sponsor (Wareham et al., 2014). Examples of platform ecosystems include operating systems, game consoles, payment card systems, ride sharing platforms, social networks, healthcare networks, and online marketplaces (Parker and Van Alstyne, 2018). Platform ecosystems are generally characterized by cross-side network externalities, i.e., by the fact that the consumption utility of a group of users depends on the presence of users of the other groups and vice versa (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005; Hagiu, 2006). This implies that platform owners (or sponsors, using the term suggested by Eisenmann et al., 2009) have to take into account the reciprocal influences of different groups of users in designing the platform business model (e.g., pricing and revenue-sharing mechanisms) as this may crucially affect the attractiveness of the platform in the eyes of different groups of users, and thus the success in the market (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005). In this regard, platforms usually make money from one or few user sides and treat the other sides as a loss loader or financially neutral (Rochet and Tirole, 2003). In many cases, the platform ecosystem takes a “hub and spoke” form where, through shared or open-source technologies and/or technical standards, a number of peripheral firms, i.e., supply side of the platform, are connected to the central platform and, therefore, can get access to its consumers, i.e., the demand side of the platform (Tiwana, 2015; Jacobides et al., 2018).

Platform ecosystems can be classified in technology-oriented and market-oriented (Gawer, 2014; Thomas et al., 2014; De Reuver et al., 2018). A technology-oriented platform has the purpose of enabling innovation and value co-creation from complementors (usually identifiable as the supply side of the platform), like for instance the creation of applications for an operating system platform (Tiwana et al., 2010; Tiwana, 2015). Technological platforms include software platforms such as operating systems and hardware platforms such as IT infrastructure, computing or gaming hardware (Fichman, 2004; Tiwana et al., 2010). Market-oriented platforms enable the exchange of information and transactions by matching supply and demand. They include marketplaces, communities, and social networks (e.g. Amazon, Airbnb, Uber, Spotify, Facebook, Kickstarter, etc.). However such classification in technology- vs. market-oriented is not mutually exclusive. For example, an app store is a marketplace enabling economic interactions between app developers and users. But, at the same time, being strictly associated with a mobile operating system technology, in the app store developers co-create value by developing apps for a specific mobile operating system, adhering to the technological standards of the platform (Schreieck et al., 2016).

Because of their peculiar function of technological and/or market intermediation among two or more groups of users, a crucial aspect of platform ecosystems is related to their governance model, which includes rules for participation (which refers to the concept of platform openness), interactions (i.e., behavior on the platform), and resolution of conflict (Rysman, 2009; Parker and Van Alstyne, 2018). In particular, platform openness is one of the most important strategic decisions that a platform is required to make (Rysman, 2009). Usually, it consists of imposing restrictions on participation in the platform development, commercialization, and use (Eisenmann et al., 2009; Boudreau, 2010). As mentioned earlier, Eisenmann et al. (2009) have suggested that a platform can be open or closed with respect to four distinct platform roles, these being the demand-side users (i.e., end-users of the platform), the supply-side users (i.e., the complementors of the platform), the platform provider (which is the primary point of contact between end-users and complementors), and the platform sponsor (actors holding property rights and responsibility for platform governance and technology issues). For instance, regarding mobile app platform ecosystems, Apple is closed at the level of platform provider and sponsor roles (Eisenmann et al., 2009). Indeed, as mentioned, the Apple’s App Store is a platform can be only accessed through a product (e.g, the Iphone), consisting of inseparable hardware and software (iOS) components designed, manufactured and distributed exclusively by Apple (platform provider role). Moreover, Apple is the platform owner and governor (platform sponsor role). Apple can be viewed as closed platform from the perspective of supply-side users as it reserves the right to reject apps that do not satisfy quality standards set by Apple (see Eisenmann et al., 2009). On the other hand, Apple is open to demand-side users as any users can buy Apple devices and have access to the platform, even though the above restrictions indirectly influence this group as well. Differently from Apple, Google Play's platform ecosystem is open not only to demand side, but also, and most importantly, with regard the platform provider role. In fact, Google has made its operating system (Android) accessible through a wide range of mobile devices, and thus hardware producers such as Samsung, Huawei, Xiaomi, etc. (platform provider role). Compared with Apple, Google's app platform ecosystem is closed at the supply side level as apps must adhere to certain quality standards (though less stringent as compared with Apple), and at the sponsor level as the company maintains the ownership, the governance and the rights to modify the platform and its associated technology (Android). Therefore, comparatively speaking, Apple is a more closed platform ecosystem than Google as the former is not open to device manufacturers, i.e., the actors providing users with the access (point of contact) to the app platform.

As our focus is on how the platform ecosystem influences the relationship between product line diversification and performance, we take the perspective of the supply side of the platform, i.e., firms developing and commercializing products/services that can be purchased by the demand side of the platform (i.e., end-users), and discuss at a theoretical level how their incentive to diversify or specialize is shaped by the characteristic of openness of a platform ecosystem. In doing so, we abstract from the specific platform ecosystem setting. Therefore, in the rest of the section, we first identify the main benefits and drawbacks of product line diversification in the context of platform ecosystems. Then, we identify how and why the type of platform (open versus closed) influences the magnitude of the advantages and disadvantages of diversification on platform supply side users' performance, thus shaping this relationship and also the moderating role of product category. We conclude formulating our hypotheses.

2.2 Advantages and disadvantages of diversification in platform ecosystems

As we rely on revenues as a measure of firm performance, our arguments reflect the implications of diversification on such measure of performance. Specifically, we argue that among the benefits generally attributed to diversification, one is particularly important in the context of platforms: the ability to exploit the excess productive capacity of certain resources that cannot be sold externally due to high transaction costs and other market imperfections

(Markides, 1992; Markides and Williamson, 1994). More specifically, in platform ecosystems, firms (i.e., supply-side users) diversified in multiple product categories can take advantage of the loyal customer (i.e., demand-side user) base already installed for their certain product categories (such as app categories in app store platforms, or physical goods categories in online marketplaces) when introducing products in a different category. Essentially, the installed customer base is an asset that diversified firms operating in platform environments can utilize for multiple products more effectively than specialized firms (Wernefelt, 1984; Markides and Williamson, 1996; Palich et al., 2000). To illustrate, consider three developers operating in app platform ecosystems, say A, B, and C (similar examples can be made considering retailers in Amazon e-marketplace or project proponents in crowdfunding platforms, etc.). Developer A decides to commercialize apps in both game and entertainment categories, while B and C decide to specialize in the game and entertainment categories, respectively. Everything else being equal, developer A has the advantage that the loyal customers initially installed for one of the two categories are more likely to choose A also for the other category, rather than opting for B or C, if they wish to satisfy their respective additional need (i.e., the need of entertainment for those who initially chose to satisfy the need of gaming and the need of gaming for those who initially chose to satisfy the need of entertainment). This is because they have already experienced the products of developer A and have become loyal to this developer. In contrast, *ceteris paribus*, the customers of developer B are equally likely to choose between A and C, and the customers of developer C are equally likely to choose between A and B, for their respective additional need. This implies that, as result of the diversified offering, developer A is more likely to attract, since the beginning, a larger customer base (and higher revenue) than the other two developers are able to do together. This advantage of relying on an installed customer base is a common feature of many different platform ecosystems. For instance, it can be observed when retailers expand their offering by making available a new product line on online marketplaces such as Amazon or eBay. It may also occur in crowdfunding platforms when serial entrepreneurs sequentially launch campaigns to secure external finance for multiple (different) projects. In this case, the crowd that has already funded prior projects of the same entrepreneur is more likely to fund the new project, *ceteris paribus* (Butticè et al., 2017).

The magnitude of this intuitive benefit of diversification (i.e., the exploitation of an installed customer base for multiple product categories) is dramatically amplified by the presence of large (positive) network externalities, which are, as discussed, a key feature in platform ecosystems (Tanriverdi and Lee, 2008). In fact, in the presence of network externalities, new customers have higher incentive to choose the product of a firm with larger initial customer base because their utility is likely to be higher when more people are using that product. This could be due to technological reasons. For instance, a large customer base is necessary for instant messanging platforms such as WhatsApp or for social network platforms such as Facebook to fully exploit their technological functionalities and thus deliver significant benefits to customers. The increase in the consumption utility when more people are using a given product could also be simply due to a “bandwagon effect”. In this case, the reasons should be connected to social and psychological motivations driving people’s desire of conformity and thus giving rise to phenomena such as fashion trends (e.g., the case of popular game apps such as Angry Birds or Ruzzle). Platform supply side users able to attract a larger initial customer base for their products are more likely to gain a competitive advantage from the virtuous circle activated by network externalities. Accordingly, this should act to amplify the intrinsic advantage of diversified firms in platform ecosystems, namely the advantage of exploiting the loyal customer base already installed for certain product categories also for other categories.

