



XXVI Riunione Scientifica Annuale  
RSA AiIG 2015

Vicenza, 15 e 16 ottobre 2015

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## Programma

Programma definitivo

**Mercoledì, 14 Ottobre 2015**

**Antica Casa della Malvasia, Contrà delle Morette**

20:30 - 22:30	Cena di benvenuto (non inclusa nella conference fee)
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**Prima giornata: giovedì, 15 Ottobre 2015**

**Complesso Universitario, Viale Margherita 87**

09:00 - 10:00	Benvenuto e Registrazione
10:00 - 10:30	Apertura lavori e saluti istituzionali
10:30 - 11:10	Erik Lehman, Mainstream Entrepreneurship in a Global Economy: Why Small is so Beautiful
11:10 - 11:50	Andy Neely, Innovating Your Service Business Model: The Capabilities to Succeed
11:50 - 13:00	Ricordo Gianluca Spina
13:00 - 14:00	Light lunch

**Prima giornata: giovedì, 15 Ottobre 2015**

**Dipartimento di Tecnica e Gestione dei sistemi industriali, Stradella San Nicola, 3**

14:15 - 16:15	Sessioni parallele
16:15 - 16:30	Coffee break
16:30 - 17:45	Sessioni parallele
17:45 - 18:00	Premio Pagliarani: premiazione
18:00 - 19:00	Assemblea AiIG
20:30	Cena sociale - Hotel Villa Michelangelo, Via Sacco 35 - Arcugnano, Vicenza

**Seconda giornata: venerdì, 16 Ottobre 2015**

**Complesso Universitario, Viale Margherita, 87**

 Italiano  English

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*Dipartimento di Tecnica e Gestione dei Sistemi Industriali*

[aigscientificmeeting2015@gest.unipd.it](mailto:aigscientificmeeting2015@gest.unipd.it)

**Segreteria Amministrativa**

[presidenzaaiig@uniroma1.it](mailto:presidenzaaiig@uniroma1.it)



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## Protetto: Paper

### General session

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**Lavori e Track**

*Dipartimento di Tecnica e Gestione  
dei Sistemi Industriali*

[aiigscientificmeeting2015@gest.unipd.it](mailto:aiigscientificmeeting2015@gest.unipd.it)

**Segreteria Amministrativa**

[presidenzaaiig@uniroma1.it](mailto:presidenzaaiig@uniroma1.it)

# The role of the distribution platform in price formation of paid apps

Paolo Roma

DICGIM – Management & Economics Research Group

Università degli Studi di Palermo

Viale delle Scienze, 90128, Palermo, Italy

paolo.roma@unipa.it

phone: +39 091 238 618 73

corresponding author

Fabio Zambuto

DICGIM – Management & Economics Research Group

Università degli Studi di Palermo

Viale delle Scienze, 90128, Palermo, Italy

fabio.zambuto@unipa.it

Giovanni Perrone

DICGIM – Management & Economics Research Group

Università degli Studi di Palermo

Viale delle Scienze, 90128, Palermo, Italy

giovanni.perrone@unipa.it

# The role of the distribution platform in price formation of paid apps

## Abstract

In this paper we study the role of the distribution platform as an important determinant of price of paid apps. We also examine whether the price implications of developers' strategic decisions at the app level hinge upon the targeted distribution platform. To these purposes, we construct a hierarchical model of price formation by using an *ad-hoc* panel dataset consisting of top paid apps from the two major app stores, namely Apple's App Store and Google Play. Our findings show that prices of paid apps strongly depend on the platform where the apps are marketed. Specifically, the App Store is associated with lower prices for paid apps than Google Play. We find evidence that this is because the impact of cross-store differences in in-store developer competition prevails over the impact of cross-store differences in average consumer willingness to pay. We also find that price premiums as a return to trialability are more likely to emerge in Google Play than in the App Store, and that developers are more likely to adopt a penetration price strategy in Google Play, arguably because the price implications of these decisions heavily rest on the willingness to pay of consumers in the store. Finally, our evidence does not confirm the argument that a more marked price reduction for paid apps operating as two-sided markets should be observed in Google Play.

**Keywords:** Mobile App Market, Online Distribution, Pricing, Electronic Commerce, Multi-level Data.

## 1 Introduction

In the very last few years, mobile software applications (apps, hereafter) have become important components of people's everyday life. As a matter of fact, the time per day spent by US consumers using apps increased by 35% in 2012, and was higher than the time spent on the web and quite close to that spent watching TV (Khalaf 2012). Also, recent estimates suggest that the revenue generated from customers buying and downloading apps for smartphones and tablets will step from \$26 billion in 2013 up to \$77 billion in 2017, whereas the number of downloads will increase from 102 billion to 268 billion (Gartner 2013; Lunden 2013).

Although apps for mobile devices have been around since the late 90s, the app market started soaring in 2008 when Apple introduced the application store distribution paradigm. An application store is essentially an online distribution platform (or e-marketplace) from which users can download apps developed by third parties for mobile devices and operating systems (OS) supported by the platform. In response to the great success obtained by Apple, several big mobile device manufacturers, such as Blackberry, Samsung and Nokia, as well as software and Internet giants, such as Google, Microsoft and Amazon, have launched their own app stores since 2008. However, as a result of growing market consolidation, two players undoubtedly dominate the scene nowadays accounting for almost 90% of global app downloads (Gartner 2013): Apple's App Store (with more than 1,400,000 apps, seventy-five billion cumulative downloads, and more than \$10 billion cumulative store revenue) and Google Play (about 1,400,000 apps, fifty billion cumulative downloads, and about \$1.3 billion cumulative store revenue).<sup>1</sup>

While the rapid growth of the app market offers numerous business opportunities to a multitude of app developers, it also provides a great opportunity for researchers to examine various theoretical issues like innovation, entry and exit strategies, platform leadership, externalities, marketing mix (Boudreau 2012). Initial studies have mostly concentrated on app demand estimation and the factors driving such demand across major app stores (Carare 2012; Garg and Telang 2013; Ghose and Han 2014) or the determinants of app success (Lee and Raghu 2014). In this paper, we instead study the role of the distribution platform in

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<sup>1</sup> Data on number of available apps, cumulative app downloads and revenue generated from apps were retrieved from the following sources: <http://www.pocketgamer.biz/metrics/app-store/?mpage=appcount>; <http://www.appbrain.com/stats/number-of-android-apps>; <http://techcrunch.com/2014/06/02/itunes-app-store-now-has-1-2-million-apps-has-seen-75-billion-downloads-to-date/>; <http://www.techrepublic.com/article/google-play-v-apple-app-store-the-battle-for-the-mobile-app-market/>; <http://www.statista.com/statistics/281106/number-of-android-app-downloads-from-google-play/>.

price formation of paid apps. Paid apps accounted for 75% of the revenue of app stores worldwide in 2013 and are expected to play a prominent role also in the future (Lunden 2013). In addition, industry figures document that price levels of paid apps change significantly across stores, suggesting that pricing decisions could depend on the distribution platform (Canalys 2012). Therefore, enhancing the understanding about the impact of the distribution platform in price formation of paid apps is clearly important to developers who have adopted paid app business model, as it can help them fine-tune their pricing decisions to the each targeted platforms in order to better monetize on their apps. Elucidating the rationale behind the potential emergence of differences in price levels across different online platforms is also particularly relevant for the literature on online price formation. In fact, although price formation across online retailers has been extensively studied in the past decade in numerous streams of literature including information systems and economics (Brynjolfsson and Smith 2000; Clay *et al.* 2002; Chevalier and Goolsbee 2003; Baye *et al.* 2004a; Chun and Kim 2005), the insights derived from these studies might not necessarily apply to app stores. Indeed, there exist two fundamental differences, which distinguish app stores from traditional online retailers and thus motivate our study on the role of the distribution platform in the app market.

First, online stores examined by previous studies are pure merchants who purchase from producers and resell to customers by charging a retail price based on the wholesale price set by upstream firms (Hagiu 2007). For this reason, the differences in price levels across stores documented by prior works in information systems and economics literature are mostly explained by the different pricing and service policies experimented by online retailers, thus implying the existence of a significant store effect in online price formation (Clay *et al.* 2002; Clemons *et al.* 2002; Baye *et al.* 2004b, Yao and Zhang 2012). Conversely, such practices are unlikely to be the sources of price differences across stores in the context of apps, given that the prices to final customers are set directly by developers, which then share the revenue for each unit sold with the platform owner according to a fixed sharing rule, common to all major stores.

