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There's an app for that! understanding the drivers of mobile application downloads

Zeynep Aydin Gokgoz [a,*], M. Berk Ataman [b], Gerrit H. van Bruggen [a]

[a] Rotterdam School of Management, Erasmus University, Burgemeester Oudlaan 50, 3062 PA Rotterdam, the Netherlands
[b] College of Administrative Sciences and Economics, Koc University, Rumelifeneri Yolu 34450, Sarıyer, Istanbul, Turkey

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ABSTRACT

Since its emergence, mobile applications market has been attracting the attention of all kinds of businesses due to the lucrative opportunities apps offer and the market's low barriers to entry. Yet, in this crowded space, only a small portion of apps can survive. Using a unique data set of 979 newly released applications, acquired from a leading mobile analytics company and enriched with publicly available data, the authors shed light on the factors associated with app downloads during an app's first year of existence. Results from time-varying-parameter models estimated separately for free and paid apps reveal that gaining traction with users shortly after release seems critical and that app platform owners can be very influential in these early days. However, as apps mature, affecting the number of downloads becomes increasingly more difficult. The findings add new insights to the growing literature on apps and provide practical implications for their developers.

1. Introduction

Since its emergence in July 2008, the mobile application[1] (app hereafter) space has been growing at an astonishing rate. The Apple App Store has gone from just 500 apps in July 2008, the month of its launch, to 1 million apps in the fall of 2013 and reportedly reached 2 million apps by 2018 (Apple Insider, 2018). Its competitor, the Google Play Store, offered 2.5 million different apps in 2018 (AppBrain, 2019). Global downloads from app stores exceeded 194 billion in 2018. Total app revenues, including revenues from paid downloads, in-app purchases and in-app subscriptions, hit $101 billion in 2018, up 75% from its level in 2016 (AppAnnie, 2019).[2] As apps become increasingly more popular among consumers, worldwide app store revenues are forecasted to reach $156.5 billion in 2022 (AppAnnie, 2018).

The growth of the app market is not surprising, because continuing advances in wireless technologies and the growing smartphone penetration have provided businesses with a new channel with unique features to approach customers (e.g., accessibility at anytime and anywhere, customization at a granular level, and location sensitivity). Apps offer businesses, big and small, an opportunity to connect with on-the-go consumers in various ways. First, apps can become an integral – or even core – part of a firm's business model and operate as an additional channel or a platform generating most of the traffic and (ad) revenues (e.g., Facebook, Twitter, Amazon). Some firms start mobile first and operate almost entirely through their apps (e.g., Uber, Instagram). Second, with the increasing importance of apps in consumers' daily lives, apps provide firms a new medium for advertising and a platform to create and maintain brand engagement (e.g., Ruffles AmiGo, IKEA Place).

This emerging market with low entry barriers and lucrative business opportunities continues to attract businesses diverging from individual developers to well-established brands and the app market has become increasingly crowded over the years. However, only a small portion of apps can gain traction with mobile phone users. In 2018, 74% of all apps were downloaded less than 1000 times, up from 70% in 2014. In contrast, 80% of the downloads in 2019, up from 76% in 2014, are generated by the top 1% of publishers in the Apple App Store or the Google Play Store (SensorTower, 2019). Moreover, the average app

* Corresponding author.
E-mail addresses: zaydin@rsm.nl (Z. Aydin Gokgoz), bataman@ku.edu.tr (M.B. Ataman), gbruggen@rsm.nl (G.H. van Bruggen).

[1] Apps are dedicated software applications that run on small, handheld devices such as smart phones, tablets and notebooks.

[2] The primary source of revenue depends on the business model apps utilize: free, paid, or freemium. Free apps are downloaded at zero cost and revenues are generated through in-app advertisements and purchases. Paid apps are downloaded at a cost and may also offer additional features for a fee (mostly $< \$5$). Lastly, developers can use the freemium model and launch both free and paid versions of the app. The free app encourages trial and promotes the paid version, which comes with extended functionalities.

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loses 77% of its daily active users within the first three days after download, whereas top apps have significantly higher retention rates (Chen, 2018). Consequently, the majority of apps don't generate the anticipated revenues, and some are even withdrawn from the market after a while.

Apps such as Everpix (a high quality app that sorts, organizes, and cloud-stores photos) and Vine (an app for sharing short videos) that satisfy unique customer needs in the first place, have learnt the importance of having the right business model, adapting to the changing landscape of the market place and to evolving consumer needs, and the power of marketing the hard way. Both apps made a promising entrance to the market and were shutdown later with great disappointment and despair (Smart Insights, 2019). Despite these challenges, firms continue developing new apps. In order to increase the success rates of apps, it is important to understand the factors that are associated with app downloads, especially in the early stages of an app's lifecycle. In this paper, we aim to contribute to developing this understanding by studying factors that are related to app adoption.

Based on a review of related studies in the literature and a detailed analysis of a user's decision journey in the path to app adoption, we identify a set of factors potentially associated with downloads. The literature review revealed a set of variables under the developer's control and variables reflecting current users' views, while the analysis of a user's decision journey revealed additional factors under the platform owner's control, whose effects are yet unexplored. Also unexplored in the literature are whether and how this comprehensive set of variables' effects differ across app types (i.e., free and paid apps) and, more importantly, vary over time in the first year following an app's release. To investigate how all variables jointly affect downloads over the first year following an app's release, we assemble a unique data set by combining daily-level transactional data for 979 apps obtained from one of the foremost mobile analytics companies with publicly available data from the Apple App Store. We observe each app since its release and study the evolution of the impact of the factors on downloads over time separately for free and paid apps.[3] By doing so, we can offer insights customized to an app's business type and time on market. We also explore the sensitivity of our findings in other pertinent sub-samples of apps.

Our findings show that the mere appearance in top apps charts have the largest effect on downloads of free and paid apps alike, followed by appearing on a top featured list, especially for paid apps. These results highlight the influence that platform owners have on users. Updates released by developers have positive effects on downloads and their effects increase proportional to the amount of improvement. Further investigation of these effects' evolutions reveals that a majority of the factors matter especially early-on following an app's release.

This paper continues as follows. In Section 2, we review the literature on apps and discuss how this study adds to the current knowledge. In Section 3, we develop the conceptual framework for our study and a series of expectations for the explored relationships. Since the field of mobile marketing is in its early stages and theory development so far seems non-existent or at least scarce, we refrain from developing formal hypotheses. In Section 4, we describe the unique data set we have compiled for the sake of this study, the specification of the model, and the operationalization of our variables of interest. Sections 5 and 6, respectively, present the results of our analyses and conclusions with the ensuing implications.