In spite of the above clear benefit ensuing from diversification, one disadvantage associated with the adoption of this strategy is particularly important in platform ecosystems: the greater difficulty encountered by diversified firms (supply side of the platform) to guarantee adequate product quality across all targeted product categories. Indeed, diversified firms may not be able to develop and consolidate the level of expertise and capabilities necessary to create products of quality comparable to that of products commercialized by specialized firms. This is because the diversified firm has to distribute the efforts for the realization of different product categories, in contrast with the specialized firm that can concentrate the effort entirely to stand out on one category (Hannan and Freeman, 1977; Hsu, 2006; Hsu et al., 2009; Negro et al., 2010). In this regard, some studies suggest that firms’ actual skills in each product category tend to degrade when attempting to diversify across multiple categories because of the higher operational difficulties that they face related to the deployment of peculiar assets and technologies, as well as to the development of category-specific expertise (Negro and Leung, 2013). Consider again the case of the app platform ecosystem: the specificity of each app category in terms of content and functionality may require developers to develop a great variety of coding skills and other capabilities necessary for the development and commercialization of apps of different nature. 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. Therefore, diversified firms may hardly deliver the same quality reached by firms focusing on one or just few specific categories (Negro and Leung, 2013). As a result, in line with the organizational arguments invoked by the literature on category spanning (Hannan and Freeman, 1977; Hsu, 2006; Hsu et al., 2009; Negro et al., 2010), because of the lower average quality implied by a diversification strategy, diversified firms could more easily fail to meet customers' expectations and thus reflect into overall inferior performance in the market.

As explained in the next section, we argue that the type of platform ecosystem (open versus closed) influences the interplay between the conflicting forces identified above for the supply side of the platform, and consequently affects the diversification-performance relationship. Specifically, the magnitude of advantage and disadvantage of diversification, and thus whether one is predominant over the other one, hinges upon the type of platform ecosystem where firms (supply-side users) operate.

2.3 The role of the platform ecosystem in the platform supply side diversification-performance relationship

We can now theorize on how the platform ecosystem should influence the magnitude of the conflicting effects identified above, thus shaping the diversification-performance relationship and the moderating role of product category from the perspective of the platform supply side (i.e., platform complementors). Figure 1 illustrates our model. Specifically, we posit that the characteristic of openness of the platform ecosystem matters in shaping this relationship. This is because whether the platform is open or closed to any of the platform roles (demand-side users, supply-side users, platform provider, and platform sponsor) may influence directly or indirectly the platform's demand side (in terms of size and type) and, in turn, the efficacy of the diversification strategy adopted by the supply side users.

INSERT FIGURE 1 ABOUT HERE

We start from explaining why the platform openness should directly or indirectly affect the size and type of demand side users. It is straightforward that any direct opening or closure to demand side users will affect the size and characteristics of this type of users acceding the platform. For instance, significantly restricting access (and thus lowering openness) to demand side users through high platform subscription fees is an obvious direct market skimming mechanism that reduces the size of the demand side users adopting the platform, attracting only those willing to pay such high fees. This is the case of élite social network platforms such as ASmallWorld as opposite to Facebook, which is instead fully free to the demand side of the platform, or the case of instant messaging platforms for business (e.g., Slack) versus those for mass users (e.g., WhatsApp). However, given the logical interconnections among the various platform roles, the impact of openness on demand side users can be indirect as well. That is, it can be the consequence of opening or closing the platform to other platform roles (Eisenmann et al., 2009; Ondrus et al., 2015). As discussed, Apple's mobile app platform ecosystem is closed with regard to the platform provider role (device maker), whereas Android platform ecosystem is open with regard to this role (Eisenmann et al., 2009). Similar considerations can be done with regard to operating systems for personal computers when comparing Windows to Mac (Eisenmann et al., 2009). This indirectly affects the demand side because, in this case, the supply side of this type of platform ecosystems (i.e., software applications developers) essentially inherits the customer base of the hardware device manufacturers in terms of size and characteristics. Thus, a software platform open to multiple device makers will have a broader and more heterogeneous demand side as compared with a closed software platform, and the characteristics of the demand side in each of the two cases will reflect the customer base of device makers. Another indirect influence of platform openness on demand side users may occur by opening or closing to the supply side of the platform. For instance, by allowing access only to supply side able to guarantee relatively high quality standards may help attract more demand through a reputational effect or by limiting the extent of modifications that complementors can make to the platform (Eisenmann et al., 2009; Parker and Van Alstyne, 2017). For instance, the great success of retail platforms, such as Amazon and eBay, among demand side users also lies on setting up mechanisms (e.g., vendor ratings and vending rules) to ensure that only vendors able to deliver quality products and maintain sufficiently high service standards survive in these platforms (Ba and Pavlou, 2002; Dellarocas, 2003; Pavlou and Gefen, 2004; Pavlou and Dimoka, 2006). In similar vein, in reward-based crowdfunding platforms, setting more stringent requirements for project proponents (supply side) may stimulate the trust and involvement of campaign contributors (demand side), increasing their propensity to fund (Mollick, 2014). But, at the same time, raising quality standards too much on the supply side or even restricting the type of products may reduce the product variety to be offered, allowing only high-end products to be transacted in the platform, which end up attracting only high-end demand side users. For instance, this is the case of luxury e-commerce platforms that have been proliferating in recent years, such as JamesEdition and Luxify. Finally, the openness at the level of platform sponsor also affects the demand side, determining much larger and more heterogeneous consumers. For instance, the fact that the platform Linux is open source and can be modified by users themselves naturally implies non-discrimination not only in platform access, but also in the process of defining platform standards (Eisenmann et al., 2009).

Based on the above considerations, closing too much to any of the platform roles will likely have a (direct or indirect) negative effect on the size of the platform demand side, whereas broad platform openness intuitively helps attract a multitude of users on the demand side. That is why a closed platform strategy, which impacts on the demand side, is usually associated with the choice of targeting high-end users on the demand side (e.g., the cited examples of Apple and luxury e-commerce platforms, or even the case of pay-per-view video-streaming platforms). That is, closed platforms usually position themselves to attract highly valuable demand-side users. Indeed, it would be certainly unprofitable to restrict (directly or indirectly) the potential market on the demand side through a closed platform strategy attracting low-end users. In other words, restricting (directly or indirectly) the demand side of the platform makes economic sense only if the targeted demand side is highly valuable and thus can guarantee adequate margins to the supply side of the platform and thus to the platform itself. Otherwise, it would be clearly more lucrative for the platform to open up to larger segments of demand side users (even those who are less willing to pay), leading the supply side and the platform itself to profit from transaction volumes rather than from transaction margins. In this regard, it is important to point out that the type of demand side that will populate the platform ecosystem follows from the openness decision made by the platform owner. A more open platform will be more likely to attract directly or indirectly larger segments of demand-side users, thus yielding a lower consumer willingness to pay on average. For instance, by running on multiple devices which overall target broader and more heterogeneous consumers, Android platform is more likely to be accessed by larger segments with lower willingness to pay on average than Apple, which instead inherits the high-end customer base exclusively from Apple's device, being a closed platform.

After explaining that closed platforms are more likely to target high-end demand side users than open platforms, we explain how this aspect affects the response of the demand side to a diversification versus specialization decision of the supply side, and how it moderates the effect of diversification on the performance of the supply side users. Specifically, we argue that in closed platform ecosystems naturally targeting highly valuable demand side users, the disadvantage associated with diversification discussed in the previous section should prevail, thus yielding a negative effect of diversification on supply side users' performance. Conversely, in platform ecosystems directly or indirectly open to large demand side user segments, being diversified should not always have negative consequences in terms of performance. In particular, in the latter case the disadvantage associated with diversification should prevail only when specialists have the predominant market share on the whole, whereas diversification should be beneficial when diversified supply side users dominate.

We explain this as the result of the different type of demand side users that populate platforms with different openness. Specifically, the fact that closed platform ecosystems tend to target on average more valuable demand side users provides supply side users (i.e., firms) with greater incentive to develop high-quality products and thus monetize from margins. This is because highly valuable consumers are more likely to reward firms offering high-quality products. According to the discussed arguments of the organizational theory of category spanning (Hannan and Freeman, 1977; Hsu, 2006; Hsu et al., 2009; Negro et al., 2010), the development of high-quality products can be achieved much more effectively through specialization because under this strategy supply side users can concentrate on building specific capabilities that allow them to market products better fitting customers' needs. In contrast, under a diversification strategy, this is more difficult to obtain as in this case development and commercialization efforts need to be distributed across a wide range of different product categories (Negro and Leung, 2013).