A second crucial difference lies in the unique relationship between the mobile OS/device market and the app market. Once consumers choose their favorite OS/mobile device (e.g., Apple or Android), they are locked in by this decision, as they rely exclusively on the sponsored platform to source their apps.<sup>2</sup> This implies that the customer base in a given platform strictly depends on the customer base of the associated product, i.e.,

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<sup>2</sup> Ghose and Han (2014) report that, at any given point in time, consumers usually own either Apple or Android devices.

the mobile device and the relative OS. Different mobile device makers and/or OS providers naturally target different segments based on their product quality and marketing capabilities. In particular, with regard to the two major mobile device ecosystems, it is largely recognized that Apple targets exclusively the (loyal) high-end of the market, whereas the sales of Android devices are mostly fueled by low-end segments of the market (Ghose and Han 2014; Nerney 2014). As a result, app developers face significantly different consumer segments in terms of willingness to pay across different platforms (Forrester Research 2012; Bensinger 2013; Edwards 2014), while this is unlikely to be the case in traditional online stores. This is because in the latter stores consumers are not forced to bear any exclusive relationship with the distribution channel, as there is no associated product and/or platform technology locking them in. Thus, the heterogeneity in the willingness to pay of consumers buying the same item (e.g., the same electronic device brand) across two traditional online retailers, e.g., Amazon.com and Newegg.com, is much lower than in the case of consumers buying the same app in App Store and Google Play. This particular feature of the app market implies that, differently from online retailers studied in previous literature, app stores can be viewed as distinct markets where developers might be required to set different prices. Therefore, the role of the distribution platform in price formation of paid apps should stem from driving forces, which are different from those highlighted in previous studies, and thus, need to be unraveled.

Our paper aims at filling this important gap by studying the role of the distribution platform as an important determinant of price of paid apps. We also add to prior literature on price formation in online markets by examining whether the price implications of common app-level decisions made by developers are contingent upon the targeted store; this being an issue that has been overlooked in such literature. Specifically, given their dominant role in this market, we compare prices of top (i.e., most downloaded) paid apps from Apple's App Store and Google Play and construct a hierarchical model of app price formation, taking into account potential non-random selection issues by means of the propensity score matching (PSM) method (Rosenbaum and Rubin 1983, 1984).

In detail, our contribution is twofold. First, we explain why the distribution platform should have a direct influence on price levels of paid apps. We argue that the existence of significant heterogeneity in consumer willingness to pay across different platforms should result in different platform attractiveness to developers. The relatively low barriers to entry in this market imply fiercer developer competition in platforms accessed

by more valuable customers. As a result, we show that the direct impact of the distribution platform on prices emerges from two contrasting forces: the average willingness to pay of consumers in the store, which favors higher prices for paid apps in the App Store, and the induced in-store developer competition, which instead favors higher prices for paid apps in Google Play. Second, we argue and find that cross-store heterogeneity in consumer willingness to pay also influences the price implications of important app-level decisions that are commonly made by developers to monetize on their paid apps. Specifically, we hypothesize and find that the positive effect of offering a free trial version on the price of the full paid version is more likely to emerge in platforms characterized by lower willingness to pay (i.e., Google Play), as less valuable consumers perceive higher risks in buying an app of unknown value. We also hypothesize and find that, differently from the App Store, the lower willingness to pay in Google Play should limit developers' ability to resort to price skimming, and thus it leads them to adopt a penetration price strategy when launching new apps. However, we do not find support for our hypothesis that the pricing of apps structured as two-sided platforms also rests on the price sensitiveness of consumers.

The remainder of this paper is organized as follows. In § 2, we present our theoretical arguments and discuss the related hypotheses. In § 3, we describe the data, the variables and the methods utilized in this paper. In § 4, we present our empirical findings and discuss their implications. In § 5, we discuss some robustness checks. Finally, we conclude in § 6.

## 2 Theory and hypotheses

The central tenet of our arguments is that the distribution platform matters for price formation of paid apps in two ways. First, we posit that the chosen distribution platform – App Store vs. Google Play – has a direct impact on the price of a paid app, ensuing from the contrasting impact of two store-level forces, i.e., cross-store differences in consumer willingness to pay and the implied extent of attracted in-store developer competition. Second, we propose that the distribution platform also impacts prices indirectly, by influencing the price implications of three important developers' decisions at the app level.

### 2.1 The main effect of the distribution platform



In our view, cross-store differences in the average consumer willingness to pay are crucial in determining price differences for paid apps across platforms.<sup>3</sup> Intuitively, higher prices should be observed for paid apps in platforms accessed by more valuable consumers (i.e. App Store rather than Google Play), as developers can potentially extract higher value from them. However, cross-store differences in terms of consumer willingness to pay also result in different platform attractiveness to developers. As mentioned, industry evidence suggests that developers (especially those selling paid apps) generally find App Store more attractive than Google Play, because Apple's customer base is on average more valuable than Android-based devices' customer base (Forrester Research 2012; Bensinger 2013; Edwards 2014; Wilcox 2014). According to the industrial organization view of strategy (Porter 1980), a more attractive market also stimulates more firms to entry to appropriate a slice of the bigger pie. In fact, when entry barriers are intrinsically low, a highly attractive market might end up being characterized by fiercer competition than a less attractive market because of the numerous firms that will actually entry and compete in the market (Siegfried and Evans 1994; Lecocq and Demil 2006). This argument applied to the app market suggests that store level differences in consumer willingness to pay could also determine significantly different levels of in-store developer competition between the two platforms, namely App Store and Google Play.

Generally speaking, barriers to entry tend to be modest in the app market. This is evident considering that traditionally important barriers to entry, namely capital requirement and product differentiation, play a marginal role in the app market. As a matter of fact, development costs and the necessary process to market most of the apps in major app stores can be afforded also by individual independent developers who can launch their apps and compete with those of established software houses, even reaching top ranks. Also, given the plethora of developers currently available in major app stores, product differentiation does not appear to deter entries either. In addition to their modest magnitude in absolute terms, entry barriers tend to be

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<sup>3</sup> One may argue that app distribution platforms also differ in several technical characteristics that might affect price. Specifically, Android OS is released under an open source license, as opposed to Apple iOS, which runs only for Apple devices. This may suggest that development costs could be higher in Google Play, due to the need for developers to customize apps for different smartphones. However, this should be balanced by the fact that app approval procedures are more stringent in the App Store, which implies higher quality control costs to ensure successful application when developing for this platform. Finally, there exist minute differences in the magnitude of the fees charged to developers to sell their apps. Accordingly, industry evidence suggests that development costs are overall comparable across the two platforms (Abrosimova 2014). More importantly, note that development costs are sunk investments rather than marginal costs, and thus should not have any bearing on pricing decisions. Finally, there are no differences in marginal costs between the two platforms as such costs are usually negligible in the app market. In fact, maintenance, scaling and user support costs are stepwise costs, and thus do not change in our short period of observation of prices. Overall, this implies that differences in the technical characteristics of the two stores (if any) are very unlikely to play a relevant role in cross-store differences in prices.

even less important in relative terms, as development costs in Apple are arguably comparable to those in Google (Abrosimova 2014). Relying on these considerations, the higher willingness to pay of consumers should attract more developers in the App Store as compared to Google Play, thus generating fiercer competition in the former. Industry figures provide some support to this argument suggesting that developers selling their apps in the App Store are almost twice as those in Google Play (Louis 2013). Moreover, this effect becomes even stronger when considering paid apps. In fact, a larger number of developers prefer selling paid apps in the App Store as a result of the higher willingness to pay of consumers in this store (Wilcox 2014).

To sum up, cross-store differences in consumer willingness to pay determine the emergence of two contrasting forces driving prices in opposite directions. On the one hand, the higher willingness to pay of consumers in the App Store should offer developers the opportunity to charge higher prices for their paid apps in this store as compared to Google Play. At the same time, the existence of more valuable consumers (coupled with the modest entry barriers characterizing the app market) also has the effect of attracting relatively fiercer developer competition in such platform as compared to Google Play, which, in turn, should counteract the above effect by favoring higher prices for paid apps in Google Play through its negative impact on price. As there is no theoretical argument a priori to anticipate which of the two effects actually prevails, we formulate two alternative hypotheses on the overall net effect of the distribution platform, as follows:

*H1a. App Store is associated with higher prices than Google Play for paid apps, due to the higher average consumer willingness to pay.*

*H1b. App Store is associated with lower prices than Google Play for paid apps, due to the higher level of in-store developer competition.*

## 2.2 Distribution platforms and the impact of developer decisions at the app level on app price

Developers can adopt a variety of strategies when selling their paid apps. They can offer limited free trials to let consumer experiment with the product before committing to the purchase of a full paid version. In addition, they can adopt different introductory pricing strategies for new apps (namely penetration price or price skimming), or adopt a two-sided market model for their apps by relying on additional revenues e.g., revenue from ads inside their apps. While the price implications of these decisions have been extensively

studied for information goods (Gallaughar and Wang 2002; Shapiro and Varian 1999; Dubé *et al.* 2010; Liu 2010), little attention has been devoted to understand whether and how these implications are contingent on the choice of the online distribution channel. More specifically, we argue that in the app market, it is important for the chosen app-level decision to be aligned with the characteristics of the consumer segment developers inherit from the associated device makers and/or OS providers, otherwise it may fail to produce the expected consequences in terms of prices, and, ultimately, profitability. Therefore, in this section, we explain that the influence on price of paid apps of three important developers' decisions at the app level – i.e., offering a free trial version, structuring an app as a two-sided market, and choosing a pricing scheme for new products – should be contingent on the chosen distribution platform.