2. Research background

Although research in marketing and human computer interaction has advanced our knowledge of the mobile consumer (Nysveen, Pedersen, & Thorbjørnsen, 2005), mobile commerce (Shankar, Venkatesh, Hofacker, & Naik, 2010), usability of and user experience with mobile devices (Zhang & Adipat, 2005), mobile usage behavior (Ghose, Goldfarb, & Han, 2013), and mobile marketing (Shankar & Balasubramanian, 2009), research related to app markets is still in its infancy. Research on apps can be discussed under two main headings: the antecedents of app adoption and the consequences of app introduction.

Starting with the latter, the effectiveness of this medium has particularly been of interest to researchers. Current research shows the positive effects of app introduction/adoption on brand attitudes and purchase intentions (Bellman, Potter, Treleaven-Hassard, Robinson, & Varan, 2011; Mclean, Osei-Frimpong, Khalid, & Marriott, 2020), cognitive and affective brand responses (Van Noort and Van Reijmersdal (2019)), subsequent purchases (Liu, Lobschat, Verhoef, & Zhao, 2019; Van Heerde, Dinner, & Neslin, 2019), and even firm value (Boyd, Kannan, & Slotegraaf, 2019; Cao, Liu, & Cao, 2018; Gill, Sridhar, & Grewal, 2017).

As to the antecedents of app adoption, previous research has advanced our understanding of the impact of user characteristics (Kim, Kim, Choi, & Trivedi, 2017), app characteristics (Schulze, Schöler, & Skiera, 2014), app pricing (Arora, Hofstede, & Mahajan, 2017; Carrare, 2012; Ghose & Han, 2014; Kübler, Pauwels, Yildirim, & Fandrich, 2018), app updates (Ghose & Han, 2014; Kübler et al., 2018), other users' experiences (Ghose & Han, 2014; Kübler et al., 2018), and, in the broader mobile eco-system, integration, ownership, and novelty of the apps (Van den Ende, Jaspers, & Rijsdijk, 2013). Our research is in line with the empirical studies focusing on the antecedents of app adoption and differs from them in the following respects (see Table 1).

First, our study differs from other empirical studies in terms of the *set of drivers influencing downloads*. Decisions and actions of three players in the app market, as suggested by Hao, Li, Tan, and Xu (2011), have the potential to drive downloads. These are app developers, app users, and app platform owners. So far, research sheds light on the important roles developers and users play in app performance. We add to this knowledge by considering the unexplored role of app platform owners. Platform-controlled variables impact the visibility and discoverability of apps and have the potential to increase downloads to a great extent (see Section 3 for more details). Specifically, we study the impacts of three types of updates, price, and discounting decisions by developers, word-of-mouth activity (valence and volume) by users, and appearance on featured lists and position in top apps charts by platform-owners on downloads. Not having to use ranking as a proxy for success, because we have access to download numbers, enables us to quantify the additional effect of merely appearing in top apps charts on downloads. In sum, our selection of variables is more comprehensive than up to date research, yet limited by the availability and extractability of the data.

Second, our study differs from existing research in terms of the *nature and composition of apps under investigation*. Previous studies almost exclusively use 'being ranked in a Top Apps Chart' as one of the sampling criteria. The use of such a sampling criterion may introduce success bias, as it takes quite a high number of downloads to enter these charts.[4] Though these studies have advanced our understanding of the drivers of relatively mature apps' downloads, the problem of generating downloads is more acute for newly released apps. As our results show, download performance early-on is critical for overall downloads. Our access to download figures allows us to study factors associated with a new app's performance from its release date onwards independent of the app's ranking status. Moreover, we believe that including low-download generating apps as well as high-download generating apps in our sample helps us develop a broader understanding of the app market dynamics.

[3] We do not treat freemium as a third category because there are very few apps in our sample offering both free and paid versions.

[4] For a few statistics on this, please see https://www.pocketgamer.biz/comment-and-opinion/67142 (last accessed on 12/14/2019) and https://www.apptweak.com/aso-blog/infographic-number-of-downloads-to-reach-top-rankings (last accessed on 12/14/2019).

Table 1
Comparison of empirical studies on App performance.

Study	App Store	Number of Apps	Sampling Criteria	Sampling Time Frame	App Performance (Operationalization)	Developer-controlled Variables	User-side Variables	Platform-controlled Variables	Contingency Factors
Carrare (2012)	Apple	912	Top 100 Apps (Free and Paid)	1/1/2009 – 6/16/2009 (166 daily obs. per app)	Sales (Inferred from rank and market shares)	Price Update	–	–	–
Ghose and Han (2014)	Google Apple	2624 4706	Top 400 Apps (Free and Paid)	9/5/2012 – 1/10/2013 (daily obs. for 4 months)	Demand (Estimated sales quantities)	Price Update	Valence Volume	–	Consumer Characteristics
Lee and Raghu (2014)	Apple	7579	Top 300 Apps (Free, Paid, Grossing)	12/2010 – 09/2011 (39 weekly obs. per app)	Appearance, duration, and number of apps by developer in Top Charts	Update Discount	Valence Volume	–	–
Kübler et al. (2018)	Apple	20	Ranked in Top 100 paid apps in at least 80% of 60 countries and remains in this ranking during the observation period	6/5/2011 – 3/27/2012 (276 daily obs. per app)	Popularity (Sales rank data)	Price Update	Valence Volume Dispersion	–	Cultural, Economic, Structural Factors and Category
This Study	Apple	979	Stratified random sample from 40,000 new free of paid apps released between 1/1/2012 and 5/31/2012	Release dates ranging from 1/1/2012 to 5/31/2012 (365 daily obs. per app)	Downloads (Estimated by a leading mobile analytics company)	Update Type Price Discount	Valence Volume	Feature Lists Top Apps Charts	Time and Business Model

Notes: The studies listed herein also control for app characteristics (e.g., app size, description length, etc.) and developer characteristics (e.g., number of previous successful apps, number of categories in which the developer offers apps, etc.) among other things. We do not list these for brevity.

Finally, our study differs from extant literature in terms of its *main focus*. Whereas past research mainly deals with the problem of estimating app demand (from rankings), the impact of price and its variation across cultural, economic, and structural factors, our goal is to develop an understanding of a comprehensive set of variables that are related to downloads for different app types (i.e., free and paid) and, more importantly, whether and how the effects of these factors *vary over time in the first year following an app's release* on the market.[5] To our knowledge, our paper is the first to link all these variables to downloads and investigate the evolution of their effects.

3. Conceptual framework and expectations

To identify the drivers of app downloads, it is vital to consider the user's decision journey that leads to app adoption (i.e., the decision to download) and factors that facilitate/hinder progression through journey stages. In what follows, we first outline the user's decision journey, which is built upon the classic demand chain or purchase funnel (Lavidge & Steiner, 1961) and is further modified with the specifics of the app market, the design of the store, and the behaviors of users therein. We then discuss the sources of information users rely on while sequencing through the decision journey and identify the drivers of downloads. We conclude this section with a discussion on the evolution of an app through its lifecycle and the unique challenges imposed by its business model to arrive at differential predictions for variables associated with downloads.