In addition, the advantage of diversification discussed above, i.e., the advantage of exploiting the loyal customer base already installed for certain product categories also for other categories, is diminished in this environment because, in presence of highly valuable demand side users, the customer loyalty and thus the size of the customer base are more likely to be driven by the ability to deliver high-quality products. Therefore, in a closed platform naturally targeting high-end demand side the disadvantage of diversification should prevail. Moreover, this negative effect of diversification on revenue performance should occur irrespective of whether diversified supply side users hold overall predominant presence (market share) than specialized supply side users. Recall that, according to Santalo and Becerra (2006, 2008), the effect of diversification is likely to depend on the considered industry. In particular, diversification should be likely to be beneficial in those industries characterized by large predominance of diversified firms because their predominance is exactly indicative of the existence of a clear competitive advantage of being diversified when operating in those industries. For the same reason, diversification should be likely to be detrimental in those industries characterized by large prevalence of specialized firms. The product categories offered in platform ecosystems (e.g., apps in mobile app platforms, physical goods in online marketplaces, creative projects in crowdfunding platforms, etc…) can be viewed as sort of industries because the needs and the technical capabilities may be considerably different across the different product categories. Transferring the intuition of Santalo and Becerra (2006, 2008) to our paper, diversification should be beneficial in categories where diversified supply side users of the platform have predominant market share on the whole, whereas it should be detrimental in categories dominated by specialists. As mentioned above, we contend that in a closed platform the beneficial effect of diversification should never dominate irrespective of the total within-category market share held by diversified supply side users (i.e., firms). This is because the benefit entailed by specialization (i.e., the development of higher quality products) is so high in the presence of highly valuable demand side that the prevalence of diversified supply side users across categories is likely to be limited in a closed platform, thus preventing the emergence of the positive effect even when the total within-category market share held by diversified supply side users increases.

In contrast, we advance that the effect of diversification on revenue performance in platforms (indirectly or directly) open to demand side is not always negative. The rationale is that open platforms tend to be accessed by a plethora of heterogeneous users, an aspect that lowers the willingness to pay at an aggregate demand side level, at least in comparison with closed platforms, which normally target highly valuable demand side. For instance, platforms open at the provider level are accessed by a very broad demand side resulting from the union of the demand sides of many diverse platform providers (e.g., the case of operating systems platforms open to many hardware manufacturers) (Ondrus et al., 2015). This implies the presence of a more heterogeneous population of users having on average more limited willingness to pay (Ghose and Han, 2014; Ondrus et al., 2015). Therefore, comparatively speaking, the incentive to develop high-quality products should be reduced in open platform ecosystems. In turn, this should diminish the benefit of building specific high-level capabilities through category specialization. In this case, supply side users may have incentive to market high-quality (high-price) products only in those product categories satisfying needs for which there are customers willing to pay high prices, while counting on large product diffusion at low prices for the remaining categories. On the opposite, the advantage of diversification assumes higher relevance in platform ecosystems (directly or indirectly) open to demand side. Indeed, by means of diversification, supply side users can better fuel the network externalities effect (even in the form of the simple bandwagon effect), which facilitates the product diffusion and success in the market. As a result, it is reasonable to expect that the advantage of specialization does not necessarily outperform the advantage of diversification in open platforms. Specifically, we expect that in these platform ecosystems specialization should yield a better supply side users' revenue performance precisely in those categories where specialists hold a larger market share overall, whereas the opposite should occur in categories where diversified supply side users are predominant. In the former case, the higher presence of specialists should indeed indicate that consumers are willing to pay for products in those categories, thus giving the incentive to supply side users to specialize in order to build the specific capabilities that will allow the commercialization of superior products more effectively. In the latter case, the prevalence of diversified supply side users should instead imply that a diversification strategy is more beneficial because demand side users' willingness to pay is limited for those categories and thus exploiting the installed customer base across categories to fuel the product diffusion becomes a more effective strategy (Tanriverdi and Lee, 2008).

To help better understand the theoretical arguments developed above for platform ecosystems at a general level, we use the two major mobile app distribution platform ecosystems (Apple's App Store and Google Play), which are our setting of study. As discussed, the Apple's App Store, which is, comparatively speaking, the closed platform, is accessed by the (loyal) high-end of the market (Hixon 2014; Ghose and Han 2014), given that this platform inherits only the customer base targeted by Apple for its high-end mobile devices. As highly valuable demand side users are more likely to recognize a price premium to high-quality apps, app developers have higher incentive to achieve high-level category-specific competences and capabilities, which are easier to get through a specialization strategy, rather than by diversifying across multiple apps categories. As a result, the disadvantage associated with diversification in platform ecosystems should always prevail in the Apple's App Store. Conversely, Google Play is open at the provider level as Google's mobile operating system (Android) can be installed on a large range of devices. This implies that, as compared with Apple's App Store, Google Play's demand side is much broader and encompasses the large and diverse plethora of consumers targeted by manufacturers for their Android-operated devices.[1] Hence, consumers populating Google Play naturally display more limited willingness to pay at an aggregate level (Ghose and Han, 2014; Hixon, 2014; Richter, 2018). Indeed, industry data suggest that, at a global level but also in several relevant countries for the app economy, Apple's App Store users spend twice more than Google Play's users, in spite of the fact that the latter download much more often; and these characteristics have

[1] Android has been the best-selling OS worldwide on smartphones since 2011. In the first quarter of 2018, Android-operated devices accounted for around 85.9 percent of all smartphone sales to end users worldwide (Statista, 2018).

remained very stable over time (SensorTower, 2017; Richter, 2018; Ciligot, 2019). As, in general, in Google Play demand side users are less receptive to highly priced apps, developers in such platform ecosystem should be less encouraged to develop high-quality apps and, therefore, they should have lower incentive to acquire specific high-level capabilities through category specialization. This should hold especially for those app categories for which customers are less willing to pay and thus do not reward the higher quality. In this case, diversified developers can take advantage of the loyal customer base already installed for certain app categories and the network externalities effect to facilitate the app diffusion in the market and thus profit from high volumes. On the opposite, in those app categories for which customers are willing to recognize the higher quality by paying higher prices, developers should be incentivized to specialize in order to develop and consolidate the level of expertise and capabilities necessary to create and commercialize high-quality (high-price) apps. As a result, in Google Play specialization should yield a better developer revenue performance precisely in those categories where specialists hold a larger market share overall, whereas the opposite should occur in categories where diversified developers are predominant.

In sum, taking again the arguments at a more general level, we suggest that in closed platform ecosystems naturally targeting mostly highly valuable demand side, the effect of diversification should always be negative. In contrast, in platform ecosystems (directly or indirectly) open to broad and heterogeneous demand side, diversification should be beneficial in categories where diversified supply side users have predominant market share on the whole (i.e., when the total within-category market share held by diversified supply side users is large), whereas it should be detrimental in categories dominated by specialists (i.e., when the total within-category market share held by diversified supply side users is small). Accordingly, we formulate the following hypotheses:

<u>Hypothesis 1</u>: *In closed platform ecosystems, which mostly tend to attract highly valuable demand side, diversified supply side users (i.e., firms) display poorer revenue performance than specialized supply side users, irrespective of the total within-category market share held by diversified supply side users.*

<u>Hypothesis 2</u>: *In open platform ecosystems, which naturally attract broad and heterogeneous demand side, diversified supply side users (i.e., firms) display better revenue performance than specialized supply side users in product categories where they hold overall a predominant market share, whereas they display poorer revenue performance in product categories where specialists prevail.*

3. Data & Variables

3.1 Data

As mentioned, to test our hypotheses, we focus on mobile app platform ecosystems. Specifically, we use data preliminarily collected in a period between March 9th, 2014 and June 7th, 2014 (120 days in total) from the United States version of 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, including all major revenue streams, i.e., sales, in-app purchase, advertising) in the above time span.[2] 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). This procedure allows inferring daily app revenue from daily app ranks by means of the well-known power law function relationship estimation, which is the standard approach in the literature linking product sales to ranks based on sales (Brynjolfsson et al., 2003, Chevalier and Goolsbee, 2003). The power law (or Pareto distribution) function equation can be expressed as: Product Sales (in quantity or in value) = b* Rank^(-a), where b and a are the parameters to be estimated in the relationship via regression. The procedure of Garg and Telang (2013) differs from previous approaches in that it does not need access to real revenue data (left hand side of the equation) to estimate the parameters of the power law function. Indeed, Garg and Telang (2013) take advantage of the fact that app stores display several (inter-related) top app rankings. Specifically, their procedure consists of laying out a system of power law function equations: one between daily app revenue and daily app ranks for top grossing apps rankings, and other two between daily app downloads and daily app ranks for top paid and top free apps rankings, respectively. Given that all revenue streams (revenue from app purchase, in-app purchase, and advertisements) depend on the number of downloads, these power law equations are inter-related, and can be combined and re-arranged in a way that the resulting equations include only easily observable variables (namely, app price, app ranks, presence of in-app purchase and advertisement) so that it becomes possible to estimate the parameters necessary to compute the daily app revenue via nonlinear regression model (with no need of retrieving data on real revenue). In the interest of length, for step-by-step details on the procedure, the reader can refer to Garg and Telang (2013), since we follow their procedure to estimate the daily app revenue. Applying the procedure yields the following parameters of the power law function equation linking app revenue to

[2] Note that, by virtue of considering all major streams including sales, in-app purchase, and advertising, the top grossing rankings display not only paid apps, but also free apps.

app rank (as observed from the top 1000 grossing apps ranking): b = 367022.89 and a = 1.03 for Apple's App Store, and b = 270859.60 and a = 0.89 for Google Play, which are similar to those obtained by Garg and Telang (2013) with a different sample. Afterwards, from the power law function we can compute the estimated daily app revenue for each developer in both stores, which is the starting point of our analysis.