### *Free trial version*

In general, trialability measures the extent to which potential adopters perceive that they have an opportunity to experiment with an innovation prior to committing to its usage (Rogers 1983; Moore and Benbasat 1991; Agarwal and Prasad 1997). Through a trial version users can test the product and resolve the uncertainty about its real value to them (Wei and Nault 2013). Also, trialability can serve to signal product quality as the knowledge that a product is available in a free trial version represents some sort of guarantee to customers. For these reasons, consumers generally pay higher price if given the opportunity to test the product before buying, consistently with the idea that they place value on reduced uncertainty surrounding the product (Gallaughar and Wang 2002).

Developers often release a free trial version associated with the paid version of their apps. Therefore, the app market is suitable to test the existence of a positive effect of trialability on the price of the paid version. Nonetheless, while we take into account the impact of free trial versions on app prices in our analysis, our main interest lies in testing whether the price implications of offering a free trial version depend on the distribution platform where the app is marketed. In this respect, we argue that consumers with different willingness to pay may have a different perception about the uncertainty surrounding an app, and thus they could react differently to price strategies of developers. A consumer with limited willingness to pay could perceive a substantial risk in buying an app of unknown value, despite the rather small price. Indeed, given the limited budget to spend on apps, even wasting a couple of dollars on the wrong app could have serious consequences because it might preclude the opportunity to increase device utility with alternative purchases.

Conversely, a more valuable consumer perceives less risk in buying an app of uncertain value, simply because with its ample budget she can more easily substitute that app by purchasing better ones in case of dissatisfaction. Therefore, consumers should be more likely to recognize price premiums for the full paid version to the developers that help them resolve such uncertainty by releasing a free trial version, especially in presence of lower willingness to pay.

As industry evidence has clearly shown that consumers have more limited willingness to pay in Google Play than in the App Store, the above considerations suggest that the positive effect of trialability on the price of the full paid version is more likely to be observed in the former store. Hence, we formulate the following hypothesis:

*H2: The positive effect of trialability on the price of paid apps is contingent upon the distribution platform. In particular, such an effect is more likely to emerge in Google Play.*

#### *Two-sided market model*

A two-sided market is a market characterized by the existence of cross-side externalities between two groups of users, as the demand from one group strongly depends on the demand from the other group, and vice versa. In such type of markets (e.g., TV and other media, game consoles), a profitable pricing structure would imply to target aggressively, i.e., subsidize, the side of users who are able to exert a larger positive externality on the other side, and monetize from the latter (Rochet and Tirole 2003; Parker and Van Alstyne 2005; Armstrong 2006; Li et al. 2010). As a consequence, the price charged to the subsidy side would be lower in presence of cross-side externalities than it would be in absence of cross-side externalities.

Depending on the specific revenue model adopted by the developer, apps can themselves operate as a two-sided market attracting app users on one side and interested third parties on the other side. Interested third parties could be advertisers or firms seeking information about consumers for specific business purposes. In fact, a considerable number of paid apps, such as games among others, contain third parties' ads (although with minor intensity as compared to free apps). Also, developers of certain apps, such as social networking applications, center their revenue model on building a large user base to attract info seekers, and thus earning from selling non-personally identifiable information (Williams 2009). As app users naturally exert an irresistible appeal to third parties, i.e., advertisers or info seekers, it follows that developers aim at subsidizing the consumer side when structuring their apps as a two-sided market. Thus, from the perspective

of app users, if there exist strong cross-side network externalities, we should observe that, *ceteris paribus*, paid apps operating as a two-sided market (e.g., ad-supported apps or apps collecting and selling data) have lower prices than those that do not exhibit such characteristics, as developers would subsidize users to attract third parties from which to monetize. In contrast, developers of apps that do not operate as a two-sided market do not have such an incentive to reduce the price to users given that they cannot rely on the money side.

While providing evidence of a two-sided market effect in the context of apps could be interesting on its own, our main interest lies in examining whether the effect of a two-sided market model hinges upon the chosen distribution platform. Our argument is that the magnitude of the price reduction necessary to attract a sufficiently large consumer base heavily depends on the type of consumers buying that app. Indeed, the extent of the subsidy offered also depends on the price sensitiveness of the subsidy side; that is, larger price reductions should be offered when the subsidy side is more price-sensitive (Rochet and Tirole 2003; Parker and Van Alstyne 2005; Eisenmann *et al.* 2006). As app stores feature significantly different consumers in terms of willingness to pay on average, this argument suggests that when a developer decides to structure an app as a two-sided market, the price implications of such decision should differ across app stores. In particular, we should expect larger price reductions, if any, for consumers in Google Play than those in App Store, given their relatively lower willingness to pay. Hence, we can formulate the following hypothesis:

*H3: The negative effect of the two-sided market model on the price of paid apps is contingent upon the distribution platform. In particular, such an effect is more likely to emerge in Google Play.*

#### *Introductory pricing strategy*

How firms should vary the price over the product life cycle to maximize their profits has been extensively studied in marketing literature (Tellis 1986; Mahajan *et al.* 1990; Noble and Gruca 1999; Spann *et al.* 2015). When introducing a new product firms can balance between two extreme pricing schemes, namely market skimming or market penetration (Dean 1950; Mahajan *et al.* 1990). Under a skimming strategy, firms initially set a high price targeting high valuable customers. Then, as the product moves forward in its lifecycle, its price is gradually decreased to attract less valuable segments. On the other hand, a penetration strategy implies the use of a low price at first to capture a larger market base. Then, once the product is established in the market, the price can be raised.

Apps reasonably belong to a product category subject to network externalities. Therefore, the existence of considerable word-of-mouth and other network effects among users should induce developers to utilize a penetration strategy to exploit the advantage of a large installed market base (Shapiro and Varian 1999; Dubé *et al.* 2010; Liu 2010). In this case, apps first released should have a lower price than more mature apps, *ceteris paribus*. However, numerous successful apps have unique features that cannot be easily imitated or substituted. Furthermore, for many apps there may be users who are highly valuable. For instance, very passionate gamers can certainly afford to purchase their preferred app right after the release at any price. In this case developers could find it optimal to skim this segment and later decrease the price to target less addicted users, due to the presence of high customer heterogeneity and product differentiation (Dean 1969; Tellis 1986; Noble and Gruca 1999). Under the circumstances, apps first released should instead have a higher price than apps already mature in the market, *ceteris paribus*.

The above considerations would suggest that in the app market both pricing strategies are equally plausible, thus yielding no univocal prediction on the relationship between the age of the app and its price. Nonetheless, we suggest that the pattern of the price of new apps could be better understood after taking into account also the characteristics of consumers accessing the given distribution platform. We argue that in Google Play there could be limited room for a price skimming strategy. Since price skimming aims at capturing the high end of a market, it requires the existence of a group of highly valuable consumers who are willing to pay significantly more than the others for the product. This market segment could be relatively small or less developed in Google Play, where consumers generally tend to have lower willingness to pay as compared to the App Store. On the other hand, price penetration could be more impactful in this platform, as less valuable and more price-sensitive users (who are the vast majority in Google) would respond more favorably to lower initial prices, thus facilitating the establishment of an ample consumer base. The situation is different in the App Store. In this platform consumers are on average wealthier and more willing to pay than those in Google Play. Thus, it is certainly possible for some developers to benefit from skimming high-end segments by charging higher prices to initial adopters. At the same time, other developers could also succeed in the implementation of a penetration strategy when their apps feature important network externalities. Accordingly, in Google Play developers should be more likely to implement a penetration strategy rather than a skimming strategy. Thus, we should observe that, *ceteris paribus*, younger paid apps

are on average priced lower than more mature paid apps as prices gradually increase over time under a penetration price strategy. Conversely, since both penetration and skimming strategies could work effectively in the App Store, it is difficult to predict the dominance of either strategy. Hence, we simply formulate the following:

*Hypothesis 4: Developers are more likely to use a price penetration strategy in Google Play than in the App Store.*

### 3 Data and methods

#### 3.1 Data

To test the above hypotheses, we built an *ad hoc* dataset by collecting data of top (i.e., most downloaded) paid apps for smartphones in the Italian version of App Store and Google Play. We recorded data from the top paid app ranking publicly available in each of these platforms on a daily basis in the period going from March 7<sup>th</sup> to May 15<sup>th</sup>, 2013 (60 observation periods in total).