3.1. The path to app adoption and variables affecting users' decisions

A user's decision journey starts with the *recognition of a need* for an app, which triggers an app search in the store. At times, the user is relatively less certain about the need, and at times, more certain because s/he has heard about an app through offline word-of-mouth or other channels. Depending on how certain the user is, s/he pursues either a browse path (i.e., browsing the app store navigated by the user interface) or a search path (i.e., searching for an app by typing in the search box). The search path is further divided into two inherently different types in terms of the specificity of the queries, indicating more refined variation around need uncertainty. These are navigational search (i.e., searching with a specific app name, such as 'Angry Birds') and categorical search (i.e., searching with generic phrases, such as 'free games').[6] Through the browse and the categorical search paths, the user arrives at pages listing several apps. We refer to this milestone in the journey as *app discovery* (i.e., the user becomes aware of apps that may satisfy her/his need).

For users following the browse path and, to a lesser extent, the categorical search path,[7] the design and information display of the store's landing page as well as those of category landing pages will play a critical role in app discovery. Prominently displayed on these pages are, *featured lists* and *top apps charts*. Although an app's appearance in a featured list or its position on a top apps chart is determined by underlying app characteristics (e.g., design, uniqueness, business model type, media coverage) and app performance (e.g., past revenues, downloads, engagement, retention (Engström & Forsell, 2018)), these lists are created by platform owners. For that reason, we refer to them as *platform-controlled variables* associated with downloads.

Following app discovery, the user chooses which app(s) to evaluate in detail (i.e., the decision to click on one of the apps in the list). We refer to this milestone as *app consideration*. Those conducting navigational search are likely to transition in and out of the consideration stage

[5] The set of factors associated with downloads change across app business models. Whereas boosting downloads by adjusting prices and offering discounts is possible for paid app developers, developers of free apps only have control over the value proposition of the app. Given this structural difference, we choose to explore the relationships separately for free and paid apps.

[6] 51% of smartphone users in the U.S. learn about apps because their friends/family are using them and 48% discover apps by browsing the app store (Google, 2016). According to Apple (2020), the search path drives majority of downloads with 65% and most of the search queries are branded (i.e., navigational).

[7] The more generic the categorical search query is, the closer the resulting list becomes to lists from browsing top apps charts.

swiftly. However, as app stores list similar items alongside the app searched for, these users may also discover the mere presence of rival apps.

Users decide which apps they would like to evaluate in detail based on the information available to them on the app list page. In addition to the app's icon, name, and position on the list, the only other pieces of information available on these pages are the app's average rating scores, the number of reviews, and price – determined by the developer. Ratings and number of reviews reflect previous adopters' views about the app and correspond to the online word-of-mouth measures of *valence* and *volume* (Dellarocas, 2003). Therefore, we refer to them as *user-side variables* associated with downloads. The findings in Colicev, Malshe, Pauwels, and O'Connor (2018) support the notion that WoM volume and valence are effective in the transition to the consideration stage.

App evaluation takes place on the app description page. These pages show the app's price, average rating score, the number of times it has been reviewed with an option to access individual ratings and reviews, static or dynamic visual and verbal descriptions of the app, and information on what's new in the most up-to-date version of the app with an option to review update history. Using these pieces of information, the user evaluates whether the app can satisfy her/his need and whether the price s/he needs to pay, if any, for gaining access to the app is acceptable. The user, then, decides whether or not to *download the app*. The decision to download terminates the journey, whereas the decision to not download may lead the user to return to earlier stages.

In addition to the *user-side variables* (i.e., WoM valence and volume), all other factors that facilitate the user's progression to the journey's end stage are directly under the control of the developer. Accordingly, we refer to them as *developer-controlled variables* associated with downloads and group them under the app's value proposition, which the developer seeks to improve by means of *updates*, and its *price* (including discounting, if any).[8]

In sum, variables under different app-market-players' controls – platform owners, users, and developers – influence a potential adopter's decision to download an app. Platform-controlled variables are primarily operational on early transitions in the journey, user-side variables on mid- and to late-stage transitions, and developer-controlled variables largely on late-stage transitions. The user's journey to app adoption along with our conceptual framework is presented in Fig. 1.

3.2. Expectations

3.2.1. Platform-controlled variables

Platform owners can create attention for apps through the *featured lists* they publish on the landing pages. Being featured helps more users discover an app in a crowded environment through its impact on visibility. Holding all else constant, discovery by a larger group of users should boost download numbers. Though empirical research on the antecedents of app adoption or the drivers of app performance has not studied the effect of being featured, research in other domains shows a substantial effect on sales of highlighting a product in its category and featuring/displaying it in a prominent position (e.g., Blattberg, Briesch, & Fox, 1995).

Likewise, as browsing through *top apps charts* is a prominent way of app discovery, appearance and the position of an app in one of these charts can attract greater attention to the app and boost downloads. Studies trying to uncover the ranking algorithms of app stores and the relationship between rankings and downloads reveal interesting insights pertaining to appearances and positions of apps in these charts. Comparing the effects of WOM metrics and app rankings for a data set of 42 days in the Google Play Store, Engström and Forsell (2018) find that a 10-percentile increase in displayed rankings increases downloads by 20%. Carrare (2012), investigating the effect of current rank on future demand based on a data set of 166 days of top 100 free and paid apps in Apple App Store, finds that consumers' willingness to pay is $4.50 higher for a top ranked app compared to an unranked app and declines steeply as the ranking of an app drops. Carrare (2012) also discovers natural breakpoints in rankings corresponding to top 5, top 25 and top 50. Findings of Garg and Telang (2013) complement those of Carrare (2012): a top ranked app for iPhone (iPad) earns 95 (110) times more revenue compared to a top 200 ranked app. Accordingly, we expect appearing in the top ranks of these charts to speed up adoption, with more prominent positions being more strongly associated with downloads.

3.2.2. User-side variables

The impact of *word-of-mouth* on consumer decisions has increased with the emergence of online feedback mechanisms. Word-of-mouth has been shown to be an important factor in determining the success of experience goods (De Vany & Walls, 1996) as well as goods in other industries (e.g., Anderson & Magruder, 2012; Chevalier & Mayzlin, 2006; Dhar & Chang, 2009; Duan, Gu, & Whinston, 2011). As to the impact of WoM on app performance, both valence and volume have been shown to have a positive impact on app demand (Ghose & Han, 2014; Hao et al., 2011; Kübler et al., 2018). Accordingly, we expect to find a relationship in the same direction.