Note that the apps considered in our sample are not only those featured in the top 1000 grossing app rankings of the two stores, but include also those not featured in these rankings provided that they are developed by a developer able to bring at least one app in one of the two top 1000 grossing rankings. 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 1000 grossing rankings. All apps commercialized by these developers are included in our sample. However, for the apps of these developers that are not featured in the top 1000 grossing app rankings, it is not possible to estimate the revenue, as not even their rank is available. Therefore, we assume that the revenue generated by these apps is equal to that generated by the 1000th app ranked in the given top 1000 grossing app ranking on the given day.[3]

The choice of relying on top app rankings is consistent with prior research analyzing the app market (Garg and Telang 2013; Ghose and Han, 2014; Roma et al., 2016). 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 Apple's 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 (Roma et al., 2016). 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. 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 (Garg and Telang 2013; Ghose and Han, 2014). More

[3] Our findings are unchanged even when the revenue of the apps not featured in the top 1000 grossing app ranking is assumed equal to zero.

importantly, it is fully in line with Lee and Raghu (2014), who first study the performance implications of diversification in the app market. In addition, as explained above, given that revenue data are not publicly available and need to be inferred from daily app rankings using the procedure of Garg and Telang (2013), the data collection and aggregation request significant effort because we need to retrieve app rankings on daily basis, then conduct estimation through the procedure of Garg and Telang (2013) on daily basis, and finally aggregate all data at developer and period of observation levels. Indeed, as we examine the effect of developers' diversification on their revenue performance, the developer is our unit of analysis. Therefore, besides being consistent with prior literature on diversification in the app market (Lee and Raghu, 2014), we believe that relying on a four month period is a good compromise between data collection and aggregation effort and the objective of our study.

In greater detail, because app rankings are released on a daily basis, some app characteristics (e.g., ranks) are first observed on daily basis during the period of observation. Then, the app characteristics related to the same developer are aggregated on a daily basis for each developer. Finally, the daily data related to each developer are aggregated over the entire period of observation. For instance, the revenue estimated by means of the Garg and Telang (2013) procedure is first computed on a daily basis for each app. Afterwards, the daily revenue of each developer in the sample is computed by summing the daily revenues of its own apps. Finally, the revenue of each developer over the entire period of observation is computed by summing all the daily revenues related the same developer. In a time span of 120 days, we obtain a quite large sample encompassing more that 3,500 apps developed by 382 developers, 205 in the Apple's App Store and 177 in Google Play, with several developers commercializing apps in both platforms. Since we are interested in the performance implications of product line diversification within each platform, it is useful to point out that the apps marketed by these developers are related to an overall number of 20 categories available in the two stores, namely Books & Consulting, Education, Entertainment, Finance, Games, Healthcare & Fitness, Lifestyle, Medicine, Music, Navigation, News, Personalization, Photo & Video, Productivity, Social Networking, Sports, Tools, Travel, Utilities, and Weather. It is important to note that we use the same app categorization provided by the considered app stores. That is, the app categories included in our sample are precisely those available in the two considered stores at the time of data collection, and thus each app is associated with the category directly provided by the store. This implies that the app categorization is exogenous to our study. Moreover, at the time of data collection, these categories, which result from retrieving developers from the top 1000 grossing app rankings of the two considered platforms, represent almost the entire universe of categories available in these platforms. Specifically, our sample encompasses 18 categories qout 23 available in Apple's App Store and 20 out 24 available in Google Play, at the time of data collection. Finally, as the developers included in our sample are retrieved from the top 1000 grossing app rankings of the two considered platforms, the categories in the sample are also the most popular ones, which is important to the purpose of studying product line (inter-category) diversification. In fact, 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.

3.2 Variables

Dependent variable

To properly compare the revenue performance of diversified developers with that of specialized developers we need to identify a measure of revenue performance that rules out the trivial size-related differences between diversified and specialized developers. To do so, we adopt the standard chop-shop approach (Lang and Stulz, 1994; Berger and Ofek, 1995; Rajan et al., 2000; Santalo and Becerra, 2008). In our setting, this consists of adjusting the revenue of diversified developers in order to ensure a correct comparison with specialized developers. Specifically, for each diversified developer we compute the ratio between the actual revenue generated by the developer over the entire period of observation in the given store (obtained by using Garg and Telang (2013) procedure), i.e., the variable *Developer Revenue* reported in Table 1, and the "what would be" revenue of the same developer in the same period and store. The latter is computed as the sum of the revenues the developer would generate if it were a specialized developer in each category where it develops apps (in the given store). The revenues the diversified developer would generate if it were a specialized developer in the categories where it operates are simply the median revenue or the mean revenue of all specialized developers (included in our sample) in each of these categories.[4] To the purpose of checking robustness of our findings, we indeed use both the median and the mean to construct the "what would be" revenue. In Table 1, the variables *What-Would-be-*

[4] Following prior studies (Lang and Stulz, 1994; Berger and Ofek, 1995; Santalo and Becerra, 2008), in order to compute the mean or the median revenue of all specialized developers in a given category, we have preliminarily excluded from the final sample the categories where only diversified developers operate, as for these categories we would have indefinite mean or median.

Developer Revenue – Median and *What-Would-be-Developer Revenue – Mean* correspond to the case where the "what would be" revenue is computed using the median revenue of all specialized developers in the categories where the given diversified developer operates and the case where the same variable is computed using the mean, respectively. For specialized developers, the computation is similar except for the fact that only one category is naturally considered. The ratio between the revenue and the "what would be" revenue (the latter computed either using the median or the mean) is essentially a category-adjusted measure of revenue performance in the given store (Lang and Stulz, 1994), where the term "category-adjusted", or more in general "industry-adjusted", refers to the fact that the performance of diversified firms is "adjusted" (in the way we discussed above) through the "what would be" measure of performance, i.e., the performance the diversified firm would have if it fictitiously were simply the sum of specialized firms in the categories (industries) where it operates (Lang and Stulz, 1994). If the diversification adds value, a diversified firm should have on average a performance superior to the performance of a fictitious firm merely being the sum of specialized firms in the same categories (industries) of the diversified firm. If the diversification subtracts value, the opposite should occur. The "what would be" performance measure captures exactly the performance of this fictitious firm (Lang and Stulz, 1994). Our dependent variable for each developer is the logarithm of the above described ratio (i.e., *Category-adjusted Developer Revenue Performance Ratio – Median* and *Category-adjusted Developer Revenue Performance Ratio – Mean*, respectively for the two cases) computed for both diversified and specialized developers.

Table 1 summarizes the descriptive statistics of the dependent variable (without logarithmic transformation) as well as the variables needed to compute it. Consistent with industry evidence (Perez, 2013; Dredge, 2015), the average developer revenue in the Apple's App Store is almost three times higher than that in Google Play (approximately \$4.5M versus \$1.6M). More importantly, it can be noted that for the entire sample the dependent variable is on average equal to 2.696 when computed using the median, whereas it is 1.094 when computed using the mean.[5] Under both measures (median and mean), the dependent variable is higher in Google Play, thus preliminarily suggesting that the revenue performance of diversified firms should be better in this store rather than in the Apple's App Store. Moreover, when the mean is utilized, the average value of the dependent variable (i.e., the average value

[5] The considerable difference between the average values of the two measures of our dependent variable suggests that the distribution of the values used to construct the "what would be" revenue is particularly skewed. This is also why we use the logarithmic transformation of our dependent variable.

of the variable *Category-adjusted Developer Revenue Performance Ratio – Mean*) is strictly lower than one (equal to 0.907) in the Apple's App Store, while being higher than one (equal to 1.312) in Google Play. Since, by construction, the average value of the variable *Category-adjusted Developer Revenue Performance Ratio – Mean* is exactly equal to one when only specialized developers are considered, the fact that this variable is less than one in the Apple's App Store for the sample including both diversified and specialized developers provides a preliminary evidence that diversified developers perform on average worse than their specialized counterparts in this store. The opposite occurs in Google Play, thus hinting at the existence of an effect of the platform ecosystem on the relationship between developers' diversification and their revenue performance. In § 4 we will unravel these aspects by using more appropriate instruments than simple descriptive statistics.