Top app rankings have been utilized by prior research analyzing the app market (e.g., Carare 2012; Garg and Telang 2013). Similarly to Carare (2012), we restricted our focus to the top 100 apps. There are several important reasons for why all studies consider top app rankings. First, these rankings are easily available from the app stores as well as third parties, such as Distimo. Second, the insights obtained from studying successful apps, rather than average apps, can be certainly more useful to developers that are planning the development and marketing of new apps. Third and most important, although both App Store and Google Play count more than one million applications available for download, the actual number of apps that can be displayed by consumers is much more limited. In both stores consumers have access only to web pages displaying top rankings (e.g., top free, top paid, top grossing) for all apps, top rankings within each app category or top new entries and sponsored apps. Essentially only the very top portion of the app market is actually visible to consumers. This implies that top rankings are arguably the primary source of information not only for researchers to study this novel market, but also for consumers to make their purchase decisions, as highlighted also by Carare (2012). Furthermore, besides the absolute relevance of paid apps (Lunden 2013), we naturally restrict to the top paid ranking and avoid considering top free apps (i.e., the most downloaded free apps), given our focus on understanding the role of the distribution platform in price formation of app prices. In this respect, we are consistent with previous econometric analyses on price

formation, which considered non-zero prices (Brynjolfsson and Kemerer 1996). Similarly, top grossing rankings were also excluded, given the presence of numerous free apps in this ranking. Finally, our choice of observing apps in a time span of about two months is in line with previous studies (Carare 2012; Garg and Telang 2013). After recording the top 100 paid apps from the two stores along the entire period of observation we obtained a rich dataset containing 11,999 observations related to 567 apps (402 apps in App Store and 165 app in Google Play, respectively), that have appeared at least once in the top paid ranking of one of the two stores during the observation period.<sup>4</sup> By construction, our sample is an unbalanced panel dataset as more successful apps appear in the rankings more often than others.

### 3.2 Variables

#### *Dependent variable*

Our theoretical arguments look at the relationship between prices of paid apps and the distribution platform, as well as the role of the distribution platform in influencing the price implications of three strategies adopted to monetize on paid apps. Hence, we consider the logarithm of price as our dependent variable and record, on a daily basis, the price (in *Euros*) of each app featured in the top 100 paid apps rankings of the two platforms during our period of observation.

#### *Independent variables*

Our hypotheses *H1a* and *H1b* suggest that the distribution platform chosen for a paid app will influence its price. *H1a* suggests that the App Store will be associated with higher prices for paid apps than Google Play due to the higher willingness to pay of App Store consumers, whereas *H2b* predicts the opposite outcome, as more valuable consumers in the App Store will also attract relatively higher level of in-store competition among developers in this platform as compared to Google Play. To test these predictions we first introduce a dummy variable, namely *Store*, which is equal to one if on a given day an app is observed in the top 100 paid app ranking of Google Play, zero if observed in the top 100 paid app ranking of App Store. Based on the sign of the reported coefficient on our dummy *Store* we can assess whether one of the two opposing effects we have theorized dominates the other, giving rise to significant differences in prices across stores.

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<sup>4</sup> The number of observations is 11,999 instead of 12,000 because we were not able to retrieve accurate and extensive information about one app appearing only once in the top ranking of Google Play. Moreover, the number of distinct apps is actually 524. This is because there are 43 apps available in the top 100 paid apps rankings of both stores during the observation period. Nevertheless, as explained later, according to our hierarchical model of price formation we consider the app-store pairs, which are indeed 567, as our statistical units.



At this point, it is important to recall that our first set of hypotheses looks at the *overall net effect* of the distribution platform on the price of paid apps. Strictly speaking, if the two opposing store-level effects we propose completely offset each other by driving prices in opposite directions, then our dummy *Store* may not have any significant impact on price. Yet, the proposed mechanisms underlying *H1a-H1b* could be still both at work in determining prices of paid apps. Thus, besides providing evidence that prices of paid apps significantly differ between Apple and Google, we also provide further evidence to show that the differences captured by our store dummy can be ascribed to the two underlying forces we propose – i.e., store level willingness to pay and in-store competition. Ideally, we would like to replace the store dummy with two (store-level) variables measuring more explicitly the average levels of consumer willingness to pay and developer competition in the store, with the expectation that they should be different across the two stores while having also an opposite impact on prices. However, while this is certainly doable for the competition variable, it is more troubling to measure store-level consumer willingness to pay. Differences in levels of in-store developer competition can vary over time because developers' entries (and exits) are very dynamic in this market, therefore making it possible to measure the impact of changes in store-level developer competition on app prices. The same approach cannot be used to measure store-level willingness to pay of consumers simply because this factor is very stable over time (especially as compared to app price), as it descends from strategic choices related to the type of market segments targeted by the associated device and/or OS providers. As a matter of fact, using secondary data on consumer willingness to pay for a larger time span (i.e., 2011-2014), we always observe a large and persistent gap in willingness to pay between Apple and Google users. Thus, even in case of a larger time span, any measure of store-level willingness to pay has almost zero variation in the sample and is highly correlated with the dummy *Store*, thus making it difficult to discern its true effect on prices from the overall net effect.

Considering the difficulties in isolating the direct effect of cross-store differences in consumer willingness to pay by explicitly measuring it, our approach to further shed light on how the distribution platform matters for prices of paid apps is twofold. First, we show that there exist significant differences in the level of in-store developer competition between the two platforms and then explicitly introduce in our models a store-level developer competition variable under the expectation that it should have a negative impact on prices. Second, to demonstrate that the store-level consumer willingness to pay can actually have the intuitive direct

impact we have theorized, we provide additional evidence that higher prices are indeed associated with App Store than Google Play when considering only low valuable apps (defined as those belonging to the lowest price quartile within each of the two app rankings) in both stores. Indeed, low valuable apps should necessarily attract a larger number of developers in Google Play, given the lower average willingness to pay of consumers accessing this platform. Accordingly, the differences in the level of developer competition between the two stores should arguably be flattened when considering low-end apps, thus implying a weakened effect of cross-store differences in competition on prices. As a result, the positive effect of store level willingness to pay should emerge more strongly in this case.

Based on the above discussion, we can only use a measure of store-level competition in addition to the dummy *Store*. However, as the number of sales or downloads of each developer in a given store is not disclosed, we cannot compute measures of competition based on market shares. In addition, as the vast majority of apps and developers are never displayed on the pages of the two stores, it is not possible to retrieve time-varying information on the number of all developers in a platform and the number of their apps, thus impeding the calculation of a Herfindahl-Hirschman Index (HHI) based on these data. To overcome this problem, we measure the extent of developer turnover in the top paid apps ranking of the store. In fact, it is straightforward that a larger turnover in the daily composition of top 100 ranking (in terms of developers and apps) reflects fiercer competition among developers to increase download as well as higher intensity of new market entries. Note that this choice is consistent with a consolidated stream in the industrial organization literature using measures of firms' turnover in the market to reflect the level of competition (Hymer and Pashigian 1962; Baldwin and Gorecki 1998; Caves 1998). To construct our measure of in-store competition (namely, *Turnover*) we compute the number of developers that never appeared in the top ranking of paid apps during our observation period over the seven days before the given day of observation.<sup>5</sup> It is important to note that our measure of competition is even more accurate than those that could be ideally computed based on the number of apps of all developers in the store (if it were possible to compute them precisely). This is because, with a multitude of apps “invisible” to consumers, the majority of developers of such apps

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<sup>5</sup> In this respect, it is important to note that looking at the turnover over the past week helps mitigate a potential endogeneity problem due to reverse causality between observed prices and our store competition variable. Also, note that our results are robust even when considering the new entries of developer in the top 100 paid apps ranking during a different number of days (e.g., 5 or 10) before the given day of observation.

are never a threat to developers of top apps, and a measure based on such information would not capture the real level of competition among developers.<sup>6</sup>