3.2.3. Developer-controlled variables

Developer-controlled variables, especially the app's value proposition, are effective in sealing the deal for potential adopters. Though an app's value proposition is determined prior to launch, *updates* serve as a tool for further development of the app. In fact, the dynamics of the app market puts pressure on developers to update apps often and on a regular basis. Fortunately, the continuous feedback from app users provides developers with the opportunity to offer customized and swift responses and enjoy favorable response as a result (Aydin Gokgoz, Ataman, & Van Bruggen, 2020).

Previous research agrees on the positive impact of updates on app performance: the demand is higher for apps that are regularly updated (Carrare, 2012; Ghose & Han, 2014; Kübler et al., 2018). Accordingly, we expect a positive relationship between updates and downloads. Though developers may generate additional downloads by means of updates, we expect the nature of the update to matter. In some updates, the developers add new features and functionalities to their apps – referred to as major updates hereafter – with the goal of improving their app's value propositions. In others, they improve the existing features – referred to as intermediate updates hereafter – or implement development tweaks and bug fixes – referred to as minor updates hereafter – to ensure effective and efficient delivery of the value proposition, respectively. We expect major updates to have a greater impact on downloads than minor updates.

Finally, developers of paid apps can influence downloads with *price* changes and the *discounts* they offer. Unlike traditional markets where regular price changes are relatively infrequent, experimenting with

[8] When asked about how important various factors are when making a decision about which app to download, smartphone users in the U.S. rank price first with 85% (Top 2 Box) followed by privacy or security of information (84%), how much they'll use the app (71%), description (71%), memory used (66%), reviews (61%), and ratings (60%) (Google, 2016). The factors listed between price and WoM variables are directly related to the efficient and effective delivery of the app's value proposition. Colicev et al. (2018) finds that social media metrics corresponding to WoM valence are strongly associated with customer satisfaction.

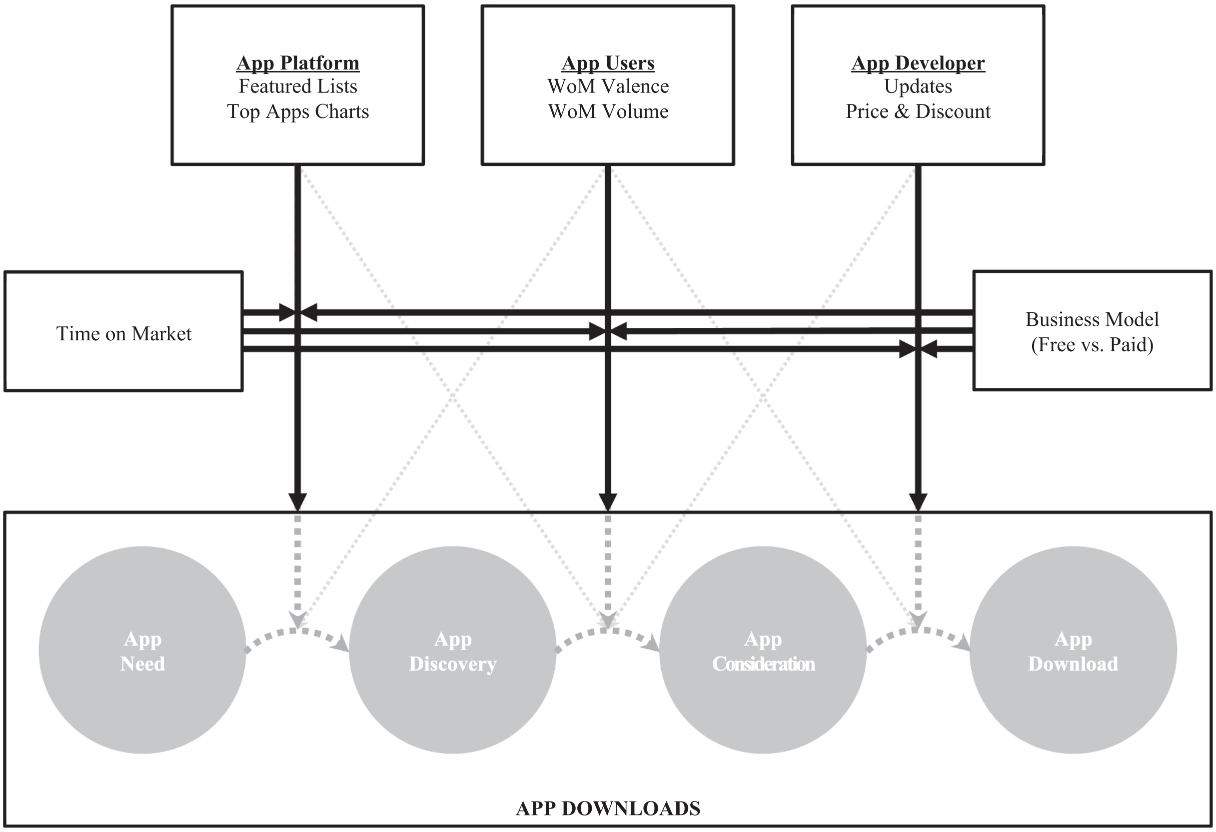


Fig. 1. Conceptual Framework.
Notes: The grey circles show the journey stages of an individual decision maker on the path to app adoption, curved grey dashed arrows the transitions, straight grey dashed arrows the factors most effective on the transitions, and thin light-grey dashed arrows the factors effective to a lesser extent on the transitions. The black solid boxes and the variables listed therein show the relationships (black solid arrows) explored in this study.

different price points to arrive at the right one, especially in the early life cycle of the apps, is a common practice in this market.[9] The app store provides developers with the opportunity to move smoothly between price points by allowing them to schedule price changes. Developers can alter price points permanently as soon as they realize that they have chosen a price point that is too high for their potential user base or they can temporarily offer discounts to expand the user base.

The effects of prices and discounts on downloads have been investigated in several studies. For instance, Kübler et al. (2018) find that the demand for apps is sensitive to prices and price sensitivity varies across countries with different economic and cultural backgrounds as well as app categories (e.g., games and non-games). Ghose and Han (2014) investigate the competition between Apple and Google stores and find that discounting increases app demand more in Google Play Store than Apple App Store. Accordingly, we expect to find a negative (positive) relationship between price (discounts) and downloads.

We summarize our expectations for the signs of the effects of all variables on downloads and how we expect these effects to vary over an app's lifecycle and across business models, discussed subsequently, in Table 2.

Table 2
Expected effects of download drivers.