Main independent variables

Diversification: in this study we focus on product line diversification of developers operating in a platform ecosystem. Specifically, we compare diversified developers with specialized developers. Therefore, we follow the approach adopted by the corporate finance literature (Lang and Stulz, 1994; Berger and Ofek, 1995; Villalonga, 2004; Santalo and Becerra, 2006, 2008) and thus introduce a dummy variable (*Diversification*) equal to one if the given developer is diversified, and equal to zero if it is 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 platforms. Also, note that no developers changed status from 'diversified' to 'specialized' or vice versa during our period of observation. In § 5, we check robustness of our results using a continuous measure of diversification in line with several studies in the strategic management literature (e.g., Palepu, 1985).

Following Santalo and Becerra (2006, 2008), we also need to take into account that the effect of diversification on performance may differ across categories depending on the predominance of diversified or specialized developers. Indeed, as we have discussed, the type of platform ecosystem (open versus closed) should also influence the moderating role of the product category in the relationship between diversification and performance. Therefore, in our models we introduce the interaction of the dummy *Diversification* with the following variable:

Total Within-Category Market Share of Diversified Developers: to construct this variable in each platform ecosystem, we first compute for each specialized developer the sum of the market shares of all specialized developers in the category where the given specialized developer is active. Note that the market share of a specialized developer is computed dividing its own actual revenue in the category by the total revenue generated by all specialized and diversified developers in that category.[6] For each specialized developer, one minus the sum of the market shares of all specialized developers in the given category (where the specialized developer operates) represents the total within-category market share held on the whole by diversified developers in that category in the given platform. Essentially, this procedure yields the total market share held on the whole by diversified developers for each category in the given platform. While the computation terminates for specialized developers, one more step is needed for diversified developers. Indeed, for each diversified developer there exist multiple values of the total within-category market share held on the whole by diversified developers, i.e., one for each category where the developer operates. Therefore, following prior literature (Santalo and Becerra, 2008), for diversified developers the final variable is computed as a weighted average of the total within-category market share held by diversified developers across each category in which the diversified developer is active. The weights used are simply the actual revenues of the diversified developer in each category divided by diversified developer's total actual revenue (Santalo and Becerra, 2008).

To test whether the effect of developers' diversification on their revenue performance is influenced by the type of platform ecosystem (open versus closed) where the developer operates, we utilize two different approaches. Under the first approach, we consider the entire sample and introduce in the regression model some interactions that allow distinguishing the role of the platform ecosystem. Specifically, we add the interaction between the dummy *Diversification* and a variable (namely, *Store*) equal to one if the given observation is related

[6] Note that we use the terms "all specialized developers" and "all diversified developers" to indicate all specialized and diversified developers in our sample. We recognize that, by using only developers in our sample to compute the market shares, we do not take into account the whole number of developers commercializing apps in the given category in the given store during our period of observation. However, this is not a relevant issue in our setting. Indeed, recall that our sample considers the revenue related to all the apps of all developers able to appear in the top 1000 grossing app rankings with at least one app. This implies that the developers in our sample are the most important developers in each of the two stores. There is overwhelming industry evidence (e.g., Smith, 2012; Perez, 2014) that top developers make the great majority of the revenue generated in the app stores, leaving to the remaining developers only extremely small portion of the market. Therefore, the error generated by our approach is very minor. In addition, as explained earlier, the vast majority of apps and developers are never displayed on the pages of the two stores and it is not possible to retrieve rank information for developers not included in such rankings. With a multitude of apps "invisible" to consumers, the majority of developers of such apps are not a threat to developers of top apps. This further supports our choice of restricting the market to the developers able to appear in the top 1000 grossing app rankings with at least one app.

to a developer operating in the Apple's App Store, i.e., the closed platform ecosystem, zero if it is related to a developer in Google Play, i.e., the open platform ecosystem.[7] To capture the role of app categories, in this case, we also add a triple interaction between the two cited dummies and the variable *Total Within-Category Market Share of Diversified Developers*. Under the second approach, we separate the sample in two subsamples, one for each distribution platform (Apple's App Store and Google Play), and run the regression models for these two subsamples separately. Finally, it is noteworthy that, in addition to their presence in the interaction terms, the variables *Total Within-Category Market Share of Diversified Developers* and *Store* are also included in our regression models as direct effects.

Control variables

In addition to our main independent variables (interactions included), we control for some other factors that may influence our dependent variable. Ideally, we would like to control for some firm-level variables normally utilized in corporate diversification studies (e.g., Lang and Stulz, 1994; Santalo and Becerra, 2008; Mackey et al., 2017) such as total assets, EBIT over sales ratio, and capital expenditures over sales ratio. However, we cannot have access to these data because, contrarily to these studies, the great majority of the developers in our sample are not public companies. Rather, most developers are small private and independent firms and, in some occurrences, even individuals. This makes firm-level data retrieval extremely challenging. Recall that not even revenues are publicly available and that we resort to the procedure of Garg and Telang (2013) to estimate the revenue developers generate from the app stores. The difficulty in accessing sensible developers' information, such as operating costs, is also the major reason we rely on revenue as a measure of performance, rather than constructing some profitability measure or even financial measures such as the market-to-book ratio. Nevertheless, we try to control for these developer-level factors indirectly by using proxies that take into account the experience and the notoriety of the developer in the given store. We also control for the level of within-category competition in each store, which may influence developers' performance. Specifically, our control variables are:

Category HHI (Herfindahl-Hirschman Index): in line with previous studies (Santalo and Becerra, 2008; Tanriverdi and Lee, 2008) we control for the level of developer concentration

[7] Note that we use the dummy *Store* to capture the type of platform ecosystem (open versus close). As this characteristic influences the type of demand side users accessing the platform (specifically, demand side with high versus low willingness to pay on average), we could have used a proxy of this variable, which is available to us. However, as suggested by industry studies the gap in average willingness to pay and spend for apps between Apple's App Store and Google Play is constant over time, with app users in the former store spending twice more than those in the latter store (Richter, 2018). Therefore, this proxy would be perfectly correlated to the dummy *Store*, providing exactly the same results. That is why we simply use the more intuitive dummy *Store*.

within each app category in the given store by computing and introducing the usual Herfindahl-Hirschman Index (HHI). The level of developer concentration (and thus the level of developer competition) within a category is indeed an important category characteristic that may affect the revenue performance of both diversified and specialized firms, and thus needs to be controlled for. To obtain the HHI we compute the market shares for each developer operating in the given category in the given store as the ratio between its own actual revenue in the category and the total revenue generated by all specialized and diversified developers in that category.[8] As before, for diversified developers the final HHI is computed as a weighted average of the HHI across each category in which the diversified developer is active. Again, the weights used are simply the actual revenues of the diversified developer in each category divided by developer's total actual revenue. From Table 1, we observe that the average level of developer concentration within category is not high (the average is overall 0.153), thus suggesting that, at least among successful developers, the competition within category tends to be fierce, with the Apple's App Store being more competitive.

Developer Age in the Store: we control for the experience and the knowledge developers have gained in the app development and commercialization in a given platform by introducing a variable, namely *Developer Age in the Store*, which indicates, at the beginning of our observation period, the number of days a developer has been marketing apps in the given store since its first app commercialization. By capturing the developer experience in the store, this measure is naturally expected to influence the developer revenue performance (Tanriverdi and Lee, 2008). Indeed, software developers gain most of their experience from both technical and managerial perspectives by means of a learning-by-doing process (Boh et al. 2007). Therefore, they have to activate a process of experimentation and become familiar with the software development kit provided by the platform before being capable of developing apps with great market potential. For these reasons, *ceteris paribus*, a developer that has marketed apps in the given store for longer time is more likely to be successful. From Table 1, we observe that the variable *Developer Age in the Store* is on average almost two years (approximately 732 days). In this case, there are considerable 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 (919 versus 514 days, respectively), consistent with the evidence that developers usually target the Apple's App Store first (Roma et al., 2016).

[8] With regard to the terms "all specialized developers" and "all diversified developers", recall footnote 6.

Brand Notoriety: we take into account the extent of developer notoriety and thus the relative marketing capabilities by including a dummy (namely, *Brand Notoriety*), which is equal to one if the brand of the given developer is worldwide established, zero otherwise. We identify a list of 25 top developers (12 in the Apple's App Store and 13 in Google Play) in our sample based on corporate revenue information and worldwide brand recognition. For instance, this list includes mobile app divisions of Adobe Systems, Apple, Disney, Electronic Arts, Gameloft, Marvel Entertainment, Sega, TomTom International, Zynga, among others.