To test our hypothesis *H2*, which suggests that the positive impact of trialability on the price of a paid app is more likely to emerge in Google Play than in App Store, we retrieve information on the existence of a free trial version for the app from the descriptions provided by app developers in the given store, and introduce a dummy (*Free trial version*) indicating whether the developer offers a free trial version for the paid app or not, as well as its interaction with our *Store* dummy.<sup>7</sup> In our hypothesis *H3* we maintain that a two-sided market effect on price should be especially evident in Google Play given the lower willingness to pay of consumers accessing this store. To test this hypothesis, we analyzed each app to check for the presence of ads inside the app, as we had no access to revenue information from third parties, e.g. advertisers. In addition, we considered all apps belonging to the social networking app category as apps operating as two-sided markets. This is because the business model of these apps (e.g., Whatsapp) is explicitly centered on gathering and selling (non-personally identifiable) data of a large user base to interested third parties. Accordingly, we introduce a dummy variable (*Two-sided market*) equal to one if the given app contains ads inside and/or belongs to the social networking category, as well as its interaction with the dummy *Store*. To test our hypothesis *H4*, which suggests that developers are more likely to adopt a penetration price strategy in Google Play than in App Store, we recorded the release date of the app in the given store. This allowed us to compute the time (number of days) since the app has been available for download in the given store (*Time since release*), i.e., the app age, and interact this variable with the dummy *Store*. Indeed, if developers in a store tend to adopt on average a penetration (skimming) strategy, this measure should have a positive (negative) impact on prices indicating that, as apps move forward in their lifecycle, developers tend to increase (decrease) their price.<sup>8</sup>

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<sup>6</sup> In spite of the mentioned weaknesses of using data on the number of developers and their apps, we found that our results are robust also when using a daily HHI obtained by computing the market shares as the number of apps (both paid and free) of each developer featured in the top paid ranking of the given store on the given day divided by the total number of apps of all the developers featured in the top paid ranking of the same store on the same day.

<sup>7</sup> Note that we distinguish between proper free trial version, i.e., version offering very limited features or being time-locked, and free version, i.e. version that does not differ much from the paid version except for the presence of (more) ads. Therefore, we include a specific dummy (*Free version*) to control for the effect of the latter type of version, which is not related to trialability.

<sup>8</sup> An important caveat related to testing our proposed interactions (i.e., *H2-H4*) is that our dummy *Store* embodies two store-level effects. Thus, although the distribution platform could influence the price implications of the developers' strategies discussed in *H2-H4*, it might be argued such influence is due to differences in in-store competition rather than to consumer willingness to pay as we propose. In order to rule out this alternative explanation we also explicitly

Finally, in addition to the variables of interest, we control for a number of other factors, which may influence app price formation. First, in addition to the store-level competition variable, we introduce a variable measuring competition at the app level in a given store. Indeed, different apps could have a different number of substitutes marketed in the given store. To compute this measure, we considered all the apps marketed by the developers observed in our sample. Based on this population, we computed for each app the number of (both paid and free) substitutes at a given time (*Substitutes*). Note that by doing so, we did not only consider the apps appearing in top 100 paid app rankings, but also those apps not appearing in the ranking, as long as they were developed and marketed by the developers present in our sample. This is consistent with our earlier argument that the major threats for an app likely come from developers that have been able to market their apps more successfully, as most of developers and apps are never visible to consumers in both app stores. To identify app substitutes more accurately we created 69 subcategories based on the real scope and functionalities of the given apps retrieved from the descriptions provided by developers. Also note that, by including free apps in computing the variable *Substitutes*, we explicitly capture the effect of the presence of free apps on the price of paid apps. We also control for the app category (we count 14 categories in our sample as indicated in Table 1), the type of developer (*Developer type*), i.e., whether the content provider is a firm or (group of) individual(s), the number of apps marketed by each observed developer in the given day and store (*Number developer apps*), and the app size in Megabyte (*App size*). We also control for whether in-app purchase (i.e., the opportunity to directly upgrade to additional features inside the app) is implemented for the given paid app, by introducing a dummy variable (*In-app purchase*). Furthermore, given that users can rate the apps they download, we recorded such information for each app to construct a measure of app quality. Specifically, both App Store and Google Play allow users to provide apps' rating on a 1-to-5 scale where 1 corresponds to the worst valuation and 5 to the best valuation. However, sometimes no rating is displayed for certain apps because the number of users who have provided a rating is too low. To cope with this issue, we construct four dummies based on the rating: low rated apps (*Low app rating*) category if the app rating is below 2.5, medium rated apps (*Medium app rating*) category if the app rating is between 2.5 and 3.5, high rated apps (*High app rating*) category if the app rating is above 3.5, and finally a category of

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interacted the app pricing strategies variables with the *Turnover* variable. Our results showed that these interactions are never significant, and thus the difference in in-store competition is unlikely to be the driving forces behind *H2-H4*.

apps displaying no rating (*No app rating*).<sup>9</sup> We also control for the extent of developer notoriety by including a dummy (*Developer fame*), which indicates whether the developer/brand of the given app is worldwide established.<sup>10</sup>

Table 1 shows the descriptive statistics of the variables employed in our study. On average, prices of paid apps in Google Play are considerably higher than those in the App Store (1.87 and 3.41, respectively), and both stores display significant within-store price variation. At the same time, observed competition levels are higher in the App Store than in Google Play both at the store level (the variable *Turnover* is 25 in the App Store and only 5.94 in Google Play) and the app level (the variable *Substitutes* is 687 in the App Store and 349 in Google Play). These figures seem to suggest that the different levels of in-store competition between the two stores could play a significant role in determining prices of paid apps. As for our categorical variables, Table 1 clearly suggests that the top paid apps rankings of the two stores do not display the same composition in terms of apps and, thus, price differences across the two platform might be due to the different apps featured in the rankings rather than to the arguments we propose. We will carefully address this issue in the subsequent sections when discussing how matching similar apps across stores helps mitigate these potential biases. Table 2 reports the correlation matrix. First, note that the dummy Store and the store-level measure of competition are extremely correlated (Pearson correlation coefficient equal to -0.92), which provides a first hint that there exist strong cross-store differences in the level of in-store developer competition. At any rate, these two variables are not introduced at the same time in the regression analyses that follow. Also note that, in such analyses, we choose the dummy *Games* and *Medium app rating* as baselines for app category and app rating variables, respectively.

### 3.3 Methods

Our unbalanced panel dataset naturally displays a multi-level structure as each observation is related to the daily price of a given app, marketed by a given developer, in a given store. Therefore, observations related to the same app in the given store, as well as those pertaining to same developer in the given store are likely to

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<sup>9</sup> Note that there might be endogeneity due to potential reverse causality between price and app rating. In the robustness section, with the support of instrumental variables (IV) regression, we show this is not the case in our sample of apps.

<sup>10</sup> Based on corporate revenue information and worldwide brand recognition we identify 22 top developers in our sample: Activision Blizzard, Adobe Systems, Apple, Autodesk, AVG Technologies, Capcom, De Agostini, Disney Interactive, Electronic Arts, Fox Digital Entertainment, Gameloft, Google, Konami, Mediaset, Namco Bandai, Research in Motion (Blackberry), Sega Sammy, Square Enix, Take-Two Interactive, TomTom International BV, Ubisoft Entertainment, Zynga.

be correlated. Similarly, observations in the same store could be correlated as they are exposed to common store-level factors. Therefore, we propose a four-level model to analyze the role the distribution platform in price formation of paid apps. The first level is the observation (i.e., the app in the given store on a given day); the second level is the app-store pair (i.e., the app in the given store), the third level is the developer-store pair (i.e., the developer in the given store), the fourth level is the store. Essentially, as app stores can be viewed as different markets, we structure our dataset so that observations are nested within app-store pairs, which are nested in developer-store pairs, which in turn are nested within stores. In presence of such multi-level data structure, the use of mixed linear effects regression models is usually suggested in literature (Raudenbush and Bryk 2002). As we are interested in shedding light explicitly on the role of the store (Apple vs. Google) in price formation of paid apps, we introduce the distribution platform variable, the relative interaction terms and control variables at both app and developers levels as fixed effects, while treating as random the effect of the app-store and developer-store pairs. Hence, our full linear mixed effects model is as follows:

$$\begin{aligned} \ln price_{tjjs} = & \delta_0 + \delta_1 \cdot Store + (\delta_2 + \delta_3 \cdot Store) \cdot Free\ trial\ version_{tjjs} + \\ & (\delta_4 + \delta_5 \cdot Store) \cdot Two_{sided}market_{tjjs} + (\delta_6 + \delta_7 \cdot Store) \cdot Time\ since\ release_{tjjs} + \quad (1) \\ & B \cdot App\ Controls_{tjjs} + \Gamma \cdot Developer\ Controls_{tjs} + u_{js} + r_{ijs} + \varepsilon_{tjjs} \end{aligned}$$

where,  $r_{ijs}$  and  $u_{js}$  are the app-store and developer-store specific random effects respectively,  $\varepsilon_{tjjs}$  is the error term, whereas the remaining terms are our variables of interests and controls modeled as fixed effects.