Variable	Prediction		Evolution
	Free Apps	Paid Apps	
Platform-controlled Variables			
Appearance on Featured Lists	++	+	Decrease over time
Position in Top App Charts	++	+	Decrease over time
User-side Variables			
Valence of WOM	+	++	Decrease over time
Volume of WOM	+	++	Decrease over time
Developer-controlled Variables			
Updates	+	++	Increase over time
Price	NA	–	Decrease over time
Discount	NA	+	Increase/Constant over time

Notes: ++ indicates that the association between a variable and downloads is stronger for a specific app type compared to the other. As for the over-time effect of price on downloads, we expect a reduction in the magnitude of price elasticity. Accordingly, a decrease over time means that price elasticity, which is negative, moves closer to zero (i.e., demand becomes less sensitive to prices).

3.3. Changes over an App's lifecycle and differences between business models

Apps and their potential adopters experience changes over the lifecycle and different conditions across app business models on three fronts: (1) the source and the amount of information available, (2) the nature and the extent of risks perceived, and (3) the perceptions and

[9] See https://mashable.com/2011/08/17/price-mobile-app/ for more details. In our sample, we observe sufficient variation in regular price and discounting variables. Specifically, 50.4% of paid applications undergo at least one regular price change over the first year of the app's existence and more apps change regular prices in the first six months of the data. Moreover, 45.9% of all apps in the sample offer at least one discount.

expectations of the untapped potential. As a result, the strength of the association between the variables and downloads can evolve over the phases of an app's lifecycle and be different for free vs. paid apps.

First, the source and the amount of information available vary over time and across apps. Because the number of users who have downloaded the app is likely to be lower in the early days of an app's lifecycle (i.e., low observability), the likelihood of discovering the app through channels other than the app store itself will be lower early on (Rogers, 2003). As an app matures and increasingly more users download it, potential adopters will gain access to more information and from various sources (e.g., offline WoM, press coverage, publicity, etc.). Moreover, the amount of information that potential adopters need to process on the platform varies substantially across free and paid apps. As 90% of Apple App Store apps are free, the adoption decision is more taxing for users looking to download a free app. The relative complexity of the free apps sub-market means greater information overload and higher search costs (Payne, Bettman, & Johnson, 1993). To reduce search costs and deal with the undesirable consequences of complexity, potential adopters of free apps may engage in selective information processing and utilize heuristics on the path to choice more than those of paid apps (Bettman, Luce, & Payne, 1998). One readily accessible source of information that may ease the burden of app discovery and app consideration is the prominence of the app in the store (Ghose et al., 2013). Accordingly, we expect the effects of platform-controlled variables to be highest early on and decrease over time, and to be greater for free apps than paid apps.

Second, perceived risks associated with the acquisition of an app evolve over the lifecycle and vary across free and paid apps. Among the various types, two strongly correlated risks are relevant for the purposes of our study: functional risk and financial risk (Jacoby & Kaplan, 1972). Perceived functional risk is higher early on in a new product's lifecycle because it is quite difficult to anticipate product performance in the early days. However, uncertainty about the product's performance reduces as it matures and potential adopters who are on the market in the later phases of the product's lifecycle perceive lower functional risk (Babić Rosario, Sotgiu, De Valck, & Bijmolt, 2016). Moreover, a crucial difference between the two business models is the monetary risk associated with the purchase. While potential users of paid apps face this risk, those of free apps don't. The mere presence of a monetary risk implies paid apps score lower on trialability compared to free apps (Rogers, 2003). As consumers rely on WoM taking place on the app store to deal with perceived risks (Babić Rosario et al., 2016; Shen, 2015), we expect the effectiveness of user-side drivers of downloads to decline over time. We also expect the relationship to be weaker for free apps than paid apps, as users can readily try free apps without any transactional costs. For paid apps, on the other hand, potential users perceive greater risk and the reviews of past users can provide them with useful additional information.

Third, the composition of potential adopters and, consequently, the variety of needs the developer should satisfy evolve over an app's lifecycle and across business models. Assuming away app discovery bottlenecks on the path to app adoption, those who download the app early on are either innovators with high willingness to try new ideas or those who value what the app's initial version(s) has to offer (Rogers, 2003). What separates the remaining users on the market who have not yet downloaded the app from those who have, are their evaluations of the app's value proposition and their willingness to pay for that value. Converting these remaining users to potential adopters requires adjustments to the value proposition and, if the app is paid, the price. Introducing new and improved versions of the app by means of updates and lower regular prices can stimulate demand and speed up growth for new offerings (Ataman, Van Heerde, & Mela, 2008). Temporary price reductions can further encourage app adoption by lowering the perceived risk of making the wrong purchase. Moreover, as perceived monetary risk is most strongly associated with functional risk among all perceived risk types (Jacoby & Kaplan, 1972), potential users of paid apps are likely to have higher expectations from the developer and place greater importance on the value the app offers compared to free apps.

Accordingly, we expect the effect of updates to increase over time, as they serve as a tool to expand the potential user base, and to be stronger for paid apps than free apps, as users have higher expectations of the app.[10] Moreover, consistent with the results in Simon (1979) and Bijmolt, van Heerde, and Pieters (2005), we expect the magnitude of price elasticity to be larger in the early phases of an app's lifecycle. In the later phases, as fewer and more attentive users with higher willingness to pay would be on the market to find the app that satisfies their unique need, price may lose its importance. As for the over-time effects of discounts, we expect this positive association to start high and either increase over time or at least stay high, as discounts may serve as an encouragement for less enthusiastic adopters throughout an app's lifecycle.

4. Methodology

4.1. Data

For the purpose of studying the drivers of app downloads, we assembled a unique data set. The data set consists of a comprehensive list of variables acquired from one of the most prominent mobile analytics companies. The variables in this data set are downloads, revenues, updates, appearance in featured lists and position in top apps charts. We augment our transactional data set with publicly available data on app ratings and reviews. To that end, we developed a web crawler to collect ratings and reviews from the web page of the iTunes app store.

To be able to answer our research question, we needed to observe each app from its initial release date in the app store. Therefore, we took a stratified random sample of 1011 apps from 40,000 apps released in the Apple App Store during the first five months of 2012 (between January 1 and May 31) and obtained daily observations for all variables over a one-year time frame starting on the day each app was released. Thirty-two apps had less than 365 usable observations and were later discarded from the sample.[11] The stratification ensures that the distribution of the twenty-two app categories and business model types (i.e., free vs. paid app) in the app store is accurately represented in the sample. Because some categories, such as Food & Drinks or Education, did not have enough new apps launched in the sampling period, they are underrepresented. Moreover, we did not have any new Newsstand apps launched in the sampling period.[12] These differences are compensated with a slight overrepresentation in some other categories, such as Games. Yet, we believe our sample provides a sufficiently accurate representation of the situation in the app store at the time of data collection and helps us avoid the risk of producing results driven by category idiosyncrasies. Next, we present the model specification and detail the definition and operationalization of each variable in the model.