Table 2 reports the correlation matrix, which suggests no serious degree of correlation between the variables employed in this study. This is fully confirmed by the fact that the Variance Inflation Factor (VIF) computed after performing our regression models is small (less than 5) for each variable included in our analysis (VIF results can be made available by authors upon request).

4. Results and discussion

Given the cross-sectional nature of our dataset, we perform several robust OLS regression models for each of the two specifications of our dependent variable (i.e., *Category-adjusted Developer Revenue Performance Ratio – Median* and *Category-adjusted Developer Revenue Performance Ratio – Mean*). Specifically, Tables 3 and 4 shows the major results of our empirical analysis when considering the entire sample (first approach) under the two specifications of the dependent variable *Category-adjusted Developer Revenue Performance Ratio – Median* and *Category-adjusted Developer Revenue Performance Ratio – Mean*, respectively. The results are fully robust across the two specifications. Therefore, we only discuss those obtained when the median is used to compute the dependent variable (Table 3), which is also the specification used in prior works, e.g., Santalo and Becerra (2008). In the first column of Table 3, we check the impact of the control variables alone.[9] As expected, factors such as notoriety and experience largely influence developer revenue performance. In contrast, the variable *Category HHI* is not significant. This implies that the chop-shop approach we use is fully effective as it already accounts for any general category effects on developer performance.

In the second column, we add the dummy *Diversification* and find that, while the significance and the sign of the control variables remain unchanged, the effect of the diversification decision is significant and negative. Given that this result is derived under the full sample (which includes observations from both Apple's App Store and Google Play), we can only

[9] We include the direct effect of the variable *Total Within-Category Market Share of Diversified Developers* only in the regression models where its interaction with the dummy *Diversification* is also included (i.e., column 4).

claim that overall a diversification decision worsen the revenue performance, but this information is *per se* useless because this negative effect of diversification may not necessarily hold in both platform ecosystems. Indeed, as we have theorized, the effect of diversification on revenue performance may vary across different type of platform ecosystems, and thus the overall effect may be simply driven by the prevalence of a negative effect emerging in one of the two platforms.

Therefore, to examine the effect of diversification on revenue performance more accurately and capture the role of the platform ecosystem, we add the interaction term between the dummies *Diversification* and *Store* in the third column. After adding this interaction, we find that the coefficient of the dummy *Diversification*, which now reflects the marginal change in the category-adjusted developer revenue performance ratio due to diversification in Google Play (*Store* = 0), is largely insignificant. On the opposite, the coefficient of the interaction term, which instead reflects the marginal change in the category-adjusted developer revenue performance ratio due to diversification in the Apple's App Store (*Store* = 1), is largely significant and negative. This suggests that the effect of diversification on revenue performance is negative in the closed platform, i.e., Apple's App Store. That is, specialized developers on average deliver superior performance than diversified developers in this platform ecosystem. In contrast, no significant revenue differences between diversified and specialized developers emerge in Google Play. These results provide evidence of a different *average* effect of diversification in the two platform ecosystems. As pointed out in previous studies (Santalo and Becerra, 2008), this average effect may result from the combination of heterogeneous effects across different app categories.

Therefore, to further disentangle the effect of diversification on revenue performance, we add in the fourth column of Table 3 the interaction of the dummy *Diversification* with the variable *Total Within-Category Market Share of Diversified Developers* as well as the triple interaction of these two variables with the dummy *Store*. Note that the latter interaction is necessary under the full sample to distinguish the role of the platform ecosystem even when disentangling the role of the category (i.e., the effect of the prevalence of diversified developers over specialists across categories). Under this complete model, we find clear support to our hypotheses. Indeed, by looking at this column, we observe that the coefficient of the dummy *Diversification* remains significant and negative (equal to -0.615), while the coefficient of the interaction between this dummy with the dummy *Store* is largely insignificant. Moreover, the coefficient of the interaction term between the dummy *Diversification* and the variable *Total Within-Category Market Share of Diversified*

Developers is significant and positive (equal to 2.096), whereas the coefficient of the triple interaction is significant and negative (equal to -2.823). This implies that the effect of diversification is negative in the Apple's App Store (closed platform) irrespective of whether the total within-category market share held by diversified developers is large. Note, indeed, that the overall effect of diversification in the Apple's App Store (dummy *Store* = 1) is -0.615+(2.096-2.823)**Total Within-Category Market Share of Diversified Developers*, which is clearly negative irrespective of whether diversified firms have a predominant presence or not in a given category. In contrast, the effect of diversification in Google Play (open platform) depends on the category a developer decides to target. We find that in this platform ecosystem the diversification strategy is detrimental when the total within-category market share held by diversified developers is small (i.e., in categories where diversified developers have small market presence), whereas it is beneficial when the total within-category market share held by diversified developers is large (i.e., in categories where the market presence of diversified developers becomes relevant). As a matter of fact, the overall effect of diversification in the Google Play (dummy *Store* = 0) is -0.615+2.096**Total Within-Category Market Share of Diversified Developers*, which is indeed negative for low values of the within-category market share held by diversified developer, but can become positive as this market share increases.

Our findings are clearer by looking at Tables 5 and 6, where the results are reported under the two separate subsamples of developers in the Apple's App Store and in Google Play for both specifications of the dependent variable (median and mean), respectively. In this case, the dummy *Store* is naturally removed from the analysis. Again, as the results are fully robust across the two dependent variable specifications, we briefly discuss those reported in Tables 5 (median). In the subsample retrieved from the Apple's App Store, when adding only the dummy *Diversification* (second column), we observe a significant and negative effect of diversification on revenue performance. This result also holds after adding the interaction term with the variable *Total Within-Category Market Share of Diversified Developers* (third column). In particular, the interaction term is shown to be insignificant, while the direct term remains significant and negative. In contrast, in the subsample retrieved from Google Play, on average no differences in terms of revenue performance emerge between diversified and specialized developers. Indeed, in the fifth column of Table 5, the coefficient of the dummy *Diversification* is largely insignificant. However, when we add the interaction terms with the variable *Total Within-Category Market Share of Diversified Developers* (sixth column), the coefficient of the direct term becomes significant and negative (equal to -0.698), whereas the coefficient of the interaction term is significant and positive (equal to 1.726). As before, this implies the diversification strategy is detrimental in categories where diversified developers have small market presence, while being beneficial in categories where the market presence of diversified developers becomes relevant. Combined together, these results provide robust evidence to our argument that the type of platform ecosystem (open or closed) where supply side users (in our case, app developers) choose to commercialize their products plays a crucial role in the performance implications of diversification across various product categories.

5. Robustness check using the entropy measure of diversification

So far we have followed the mainstream approach in finance and strategic management literature (Lang and Stulz, 1994; Berger and Ofek, 1995; Santalo and Becerra, 2006, 2008; Kuppuswamy and Villalonga, 2015) considering the diversification strategy as a dichotomous decision, i.e., diversification versus specialization. However, as mentioned earlier, several studies in strategic management literature have examined diversification as a multi-level or even continuous decision variable positing and testing curvilinear relationships between these variables, such as the inverted-U and the intermediate models (Palich et al., 2000). Under this approach the decision to diversify is longer dichotomous, rather it requires choosing in how many different categories (or industries) to diversify and the amount of diversification in each of them (how important the given category is for the firm in terms of revenue as compared with the other categories where the firm operates). Therefore, in this section, we check whether our findings are robust when the diversification is not a dichotomous (diversification versus specialization) decision. Specifically, we follow most of the extant literature (e.g., Jacquemin and Berry, 1979; Palepu, 1985; Khanna and Palepu, 2000; Tanriverdi and Lee, 2008; Su and Tsang, 2015) in considering a continuous diversification decision variable computed through the well-known entropy measure defined by Jacquemin and Berry (1979). For a given firm, this measure is a weighted average of the ratio between firm's sales in each product category (or industry) and firm's total sales, with the weight for each category being the logarithm of the inverse of the ratio (for greater detail on the computation, see Palepu, 1985). Essentially, the measure takes into account two elements of diversification, namely the number of categories (or industries) in which a firm operates, and the relative importance of each of the category (industry) in the total sales of the firm (Palepu, 1985).

We perform the same econometric analysis as before, simply substituting the dummy *Diversification* with the *Diversification (Entropy Measure)*. We report the results in Table 7 for the separate subsamples of Apple's App Store and Google Play developers, respectively.