Another important concern in assessing the impact of the distribution platform on prices of paid apps is related to the fact that consumers self-select in any of the two stores based on the type of device they possess. This suggests that, in addition to the different willingness to pay, which is our object of study, consumers could have substantially different tastes and needs across stores. As a consequence, developers might strategically self-select in any of the two stores to offer apps that better match the tastes and needs of consumers in that market, implying that apps observed in the top ranking of App Store could be systematically different from those observed for Google Play. This might generate significant selection bias, possibly invalidating our findings. In fact, as apps in our sample are not randomly assigned to the two platforms, cross-store differences in prices could be simply due to the different types of paid apps featured in the two stores, rather than to the two driving forces we have theorized. Ideally, considering exactly the same apps in the two stores would arguably solve this issue. However, only 43 apps out of 567 apps are available

in the top 100 paid apps rankings of both stores during the observation period, thus not allowing a reliable econometric analysis. Therefore, in order to mitigate this selection problem and ensure a comparison across stores for relatively similar apps, we apply the Propensity Score Matching (PSM) method (Rosenbaum and Rubin 1983, 1984). To avoid the biases that nonrandom assignment to treatment may generate, matching algorithms are commonly used to find a non-treated unit that is similar to a participating unit across several dimensions.

We performed the matching based on a set of both categorical as well as integer/continuous variables, and considered observations in App Store as treated units, while those in Google Play as non-treated units.<sup>11</sup> We applied PSM within strata, by considering exact matching for app categories (which identifies the app functionalities) and app rating levels (a proxy for quality). For instance, we matched games having high rating in App Store only with games having the same rating in Google Play, and so forth. Within each of these strata, we applied the PSM and considered a set of integer/continuous covariates to further match treated and non-treated apps. We used the variable *Time since release*, as price changes along the app life cycle and stores could feature apps of different maturity. Similarly, we considered the daily rank of the app to pair apps enjoying similar exposure to consumers in the two stores. After matching, our sample is reduced to 3,520 observations of which half are from App Store and half from Google Play, due to the fact that we apply one-to-one matching. By construction, these matched samples have the very same composition in terms of app categories and rating level. Unreported t-tests and ANOVA analyses also confirm that matched apps in the two stores do not differ significantly in terms of age and ranking (covariates used for the matching), as well as in terms of app size. Hence, we are confident that performing the above matching helps mitigate potential biases in our sample arising from both consumers' as well as developers' self-selection in the two stores. Finally, note that for robustness purposes we created alternative matched samples by pairing apps also based on additional covariates<sup>12</sup>, and implemented alternative matching procedures such as

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<sup>11</sup> We imposed a common support (overlap condition) with no-replacement by removing treatment observations for which the propensity score was higher than the maximum or less than the minimum of the score of non-treatment observations. We also used the caliper options to select one and only one non-treated unit for each treated unit only when the propensity score difference was at most 0.001 (i.e., caliper set equal to 0.001).

<sup>12</sup> For our main analyses we did not consider the variable *App size* as one of the features utilized for the matching, because the app size differ across the two stores, even for the very same apps. To give the idea, the size of TomTom Italy navigator is 404 Mbyte in App Store, whereas it is only about 29 Mbyte in Google Play. Therefore, using the size might actually distort our matching algorithm to the extent that it would not even pair the very same apps. At any rate, as we will discuss later, we created several matched samples based also on the variable *App size* as well as other covariates, such as *Free trial version*, *In-app purchase*, and *Two-sided market*, showing full robustness of our results.

coarsened exact matching. These additional analyses are fully consistent with those reported in the paper, and are available from the authors upon request.

#### 4 Results and discussion

Descriptive statistics in Table 1 show that on average paid apps have higher prices in Google Play than in the App Store (3.41 versus 1.87). This difference seems inconsistent with the intuitive direct effect of store-level consumer willingness to pay, which should favor higher prices for paid apps in the App Store. Still, this does not guarantee that the lower prices in the App Store are the result of the fiercer developer competition in this store. In fact, differences in mean prices might still be driven by the different app composition in the top paid apps rankings resulting from the choices of consumers and developers that self-select in the two platforms. We have pointed out that matching apps according to their basic features should reduce (if not eliminate) such potential biases. Thus, before presenting our more formal regression models based on (1), we provide some preliminary evidence of the effect of our matching procedure on our dependent variable, i.e., the app price. T-test results reported in Table 3 show that significant differences (0.1% level of significance) between the average prices of the two stores emerge even when comparing matched pair of similar apps, although the magnitude of this difference is considerably reduced (from 1.54 to 0.53). Therefore, price differences across the two stores cannot be explained exclusively by different app composition of the two stores. Table 3 also reports the cross-store difference in the means of our two competition measures at both store and app-store levels, i.e., *Turnover* and *Substitutes*, respectively. The results clearly show that, even after matching similar apps, the two platforms differ significantly in terms of competition with the App Store displaying considerably higher competition. Overall, this preliminary univariate analysis provides first support to our general argument that the distribution platform could influence price formation of paid apps and that the two major app distribution platforms differ not only in terms of consumers willingness to pay, but also in terms of in-store developer competition.

To test our hypotheses more formally we conduct a number of regression models based on the mixed linear model presented in (1). Given the potential presence of selection bias in the full sample, we run these models for the matched sample and report the results in Table 4 (the results under the full sample are qualitatively unchanged and available from the authors). With regard to our contrasting hypotheses (*H1a* and *H1b*) on the overall effect of the distribution platform, the first column of Table 5 shows that Google Play is associated



with higher prices than App Store due to the positive (and significant) coefficient of the dummy *Store* ( $\delta_7=0.232$  and  $p<0.001$ ). First, this finding confirms that price levels of paid apps vary across the distribution platforms. Second, it provides support to *H1b* against *H1a*, suggesting that the effect of the lower in-store competition in Google Play prevails over the direct (and opposing) effect of the lower consumer willingness to pay in this store, thus leading to higher prices in this platform than in the App Store. To further increase confidence about this interpretation, we substitute the dummy *Store* with our competition measure at the platform level, namely *Turnover*. The second column of Table 4 shows that the coefficient of this variable is negative and strongly significant, thus substantially capturing the impact of the dummy *Store*. This result combined with the highly significant gap in competition between the two platforms (shown in Table 3) provides stronger support to the argument that the level of in-store competition is the major driving force behind the overall effect of the distribution platform on prices, thus leading to higher prices in Google Play for paid apps.

Although results in the first two columns support *H1b*, one could question the existence of a conflict between the effects of the different willingness to pay of consumers in the two stores and the consequent different in-store competition. In columns 3-4 we provide evidence that, while in-store competition seems to explain overall price differences across stores, the willingness to pay does actually have a direct impact on price levels of paid apps. As explained, since we are unable to measure such variable explicitly, as an alternative approach we show its impact by focusing on a sample of low valuable paid apps. In presence of low valuable paid apps the differences in the level of in-store developer competition between the two stores should arguably be lessened, as developers in Google Play should be more likely to concentrate on marketing low valuable apps given the lower average willingness to pay of consumers accessing this platform. In fact, our data show that, while the average number of app substitutes in Google is roughly only 50% of that observed in Apple in the full sample, this difference significantly shrinks for the subsample of low-end apps, for which the number of substitutes in Google is almost 88% of that in Apple. Yet, while competition levels become more similar, there may still persist differences in terms of willingness to pay of consumers accessing the different platforms. Thus, if the role of the distribution platform actually emerges from the trade-off between these two factors, the negative impact of the dummy *Store* should be mitigated in this subsample of apps or eventually revert. Results in column 3 confirm this by showing that the coefficient of the dummy *Store*

becomes significant and negative when we run our mixed model for the subsample of low valuable apps. The marginal role of competition in presence of low valuable apps is confirmed by observing that our measures of competition at the app level and store level are never significant in columns 3-4. Thus, in the case of low-end apps price differences across the two platforms seem to be explained more by different store-level consumer willingness to pay rather than by different in-store developer competition. Overall, this first set of evidences provides support for our *H1b*, and confirms that the impact of the distribution platform on app prices emerges as the result of a trade-off between the effect of differences in consumer willingness to pay and the implied differences in in-store competition.

Columns 4-8 of Table 4 report the results for our second set of hypotheses predicting how the distribution platform influences the role of some important developers' decisions at the app level in price formation of paid apps. Specifically, in the fifth column, we add the interaction term between the dummy *Store* and the dummy *Free trial version* to the model in column 1. First, note that in column 1 the coefficient of the dummy *Free trial version* was not significant, suggesting that on average trialability does not imply any price premium for the full paid version. After introducing the interaction term, the coefficient of this dummy, which now reflects the marginal change in price due to trialability in the App Store, is still not significant. However, the coefficient of the interaction term, which instead reflects the marginal change in price in Google Play due to trialability, is largely significant (at the 1% level) with a positive sign ( $\delta_3 = 0.305$ ), thus supporting our hypothesis *H2*, which suggests that the impact of a free trial version on the price of the full paid version is more likely to emerge in Google Play. As we have argued, consumers in Google Play perceive higher risks in buying an app of unknown value than consumers in the App Store due to their lower willingness to pay. Thus, they seem to be willing to recognize a price premium to developers offering a free trial version to resolve the uncertainty surrounding the value of the paid version.