4.2. Model specification and estimation strategy

As our goal is to explain which factors are related to downloads and how these relationships evolve over the first year of an app's life cycle,

[10] When asked about why users have chosen to pay for apps over free alternatives, smartphone owners in the U.S. list app's content as the top reason (45%) and app's features/functionality as the second reason (35%) for paying for apps (Google, 2016).

[11] Eight of these applications were withdrawn before reaching the 1-year mark and 24 either had a name change or were withdrawn after the first year rendering access to publicly available data impossible.

[12] The twenty-two application categories are Books, Education, Lifestyle, Magazines/Papers, News, Reference, Entertainment, Music, Photo/Video, Social Networking, Games, Food/Drink, Health/Fitness, Medical, Sports, Business, Finance, Navigation, Productivity, Travel, Utilities, and Weather (Source: Apple, 2018). Newsstand was later removed by Apple.

we specify a download response model with time varying parameters. The model explains downloads as a function of variables under the control of app platform owners, app users, app developers, and several control variables:

$$\ln(D_{it}) = \alpha_i + \ln(D_{it-1}) + \sum_{m=1}^{M} \beta_{mt}^{PLT} X_{imt} + \sum_{n=1}^{N} \beta_{nt}^{USR} X_{int} + \sum_{p=1}^{P} \beta_{pt}^{DEV} X_{ipt} + \sum_{k=1}^{K} \gamma_k Z_{ikt} + u_{it} \tag{1}$$

where $\ln(D_{it})$ is the natural logarithm of the number of times app i was downloaded on day t. Because there are a few days with no downloads (0.55%), we add 1 to all observations before taking the logarithm. α_i is an app-specific constant.[13] X_{imt}, X_{int}, X_{ipt} and Z_{ikt} are, respectively, platform-controlled ($m = 1, \cdots, M$), user-side ($n = 1, \cdots, N$), developer-controlled ($p = 1, \cdots, P$), and control ($k = 1, \cdots, K$) variables that explain daily downloads.

Following Chevalier and Mayzlin (2006), we specify a log–log model, as there are scale effects emerging from higher views of popular apps compared to that of less popular apps. Because all our continuous independent variables are log-transformed, their coefficients can be interpreted as elasticities. The coefficients of the dummy variables, on the other hand, are semi-elasticities.

To give the model the flexibility to capture the changing relationship between the explanatory variables and downloads during the first year of the app's life cycle, we specify the (semi-)elasticities as a function of linear and quadratic time trend:

$$\beta_{mt}^{PLT} = \beta_{m0}^{PLT} + \beta_{m1}^{PLT} t^* + \beta_{m2}^{PLT} t^{*2} \tag{2a}$$

$$\beta_{nt}^{USR} = \beta_{n0}^{USR} + \beta_{n1}^{USR} t^* + \beta_{n2}^{USR} t^{*2} \tag{2b}$$

$$\beta_{pt}^{DEV} = \beta_{p0}^{DEV} + \beta_{p1}^{DEV} t^* + \beta_{p2}^{DEV} t^{*2} \tag{2c}$$

The quadratic time trend allows us to capture possible curvilinear relationships over time. Following Liechty, Fong, and DeSarbo (2005), we apply a transformation to time trend in the quadratic model for interpretation purposes: $t^* = (t/365 - 1/2)$.

Since the challenges faced by free and paid apps and the set of variables associated with downloads for these apps are different, we estimate the model separately for free and paid apps.[14] Moreover, as sensitivity checks, we explore whether there are any discrepancies in the results for different subsets of apps with respect to app categories (games vs. non-games), brands (new apps vs. apps by existing brands), and an app's ranking status (all apps vs. apps ranked at least 120 days) by estimating the model separately for these sub-samples.

4.3. Variable definitions and operationalization

The dependent variable in Eq. (1) is the natural logarithm of the *daily number of unique downloads* of app i obtained from our data provider. They are first time downloads that are unique to the user and do not contain updates. Download numbers are estimated using transactional download data available to the mobile analytic company through their clients and public ranking charts. The mobile analytic company's access to transactional data from over 100,000 apps with over 1.5 billion downloads leverages a level of accuracy that is unmatched in the industry. In terms of iOS downloads in particular, the majority of apps are claimed to be estimated with a margin of error below 3% and 95% of apps with a margin of error below 10%.

The *platform-controlled variables* include appearance on featured lists and position in top app charts. Our data set contains information on (1) whether an app was on a "Featured List" and which list it was featured on and (2) the position of an app in a top apps chart and which chart it was in. We classify the "Featured List"'s into two main categories, top featured lists and other featured lists, and code *appearance on top (other) featured lists* as a dummy variable.[15] We operationalized *appearance in top apps chart* considering only the "Top Free" and "Top Paid" charts, as they are the most important ones with the highest traffic. Inspired by the findings of Carrare (2012) and the design of the app store at the time of data collection, we acknowledge the natural break points in these charts and code appearance in a top apps chart using three dummy variables: above-the-fold (i.e., if an app was among the first five apps in the chart), below-the-fold (i.e., if an app was among the second five apps in the chart), and below-the-2nd-fold (i.e., if an app was among the apps listed between the 11th and 25th positions).[16]

The *user-side factors* associated with downloads include valence and volume of WoM. *Valence of WoM* is operationalized as the average rating score of the app's most recent version. Using the ratings and reviews data we crawled from the official web-page of iTunes, we calculated the average rating score for an app's most recent version by dividing the sum of all user ratings up to day t to the cumulative number of reviews up to day t, which is our measure for *volume of WoM*.

The *developer-controlled variables* associated with downloads include updates and regular price and discount depth (only for paid apps). We operationalize *updates* using the information in the three-digit number known as the version number (e.g., Version 2.3.1). We infer the nature of the changes made to the app from the digit changes between two consecutive versions: a change in the first digit indicates a major improvement; a change in the second digit indicates an intermediate improvement, while a change in the third digit indicates a minor improvement.[17] We code each update as a step dummy that is switched on for five days following an update.

In addition to daily downloads, our data set contains information on total revenues from downloads. We use these data to calculate the actual price of a paid app on a daily basis (in cents) and determine the *regular*

[13] We assessed whether fixed-effects or random-effects correction would be appropriate to control for time invariant differences across applications using the Hausmann test. The results of this test suggested that the fixed-effects model is appropriate in our case.

[14] With the help of a Chow test, we assessed whether we can pool the coefficients. The test result suggests estimating separate coefficients for free and paid apps ($F_{77,357181} = 14.699$, $p < .01$).