Specifically, the first two columns of Table 7 report the results for the Apple's App Store subsample under the full model (i.e., the model including the interaction between the variables *Diversification (Entropy Measure)* and *Total Within-Category Market Share of Diversified Developers*) when the dependent variable is computed using the mean and the median, respectively. In both columns, the coefficient of the variable *Diversification Entropy Measure* is significant and negative, whereas the interaction variable is insignificant, thus fully confirming that the effect of diversification on developer's revenue performance is negative in the Apple's App Store (i.e., the closed platform ecosystem). The third and fourth columns of Table 7 report, instead, the results for the Google Play subsample under the full model, again when the dependent variable is computed using the mean and the median, respectively. In both columns, the coefficient of the variable *Diversification (Entropy Measure)* is significant and negative, whereas the interaction with the variable *Total Within-Category Market Share of Diversified Developers* is significant and positive, thus once again fully confirming that in Google Play (i.e., the open platform ecosystem) the effect of diversification is detrimental in categories where diversified developers have small market presence, while being beneficial in categories where the market presence of diversified developers becomes relevant. This implies robustness of our findings to a change in the manner the diversification decision is considered and computed (dichotomous versus continuous).

5. Managerial implications and conclusions

In this paper, we have contributed to the vast literature on the effects of diversification on firm performance by addressing this issue in the context of the mobile app market, where developers can diversify by marketing apps in different categories, but still in the same competitive ecosystem, i.e., the app distribution platform ecosystem. More importantly, from a theoretical perspective, we have contributed to both strategic management and information systems disciplines by investigating how the platform ecosystem, and specifically its characteristic of openness, can influence the performance-diversification relationship and the moderating role of the product category for firms operating in the ecosystem. Applying the arguments of Santalo and Becerra (2008) to the context of platform ecosystem, we have indeed argued that the effect of diversification on performance of firms operating in the platform ecosystem hinges upon the type of platform ecosystem (open or closed), and the consequent different demand side users populating the ecosystem.

Our findings indeed suggest that, while in the Apple's App Store (closed platform ecosystem) the effect of diversification is always negative, in Google Play (open platform ecosystem) whether diversified developers perform better than their specialized counterparts depends on the categories targeted by diversified developers. In the latter platform, in categories where the presence of diversified developers is limited, diversification destroys value because the limited presence is itself a signal that some competitive advantage associated with specialization exists in the given category. Vice versa, in categories where the presence of diversified developers is considerable, diversification creates value as the large presence indicates that the competitive advantage is associated with diversification. As we have argued, due to the differences in platform openness, the two major app platform ecosystems are characterized by large differences in average willingness to pay on the demand side (Ghose and Han, 2014). In a closed platform such as Apple's App Store demand side users have relatively high willingness to pay and thus developers have greater incentive to develop high-quality apps. In this case, a specialization strategy is more suitable because under this strategy developers (supply side users) are naturally better positioned to build specific capabilities that allow them to deliver apps better matching customers' needs. In a platform such as Google Play opened to multiple device makers and thus also to a very broad and heterogeneous demand side, consumers have on average more limited willingness to pay. This diminishes the benefits associated with category specialization, while amplifying the main advantage of diversification, i.e., the advantage of exploiting the loyal customer base already installed for certain product categories also for other categories. Our analysis suggests that, in this case, specialization is preferable (in terms of revenue) in those categories satisfying needs on which consumers tend to concentrate all their more limited willingness to pay, whereas diversification is preferable in those categories where the benefits of exploiting the installed customer base across categories to fuel product diffusion are larger.

This study has important implications for developers (and more in general for platform supply side users) as well as for platform owners. First, we inform developers (and other platform supply side users) that they should factor in the type of platform ecosystem where they operate before making diversification decisions as their decision to diversify across product categories is likely to have different consequences in terms of revenue performance in different platforms. In particular, they should consider the important role of cross-platform differences in the characteristic of openness and, as consequence, in the characteristics of demand side users. In this regard, they should pay attention to how these aspects influence the discussed interplay between the main advantage and disadvantage of diversification across different product categories. Second, our findings help increase platform owners' awareness on the role of the platform ecosystem characteristics in the relationship diversification-performance and rethink their strategies to attract and support both demand- and supply-side users in order to improve platform ecosystem profitability.

There are of course some limitations in our study, which may however offer opportunities for future improvements. First, 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 any performance measure. 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. Hence, they cannot be used as exogenous instruments. Moreover, firm characteristics are also endogenous as most of them can be manipulated at least in the long run to improve the firm performance. As a result, the use of the IVs approach in this stream of research is limited by the difficulty to find completely exogenous instruments. In our study, the alternative would be to identify and restrict to a sample of only developers who change their status from 'diversified' to 'specialized' (or vice versa) during the period of observation. By observing only these developers before and after their diversification or specialization decisions and thus studying how within-developer changes in diversification affect performance (through fixed effects models), the endogeneity concerns should be mitigated, if not completely removed. However, the main problem with this procedure is that the number of diversified developers is quite low (we count 75 diversified developers out of 382 during our period of observation) and the number of developers who change status during a given period of observation is even lower (no developers changed status during our period of observation). As a result, no reliable statistical analysis can be conducted. Even the extension of the observation period to increase the number of developers who change status is problematic. Indeed, the absence of aggregated (e.g., monthly or weekly) data on developers' revenue implies that any measure of performance must be constructed by observing daily rankings and using the procedure proposed by Garg and Telang (2013). Therefore, to ensure a sufficient number of developers who change status, we may be required to observe rankings on a daily basis for a duration not known *a priori*, which makes this approach extremely laborious with no certainty of being successful. In absence of a good alternative, we preferred relying on our standard OLS regression model for our study. To further support our choice, it is important to note that, while potential endogeneity concerns may arise in the relationship diversification-performance, it is less likely that the resulting bias affects the role of the platform ecosystem in such relationship, which is the goal of our study. Indeed, typically the presence of endogeneity, if any, would tend to bias the effect of diversification on performance downward (Campa and Kedia, 2002; Villalonga, 2004; Santalo and Becerra, 2008). However, there is no reason to believe that endogeneity, if any, should have a different influence in the two considered platforms. Therefore, our findings that the platform ecosystem matters in the relationship diversification-performance, and specifically that open platforms are a more suitable environment for diversification, is likely to hold even after controlling for the bias. At any rate, we leave the issue of endogeneity for future studies when rankings on aggregated data will be made available.

Finally, this study would benefit from future corroboration using longer period of observation when aggregated data will be made available, to check consistency over time. As we have pointed out, the fact that data availability is restricted to daily data requires significant data collection and aggregation effort, which is why all studies examining the app market consider observation periods of a few months. Also, in line with recent studies focusing on information goods (Tanriverdi and Lee, 2008; Lee and Raghu, 2014), we use revenue as a measure of firm performance to cope with the absence of cost information. Accordingly, our arguments on the advantages and/or disadvantages of diversification reflect the implications of diversification on such measure of performance. However, because diversification comes at a cost, our study would certainly benefit from a further validation through a large survey aimed at obtaining cost information. We conjecture that our main finding that the platform ecosystem matters in the relationship diversification-performance, and specifically that open platforms (e.g., Google Play) are a more suitable environment for diversification, would still hold. This is because the main force generating differences across platforms is related to the effect of platform openness on demand side users. As a result, the cost of diversification should not impact differently in different types of platforms. Finally, to examine the effect of the platform ecosystem, our analysis focuses on product line (category) diversification within the platform, rather than on inter-store diversification (i.e., or multi-homing). The study of diversification among different platforms (e.g., the decision to market apps in multiple app stores) and the study of diversification from a platform perspective are worth future research.

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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 Revenue Performance Ratio – Median (constructed using the What-Would-be-Revenue – Median)	2.696	5.184	2.495	4.512	2.930	5.872
Category-adjusted Developer Revenue Performance Ratio – Mean (constructed using the What-Would-be-Revenue – Mean)	1.094	2.091	0.907	1.439	1.312	2.642
Revenue (in $)	3,215,613	7,308,964	4,558,057	9,167,576	1,660,806	3,701,190
What-Would-be-Revenue – Median (constructed using the median revenue in $ of specialized developers in a given category)	1,276,806	1,008,620	1,881,676	996,886.8	576,249.4	361,450.9
What-would-be-Revenue – Mean (constructed using the mean revenue in $ of specialized developers in a given category)	3,512,929	2,765,878	5,262,638	2,675,038	1,486,429	755,296.6
Diversification	0.196	0.398	0.195	0.397	0.198	0.399
Brand Notoriety	0.065	0.373	0.059	0.235	0.073	0.262
Category HHI	0.153	0.185	0.128	0.158	0.181	0.210
Developer Age in the Store (days)	731.516	454.726	919.420	502.860	513.887	256.455
Store	0.537	0.499	-	-	-	-
Total Within-Category Market Share of Diversified Developers	0.278	0.283	0.232	0.234	0.332	0.324

Table 2. Correlation matrix

	Diversification	**Brand Notoriety**	**Category HII**	**Developer Experience**	**Store**
Brand Notoriety	0.269*				
Category HHI	0.204*	-0.001			
Developer Age in the Store	0.261*	0.181*	0.0003		
Store	-0.003	-0.030	-0.142*	0.445*	
Total Within-Category Market Share of Diversified Developers	0.391*	0.060	0.679*	0.057	-0.177*