In the sixth column we add the interaction term between the dummy *Store* and the dummy *Two-sided market* to our baseline model shown in column 1 (where the latter was not significant). We find that the coefficients of the two-sided market dummy and its interaction term with the distribution platform are both shown to be not significant. Therefore, *H3* is not confirmed in our sample, and apps operating as two-sided markets do not seem to be associated with significantly different prices across the two platforms.

In the seventh column we add the interaction term between the dummy *Store* and the variable *Time since release* to the baseline model in column 1. The coefficient on this variable was shown to be strongly significant with a positive sign in column 1, which suggested that, on average, developers increase prices as apps move forward in their lifecycle, consistently with the adoption of a penetration price strategy. However, after adding the interaction term, the coefficient on the variable *Time since release*, which now reflects the marginal change in price in the App Store due to the increase in app age, is no longer significant. Conversely, the interaction of this variable with the distribution platform, which now reflects the potential marginal change in price in Google Play due to the increase in the age of the app, is significant with a positive sign ( $\delta_7 = 0.0004$  and  $p < 0.001$ ). This result supports *H4*, by showing that price penetration is more impactful in Google Play than in App Store, arguably because the segment of highly valuable consumers could be relatively less developed in the former platform to allow the adoption of price skimming practice, given their lower willingness to pay. The last column of Table 4 reports our full model including all three interaction terms and shows full consistency with the results in the previous models.

At this point, it is important to recall that the results in Table 4 are based on a sub-sample obtained by matching apps according their basic characteristics. Therefore, one could argue that the results on the interactions between the distribution platform and app-level decisions might be still biased by the fact the two rankings display different composition in terms of percentage of free trial version, app operating as two-sided markets, and so forth. Nevertheless, even after refining our matching procedure by exactly matching also for all app-level decisions variables (e.g., observations of apps offering a free trial version in App Store matched only with observations of apps offering free trial version in Google Play, and so forth), our findings remain unchanged in spite of a considerable reduction in the number of observations (from 3,520 to 1,520).<sup>13</sup>

## 5 Robustness checks and further discussion

In this section, we briefly discuss the results of further additional analyses we conducted to test the robustness of our prior findings. The details of these robustness checks are available from the authors. First, our results are qualitatively unchanged when eliminating those apps featured in the top paid app ranking sporadically (e.g., less than three or four occurrences) to ensure comparison among apps of similar success. Our second extension addresses potential endogeneity concerns related to time-varying app characteristics.

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<sup>13</sup> The analysis under this refined matching procedure is available from authors upon request.

Specifically, while in the models above we control for unobserved app quality by means of app rating, we do not control for the potential effect of mobile app trend due to advertising or online word-of-mouth. As we do not have access to explicit information about the advertising expenditures or the extent of word-of-mouth, we utilize a proxy that reflects the mobile app trend over time. Specifically, we utilize the tool Google Trend provided by Google, which provides a weekly index on a 0-100 scale of search popularity of words on Google search engine in specific geographical regions. We recorded such weekly index during our period of observation by searching the exact name of all the apps in our sample. Given the popularity of Google search engine, this measure reflects the trend of an app in a given period, as a higher index is the result of greater knowledge and interest about the product, which, in turn, is likely to be the consequence of more effective advertising and online word-of-mouth over time. While being not significant, this new variable does not change our main results. Our findings are also robust when we include one dummy for each day of observation to account for the effect of trends common to both app stores and all observed apps.

Finally, endogeneity concerns might emerge also from reverse causality in the relationship between price and app rating. In fact, the rating of an app might be affected by the price of the same app as a higher price might create higher expectations of consumers, who will be more likely to complain about product flaws and provide lower ratings to the given app. To address this concern, we perform instrumental variables (IV) regression models, where we use developer rating as an instrument for app-level rating. This choice is motivated by the idea that, on average, a developer marketing high quality apps is more likely to develop an app of high quality than a developer that has been marketing low quality apps. We obtain the developer rating in a store as the average rating of all the apps (except the considered app) marketed by the developer in the given store until the given day. As both exogeneity test as well as the Sargan-Hansen overidentification test (which evaluates the statistical validity of instruments) are consistently insignificant, we can be sufficiently confident that our main findings are not affected by potential endogeneity concerns due to the app rating variable. At any rate, the findings are robust even under the IV regression model.

## 6 Conclusions

In this paper, we have contributed to the literature on price formation in online markets by examining the unique role of online distribution platform, specifically App Store vs. Google Play, in price formation of paid apps. Differently from online retailers studied in previous literature, in app stores prices to final consumers

are set by developers and, more importantly, app consumers are locked-in by their decision to purchase a device linked to an exclusive distribution platform. Accordingly, we have argued that differences in price levels across different stores emerge as a result of the fact that developers face different consumer segments and market conditions in different app stores, rather than heterogeneous pricing and service policies across retailers.

In detail our findings are as follows. First, price levels of paid apps strongly depend on the targeted distribution platform, and specifically on average Google Play is associated with higher prices than App Store for paid apps. We have argued that the platform effect emerges as the result of two contrasting forces, i.e., the consumer willingness to pay (which would imply higher prices in the App Store), and the in-store developer competition (which would instead imply higher prices in Google Play). Our findings suggest that in general differences in developer competition at the store level seem to be more influential in determining different prices across the two stores than differences in average consumer willingness to pay. Further confirming the existence of a trade-off, we find that price differences across stores are actually reversed for the restricted subsample of less valuable apps. Second, our findings suggest that the distribution platform heavily bears on the price implications of two important strategies adopted by developers. Specifically, we find that price premiums on the full paid version of the app as a return to the provision of a free trial version are more likely to be observed in Google Play, where consumers are more likely to suffer from information asymmetry given their limited willingness to pay. Also, the distribution platform appears to be important for pricing strategies used when launching new apps. In this respect, we find developers are more likely to use a penetration price strategy in Google Play, whereas they possibly use both penetration price and price skimming strategies in App Store. The rationale is that the segment of highly valuable consumers could be relatively less developed in Google Play to allow the adoption of a profitable price skimming practice. Finally, no univocal evidence supports the claim that adopting a two-sided market model should yield a larger price reduction in Google Play than in App Store as a result of the lower willingness to pay of consumers accessing this store.

These findings offer several remarkable implications for more informed decisions in the app market. A primary implication of our findings is that app developers need to adjust their pricing decisions to the targeted store, as different platforms imply consumers with different willingness to pay and, ultimately, also

different levels of developer competition. Also, they may need to make accurate app-level decisions, especially those related to free trial version release and introductory price for new apps, according to the targeted platform in order to better profit from their apps. Finally, our findings help increase distribution platform owners' awareness on the role of store-level factors in price formation and rethink their strategies to attract both users and developers.

We expect that many researchers will devote themselves to the study of the app market given its growing popularity. Accordingly, we believe that there is large room for further investigating the role of the distribution platform. For instance, to complement our study, it would be interesting to investigate whether developer choices related to app characteristics are influenced by the store choice, thus going beyond their mere price implication as done here. Further research could also examine the factors guiding developers entry in the platform choice when launching a new app. Specifically, this direction could provide answers to questions such as whether to launch the new app only in one store, which store to target first, whether to entry simultaneously, and the relative rationale and performance implications of such choices.