[15] 'Featured List' is a general term for all curated lists published by the platform. We observe 189 apps (out of 979) featured in 180 different lists. Given the scattered nature of these lists and the low number of featured apps, we decided to classify these lists under top featured lists and other featured lists. The reasoning behind this distinction is that top featured lists are the main lists that are the easiest for users to notice, while others are not. Users are exposed to the top featured lists on the landing page and need to actively search for the other lists. 'Top Overall', 'New and Noteworthy', or 'Editor's Choice' are examples of top featured lists. Other featured lists include category specific or curated lists for special days (e.g., Mother's Day Gift Guide, Apps for Graduates).

[16] At the time of data collection, Apple App Store top apps charts rolled on a continuous scrolling basis where each screen contained five apps. Therefore, we separated the effect of being visible on the first page (referred to as 'above-the-fold') from that of the second page (referred to as 'below-the-fold') and the following pages (referred to as 'below-the-2nd-fold') We think 5-page-views-by-scrolling corresponding to the natural breakpoint at 25 provides us with a comprehensive list of top apps.

[17] To illustrate the association between changes in version number digits and the nature of the updates consider an app with the following history: Version 2.3 "Added History option". Version 2.4 "Added a screenshot option. Now can save the picture in your iPad gallery any time you want. Find this option in game menu". Version 2.4.1 "Updated ABOUT and HISTORY views". Version 3 "Clear option for removing the packages and images, UI changes, New packages at the top of the list in selector, Ability to share packages to your friends (email, FB, twitter), Ability to create own packages". The update from Version 2.4.1 to Version 3 is a major update, from Version 2.3 to Version 2.4 is an intermediate update, and from Version 2.4 to Version 2.4.1 is a minor update.

price dynamically by checking the mode of actual prices in a fixed time window. Specifically, after setting the actual price on the first day equal to the regular price, we calculate the difference between the actual price on a given day and the regular price of the previous day. If this difference is zero (i.e., no price change), we set the regular price equal to the actual price. Otherwise, we look forward 30 days, calculate the mode of actual prices in this time window, and set the regular price to the mode if the mode is equal to the current price, if they are not equal the regular price is set to previous day's price.[18] This procedure allows us to separate temporary changes in prices from permanent changes. We define *discount depth* as the ratio of cents-off to the regular price of the app.

Finally, as *control variables* we include (1) previous day's downloads, which helps us to account for the unobserved effects of offline WOM, ads and other forms of publicity, (2) the number of days passed since an app has been updated, to capture the effect of the frequency of updates, (3) dummy variables for days of the week, special dates such as holidays (Christmas, New Year's Eve etc.) and special occasions (Mother's/Father's Day, Valentine's Day etc.), and (4) several step dummies to control for the introduction of new devices and new iOS software updates.

Table 3 summarizes the definition and operationalization of the variables in the model and Table 4 presents summary statistics per business model type.

5. Results

Table 5 displays the coefficient estimates of our main models (i.e., for free and paid apps) and of models we estimated for sensitivity checks. Because our model includes interactions among all regressors and first- and second-order time trend, discussing the results coefficient-by-coefficient is not fruitful. Instead, we calculated the marginal effect of each variable over time – starting on the day of the release and reaching 365 with increments of two weeks – and the 95% confidence interval around this estimate using the Delta method. Fig. 2 displays the effects of platform-controlled variables, Fig. 3 the effects of user-side variables, and Fig. 4 the effects of developer-controlled variables.

In what follows, we first discuss the impact of each variable on downloads using the average of the marginal effects over time and, if available, compare the (semi-)elasticities to earlier findings. We then present our findings as to how these effects vary over the course of an app's first year of existence. To facilitate comparison with our expectations, we summarize the key findings in Table 6. We conclude this section by discussing whether and how our main findings change under different sub-samples of apps.

5.1. Platform-controlled variables

Being *featured in a top list* increases downloads of a free app by 3.93% and a paid app by 12.73% on average (Fig. 2 Panel A). Contrary to our expectations, it benefits a paid app about three times as much. This result may suggest that appearance in the top curated lists (e.g., Top Overall, New and Noteworthy, or Editor's Choice) improves app discovery rates more in less-crowded app categories than it does in more-crowded categories. Alternatively, it may indicate that, potential adopters of paid apps consider these curated lists as a reliable source for a quality signal in their search for confirmation and uncertainty reduction before they commit to a transaction. As to the temporal variation of

[18] In a highly dynamic market where 5-day price drops have been claimed to have considerable effects on downloads, we choose 30 days as a long enough time window to outrun temporary price discounts and identify a new regular price level. Moreover, we checked the sensitivity of our findings by considering 15- and 45-day time windows and find that our results are robust. (https://techcrunch.com/2013/01/31/app-sales-work-five-day-iphone-app-price-drops-boost-downloads-by-1665-on-ipad-by-871-revenue-growth-by-day-3/, last accessed on 27/12/2019).

Table 3
Definition and operationalization of variables.

Variable	Definition	Operationalization	Type/ Transformation (Range before trans.)	Source
Downloads	Daily downloads of an app	Number of times app i was downloaded on day t.	Continuous/ Log (0–354,395)	Data Provider
Platform-controlled Variables				
Appearance on Featured Lists	Whether an app has been featured by the platform	Divided into two categories: Top and Other. "1" if the app exists on one of the featured lists under each category and "0" otherwise.	Dummy/N.A. (N.A.)	Data Provider
Appearance in Top App Charts	Whether and where an app has been placed in the top app charts	Divided into three categories: above-the-fold, below-the-fold, and below-the-2nd-fold. "1" if the app exists in one of these positions and "0" otherwise.	Dummy/N.A. (N.A.)	Data Provider
User-side Variables				
Valence of WOM	Average Rating Score	Average rating score of the current version of app i on day t calculated from the ratings of users who also wrote a review for the app up to day t	Continuous/ Log (1–5)	iTunes Web page
Volume of WOM	Cumulative number of reviews	Total number of reviews of app i up to day t.	Continuous/ Log (0–160,285)	iTunes Web page
Developer-controlled Variables				
Updates	Whether an app has been updated	Divided into 3 categories: minor, intermediate, and major. Dummy variable for each update category for five days following the release of a new version.	Dummy/N.A. (0–1)	Data Provider
Price	Regular price of an app in cents	Inferred from a dynamic search over daily actual prices.	Continuous/ Log (0–49.99)	Data Provider
Discount	% cents-off	(Regular Price – Actual Price)/ Regular Price	Continuous/ None (0–100%)	Data Provider
Control Variables				
Day of the week	Control for day of the week	Monday is chosen as the baseline.	Categorical/ NA (1–7)	NA
Days since last update	Counts days since last update	Number of days since last either of the update categories.	Continuous (0–365)	Data Provider

Notes: Before applying the log transformation, we add 1 to all downloads as we have a few days with no downloads (0.55% of all observations). Exploratory analysis of average download numbers centered on each update and the observation that users give most feedback in the first few days after a new version release (Pagano & Maalej, 2013) supports our choice of 5-day time window. We check the sensitivity of our findings by considering a 4-day time window, the second likely candidate, and find that the results are robust.