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

Table 3. OLS regression models with full sample and "Category-adjusted Developer Revenue Performance Ratio – Median" as dependent variable

	(1)	(2)	(3)	(4)
Brand Notoriety	0.929***	1.083***	1.040***	1.105***
	(0.238)	(0.233)	(0.225)	(0.220)
Category HHI	0.390	0.570	0.472	0.573
	(0.361)	(0.363)	(0.356)	(0.406)
Developer Age in the Store	0.0007***	0.0008***	0.0008***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Store	-0.827***	-0.856***	-0.714***	-0.687***
	(0.195)	(0.195)	(0.215)	(0.218)
Diversification		-0.436**	0.017	-0.615**
		(0.177)	(0.223)	(0.292)
Diversification X Store			-0.839**	-0.085
			(0.342)	(0.416)
Diversification X Total Within-Category Market Share of Diversified Developers				2.096***
				(0.683)
Total Within-Category Market Share of Diversified Developers				-0.228
				(0.304)
Diversification X Total Within-Category Market Share of Diversified Developers X Store				-2.823***
				(1.063)
Constant	-0.337*	-0.345*	-0.434**	-0.457**
	(0.177)	(0.176)	(0.179)	(0.193)
N of observations	382	382	382	382
R^2	0.088	0.097	0.107	0.119

Robust standard errors in parentheses - * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note that the magnitude of the R^2 is consistent with similar models presented in prior literature (e.g., Santalo and Becerra, 2008).

Table 4. OLS regression models with full sample and "Category-adjusted Developer Revenue Performance Ratio – Mean" as dependent variable

	(1)	(2)	(3)	(4)
Brand Notoriety	1.006***	1.124***	1.075***	1.139***
	(0.262)	(0.264)	(0.251)	(0.251)
Category HHI	1.740***	1.877***	1.767***	1.408***
	(0.377)	(0.384)	(0.371)	(0.415)
Developer Age in the Store	0.0007***	0.0008***	0.0009***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Store	-0.824***	-0.846***	-0.686***	-0.699***
	(0.194)	(0.194)	(0.213)	(0.217)
Diversification		-0.333*	0.174	-0.516*
		(0.186)	(0.246)	(0.307)
Diversification X Store			-0.941***	-0.149
			(0.358)	(0.427)
Diversification X Total Within-Category Market Share of Diversified Developers				1.777**
				(0.741)
Total Within-Category Market Share of Diversified Developers				0.333
				(0.318)
Diversification X Total Within-Category Market Share of Diversified Developers X Store				-2.800**
				(1.104)
Constant	-1.518***	-1.524***	-1.624***	-1.523***
	(0.177)	(0.178)	(0.181)	(0.196)
N of observations	382	382	382	382
R^2	0.132	0.137	0.148	0.161

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

Note that the magnitude of the R^2 is consistent with similar models presented in prior literature (e.g., Santalo and Becerra, 2008).

Table 5. OLS regression models with separate samples and "Category-adjusted Developer Revenue Performance Ratio – Median" as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
	Apple's App Store			Google Play		
Brand Notoriety	1.130***	1.358***	1.303***	0.741**	0.821***	0.947***
	(0.379)	(0.339)	(0.343)	(0.305)	(0.303)	(0.292)
Category HHI	0.211	0.424	0.959	0.450	0.548	0.462
	(0.626)	(0.611)	(0.778)	(0.411)	(0.409)	(0.420)
Developer Age in the Store	0.0004	0.0005*	0.0005*	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Diversification		-0.757***	-0.631**		-0.202	-0.698**
		(0.256)	(0.282)		(0.216)	(0.284)
Diversification X Total Within-Category Market Share of Diversified Developers			-0.673			1.726**
			(0.958)			(0.744)
Total Within-Category Market Share of Diversified Developers			-0.417			-0.167
			(0.549)			(0.331)
Constant	-0.884***	-0.908***	-0.434**	-0.965***	-0.993***	-0.938***
	(0.318)	(0.320)	(0.179)	(0.258)	(0.259)	(0.279)
N of observations	205	205	205	177	177	177
R^2	0.039	0.061	0.065	0.168	0.171	0.193

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

Note that the magnitude of the R^2 is consistent with similar models presented in prior literature (e.g., Santalo and Becerra, 2008).

Table 6. OLS regression models with separate samples and "Category-adjusted Developer Revenue Performance Ratio – Mean" as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
	Apple's App Store			Google Play		
Brand Notoriety	1.152***	1.368***	1.348***	0.869**	0.869**	1.009***
	(0.390)	(0.358)	(0.355)	(0.359)	(0.360)	(0.362)
Category HHI	1.979***	2.182***	1.737**	1.521***	1.521***	1.380***
	(0.605)	(0.5591)	(0.760)	(0.449)	(0.446)	(0.448)
Developer Age in the Store	0.0004	0.0006**	0.0005**	0.002***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Diversification		-0.719***	-0.613**		-0.0003	-0.565*
		(0.260)	(0.284)		(0.245)	(0.303)
Diversification X Total Within-Category Market Share of Diversified Developers			-1.605*			1.917**
			(0.962)			(0.816)
Total Within-Category Market Share of Diversified Developers			0.807			-0.134
			(0.531)			(0.380)
Constant	-2.096***	-2.119***	-2.031***	-2.135***	-2.135***	-2.059***
	(0.317)	(0.319)	(0.327)	(0.264)	(0.266)	(0.287)
N of observations	205	205	205	177	177	177
R^2	0.072	0.092	0.100	0.223	0.223	0.247

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

Note that the magnitude of the R^2 is consistent with similar models presented in prior literature (e.g., Santalo and Becerra, 2008).

Table 7. Robustness check using entropy-based diversification measure, and "Category-adjusted Developer Revenue Performance Ratio – Median" as dependent variable

	"Category-adjusted Developer Revenue Performance Ratio – Median" as dependent variable	"Category-adjusted Developer Revenue Performance Ratio – Mean" as dependent variable	"Category-adjusted Developer Revenue Performance Ratio – Median" as dependent variable	"Category-adjusted Developer Revenue Performance Ratio – Mean" as dependent variable
	Apple's App Store		Google Play	
Brand Notoriety	1.405***	1.448***	0.950***	1.022***
	(0.312)	(0.329)	(0.291)	(0.367)
Category HHI	0.974	1.754**	0.444	1.364***
	(0.764)	(0.748)	(0.421)	(0.453)
Developer Age in the Store	0.0006**	0.0006**	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Diversification (Entropy Measure)	-1.482***	-1.389***	-1.200***	-1.052***
	(0.421)	(0.437)	(0.274)	(0.306)
Diversification (Entropy Measure) X Total Within-Category Market Share of Diversified Developers	0.686	-0.625	2.234***	2.436***
	(1.264)	(1.286)	(0.818)	(0.933)
Total Within-Category Market Share of Diversified Developers	-0.436	0.784	-0.008	0.050
	(0.540)	(0.526)	(0.325)	(0.361)
Constant	-0.996***	-2.037***	-0.926***	-2.045***
	(0.327)	(0.325)	(0.277)	(0.286)
N of observations	205	205	177	177
R^2	0.083	0.115	0.201	0.252

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

Note that the magnitude of the R^2 is consistent with similar models presented in prior literature (e.g., Santalo and Becerra, 2008).

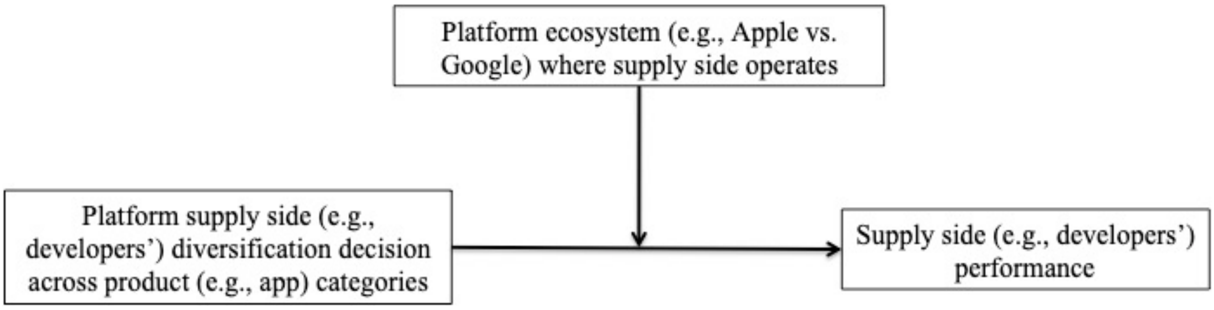

Figure 1. The role of the platform ecosystem in shaping the relationship between supply side diversification decision and performance