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Table 1. Descriptive Statistics

<i>Panel A:</i>				<i>Descriptive statistics for categorical (dummy) variables</i>			
<i>Variables:</i>	<i>Mean (%)</i>			<i>Variables:</i>	<i>Mean (%)</i>		
	Total	App Store	Google Play		Total	App Store	Google Play
<i>Store</i>	50.00%	0.00%	100.00%	<i>Games</i>	38.20%	46.70%	29.70%
<i>Free trial version</i>	15.63%	8.50%	22.77%	<i>Healthcare &amp; Fitness</i>	2.83%	3.67%	2.00%
<i>Two-sided market</i>	8.98%	8.52%	9.45%	<i>Money &amp; Finance</i>	0.50%	0.00%	1.00%
<i>Free version</i>	31.86%	24.20%	39.52%	<i>Music</i>	5.85%	6.17%	5.53%
<i>In-app purchase</i>	35.91%	44.15%	27.67%	<i>News &amp; Info</i>	0.42%	0.83%	0.00%
<i>No app rating</i>	0.96%	1.92%	0.00%	<i>Photo &amp; Video</i>	7.57%	11.37%	3.77%
<i>Low app rating</i>	2.43%	4.85%	0.00%	<i>Social Network</i>	2.10%	2.17%	2.03%
<i>Medium app rating</i>	12.93%	18.23%	7.63%	<i>Themes &amp; Customization</i>	7.73%	5.57%	9.88%
<i>High app rating</i>	83.68%	75.00%	92.37%	<i>Travel</i>	3.89%	2.75%	5.03%
<i>Developer Type</i>	86.03%	84.23%	87.83%	<i>TV</i>	0.65%	1.30%	0.00%
<i>Developer fame</i>	22.37%	24.70%	20.04%	<i>Utility</i>	21.52%	9.38%	33.66%
<i>Education</i>	1.98%	2.23%	1.72%	<i>Weather</i>	3.09%	2.32%	3.87%
<i>Entertainment</i>	3.68%	5.55%	1.80%				

  

<i>Panel B:</i>				<i>Descriptive statistics for continuous/integer variables</i>								
	<i>Total sample</i>				<i>App Store</i>				<i>Google Play</i>			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
<i>App size (Mbyte)</i>	81.59	252.82	0.02	1945.6	108.27	265.56	0.2	1730.6	54.92	236.42	0.02	1945.6
<i>Turnover</i>	15.82	10.92	2	45	25.70	6.13	16	45	5.94	2.42	2	11
<i>Number developer apps</i>	23.73	55.26	1	480	29.90	55.02	1	354	17.57	54.81	1	480
<i>Substitutes</i>	518.54	623.20	0	1665	687.19	743.12	0	1665	349.86	409.45	0	1104
<i>Time since release</i>	575.98	423.14	1	1770	503.40	442.13	2	1770	648.57	390.00	1	1428
<i>Price (€)</i>	2.64	4.05	0.39	49.99	1.87	3.52	0.89	49.99	3.41	4.38	0.39	49.99

Table 2. Correlation matrix

<i>Variables</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Developer Type															
(2) Developer fame	0.22														
(3) Number developer	0.20	0.51													
(4) Free trial version	0.08	-0.04	-0.05												
(5) Free version	0.02	-0.26	0.00	-0.29											
(6) In-app purchase	0.23	0.26	0.26	-0.13	-0.05										
(7) Two-sided market	-0.03	-0.01	-0.01	-0.03	0.05	0.09									
(8) Time since release	0.04	-0.08	-0.03	0.14	0.13	-0.14	0.09								
(9) App size (Mbyte)	0.25	0.46	0.30	-0.12	-0.28	0.44	0.00	-0.25							
(10) Substitutes	0.14	0.21	0.16	-0.12	-0.10	0.32	-0.01	-0.23	0.24						
(11) No app rating	-0.05	-0.04	-0.03	-0.04	-0.03	-0.05	-0.02	-0.09	-0.01	-0.01					
(12) Low app rating	-0.12	-0.04	-0.02	0.01	-0.05	-0.08	0.14	-0.10	-0.07	-0.06	-0.02				
(13) Medium app rating	-0.07	0.28	0.11	-0.11	-0.19	-0.04	0.07	0.03	0.11	-0.03	-0.04	-0.06			
(14) High app rating	0.13	-0.22	-0.08	0.12	0.20	0.08	-0.12	0.04	-0.07	0.06	-0.22	-0.36	-0.87		
(15) Store	0.05	-0.06	-0.16	0.20	0.16	-0.17	0.02	0.17	-0.43	-0.14	-0.10	-0.16	-0.16	0.24	
(16) Turnover	-0.05	0.04	0.14	-0.18	-0.15	0.16	-0.01	-0.16	0.39	0.12	0.10	0.15	0.14	-0.22	-0.92

Pearson correlation coefficients are shown to be significant (at 5% level) when above 0.03 in absolute value. Note also that sake of space we do not report Pearson correlation coefficients related to category dummies. At any rate, the correlation coefficient between *Games* and *Substitutes* (equal to 0.70) is the only relevant correlation coefficient involving category dummies, but this does not affect our results as we choose *Games* as the baseline category.

Table 3. Means and relative differences before and after matching

	Means before base matching			Means after base matching		
	App Store	Google Play	Mean Difference	App Store	Google Play	Mean Difference
<i>Price</i>	1.87	3.41	1.54***	1.60	2.13	0.53***
<i>Turnover</i>	25.70	5.94	19.76***	25.68	5.96	19.72***
<i>Substitutes</i>	687.19	349.86	337.33***	1050.30	682.37	367.93***

Legend: +  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 4. Distribution platform effect and its interaction with developer decisions at the app level under the matched sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Developer type	0.199** (0.0696)	0.257*** (0.0748)	-0.00619 (0.00842)	-0.0117 (0.00994)	0.185** (0.0691)	0.196** (0.0697)	0.215** (0.0678)	0.198** (0.0675)
Developer fame	0.246** (0.0783)	0.259** (0.0855)	0.0208* (0.00973)	0.0108 (0.0111)	0.243** (0.0777)	0.247** (0.0785)	0.218** (0.0757)	0.217** (0.0756)
Number developer apps (Ln)	-0.0275 (0.0192)	-0.0358+ (0.0202)	-0.00334 (0.00257)	0.00177 (0.00292)	-0.0275 (0.0191)	-0.0272 (0.0192)	-0.0289 (0.0187)	-0.0284 (0.0186)
Free trial version	0.0428 (0.0488)	0.0839 (0.0510)	-0.0155** (0.00579)	-0.0224*** (0.00615)	-0.0499 (0.0576)	0.0369 (0.0490)	0.0520 (0.0482)	-0.0363 (0.0575)
Free version	-0.0650 (0.0580)	-0.0304 (0.0608)	0.000421 (0.00548)	-0.00572 (0.00607)	-0.0360 (0.0581)	-0.0644 (0.0579)	-0.0906 (0.0569)	-0.0649 (0.0572)
In-app purchase	-0.0259 (0.0521)	-0.0338 (0.0541)	-0.00139 (0.00450)	-0.00370 (0.00487)	-0.0247 (0.0514)	-0.0243 (0.0520)	-0.0138 (0.0510)	-0.0114 (0.0504)
Two-sided market	-0.151 (0.100)	-0.0845 (0.101)	-0.00252 (0.00619)	-0.0121+ (0.00632)	-0.120 (0.0995)	0.0146 (0.173)	-0.163+ (0.0986)	0.0681 (0.169)
Time since release	0.000246*** (0.0000560)	0.000168** (0.0000593)	0.00000672 (0.00000585)	0.0000161** (0.00000625)	0.000248*** (0.0000554)	0.000243*** (0.0000559)	0.0000848 (0.0000666)	0.0000891 (0.0000663)
App size (Ln)	0.0391** (0.0148)	0.0198 (0.0146)	0.000554 (0.00196)	0.00409+ (0.00217)	0.0385** (0.0147)	0.0396** (0.0148)	0.0430** (0.0146)	0.0430** (0.0146)
Substitutes (Ln)	-0.0585** (0.0209)	-0.0756*** (0.0223)	0.0000464 (0.00254)	0.00371 (0.00306)	-0.0602** (0.0207)	-0.0583** (0.0209)	-0.0592** (0.0204)	-0.0603** (0.0202)
High app rating	0.0706 (0.0461)	0.0763+ (0.0441)	0.00595 (0.00694)	0.00820 (0.00755)	0.0692 (0.0460)	0.0683 (0.0462)	0.0751 (0.0458)	0.0709 (0.0457)
Store	0.232*** (0.0521)		-0.0317*** (0.00650)		0.173** (0.0553)	0.243*** (0.0530)	0.209*** (0.0508)	0.174** (0.0547)
Turnover (Ln)		-0.0345*** (0.00767)		-0.00354 (0.00233)				
Free trial version x Store					0.305** (0.102)			0.259* (0.101)
Two-sided market x Store						-0.246 (0.210)		-0.300 (0.205)
Time since release x Store							0.000436*** (0.000102)	0.000420*** (0.000102)
App Category dummies	YES	YES	YES	YES	YES	YES	YES	YES
<i>N</i>	3520	3124	1446	1283	3520	3520	3520	3520
<i>Developer-Store obs</i>	262	244	126	117	262	262	262	262
<i>App-Store obs</i>	347	322	169	158	347	347	347	347
Wald test - pvalue	0.0000	0.0000	0.0000	0.0076	0.0000	0.0000	0.0000	0.0000

Legend: +  $p < 0.10$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ . Standard errors in parentheses. Note that the constant and the app-store and developer-store pair random effects are always strongly significant. Also, No app rating and Low Rating dummies are not reported as they display no observations in the matched sample.