Table 4
Summary statistics.

	Free Apps	Paid Apps
Number of Apps	602	377
Downloads	1350.337	322.697
	(5857.519)	(2348.376)
Platform-controlled Variables		
Appearance on Top Featured List	0.004	0.009
	(0.065)	(0.094)
Appearance on Other Featured List	0.010	0.015
	(0.100)	(0.121)
Appearance Above-the-fold	0.001	0.002
	(0.034)	(0.047)
Appearance Below-the-fold	0.001	0.002
	(0.032)	(0.045)
Appearance Below-the-2nd-fold	0.003	0.005
	(0.055)	(0.072)
User-side Variables		
Valence of WOM	2.963	3.453
	(1.684)	(1.503)
Volume of WOM	143.052	126.289
	(1231.176)	(545.603)
Developer-controlled Variables		
Minor Update	0.028	0.024
	(0.165)	(0.153)
Intermediate Update	0.032	0.033
	(0.177)	(0.179)
Major Update	0.001	0.004
	(0.036)	(0.066)
Price	NA	2.621
		(3.742)
Discount	NA	0.009
		(0.083)
Control Variables		
Days since last update	81.615	92.594
	(83.650)	(89.565)

Notes: Cell entries are means and standard deviations, in parentheses, across all apps and time periods.

this factor's effectiveness, free apps enjoy a similar lift, in terms of magnitude, throughout the year. Appearance on a top featured list starts to boost downloads significantly only later in a free app's first year of existence. For paid apps, being featured in top lists has a substantial effect on downloads early on. The effectiveness of this tool gradually decreases over time and reaches a similar level of effectiveness observed for free apps.

In contrast, being *featured in other lists* fails to increase downloads: averaged over the entire year, downloads of free apps decline by 6.37% and paid apps by 4.24% (Fig. 2, Panel B). Although contrary to our expectations, this result is not very surprising due to the very narrow and scattered nature of other featured lists. An obvious distinction between the top featured lists and others leaps out. Considering there are about 180 different lists, one may suggest that, instead of boosting downloads, appearing in these lists limits the general interest in the app and may even prevent users who normally would have downloaded the app to shy away. The magnitude of the deleterious effect declines over time but never completely disappears for free apps. Interestingly, being featured in other lists becomes effective for paid apps towards the end of the year.

In line with our expectations, merely *appearing in top apps charts* has a positive effect on downloads except for paid apps appearing above-the-fold later in their first year of existence (see Fig. 2, Panels C-D).[19] On average, getting into the list of apps presented above-the-fold increases downloads of free apps by 80.28%, below-the-fold by 60.95%, and below-the-2nd-fold by 57.36%. For paid apps, appearing above-the-fold has a negligibly small effect on average, whereas appearing below-the-fold increases downloads by 19.55% and below-the-2nd-fold by 27.35%. The effects are notably larger for free apps, as expected, and change sharply with each fold. Moreover, appearing in top apps charts has a much larger impact than (top) featured lists.

As to how the effects of appearing in top apps charts evolve over time, we observe that appearing above and below the fold has a relatively stable effect on free app downloads and a diminishing effect on paid app downloads. The effectiveness of appearing below-the-2nd-fold declines following the release of an app, for free and paid alike, and increases back to the initial level of effectiveness towards the end of the year. Collectively, these results suggest that appearing in top apps charts, anywhere above the 2nd fold, increases the speed with which paid app downloads reach their market potential and gradually lose their ability to bring in new users.

5.2. User-side variables

Panel A and Panel B in Fig. 3 display, respectively, *WoM valence* and *WoM volume* elasticities for free and paid apps. In line with Babić Rosario et al. (2016), we find that not all WOM metrics are positively associated with performance. Specifically, we find that a 10% increase in average rating score decreases free app downloads by 0.13% and increases paid app downloads by 0.23% on average. As expected, WoM valence has a higher impact on downloads in high risk situations (i.e., paid apps).

More interesting patterns emerge when the evolution of valence elasticities is considered. App download's sensitivity to changes in WoM valence early on is quite different for free and paid apps: an increase in average rating scores lowers the demand for free apps (by 0.42%, on average, in the first six months) but boosts download numbers for paid apps (by 0.22%, on average, in the first six months). The difference disappears as apps mature and valence elasticities of free and paid apps converge towards the end of the first year – approximately 0.02% and 0.05% increase for free and paid apps, respectively.

These findings raise concerns about the credibility of reviews for free apps written early on, where users may be less involved or the barrier to leave a review may be quite low – a particularly interesting issue considering the growing literature on fake reviews and their effects on sales (Dellarocas, 2006; Hu, Bose, Koh, & Liu, 2012; Mayzlin, Dover, & Chevalier, 2014; Streitfeld, 2011). Our finding suggests that users take the reviews of free apps written early on less seriously and even step back from downloading the app. However, as time passes and the average rating score of a free app stabilizes around a certain value, potential adopters start taking this information more seriously and into account.

As for paid apps, the results support the notion that potential adopters want to reduce perceived risks when purchasing apps by processing the information provided by current users. The experiences encoded in these reviews matter more in potential adopters' decisions in the first half of the year and increasingly less from then on.

WoM volume elasticities of downloads and their behaviors over time are quite similar across free and paid apps. On average, a 10% increase in WoM volume increases free app downloads by 0.13% and paid apps by 0.16%. This effect increases towards the mid-year of the app's release and declines at an increasing rate as apps mature.

5.3. Developer-controlled variables

Panels A-C in Fig. 4 display the relationships between *minor, intermediate, and major updates* and downloads of free and paid apps. As expected, updates benefit app demand in general. On average, downloads increase by 1.07% (minor), 0.83% (intermediate), and 22.30%

[19] This unexpected result is due to a data peculiarity. We observe very few paid apps appearing above-the-fold in this sub-section of the time window. Accordingly, we are cautious about drawing strong conclusions about that particular data partition.

Table 5
Parameter estimates per App type.

	Main Models		Models for Sensitivity Checks					
Variable	Free Apps	Paid Apps	Games	Non-Games	New Apps	Existing Apps	All Apps	Ranked Apps
Constant	1.346***	1.503***	1.632***	1.348***	1.429***	1.372***	1.409***	1.910***
Time	−0.324***	−0.466***	−0.349***	−0.267***	−0.283***	−0.305***	−0.289***	−0.287***
Time^2	0.775***	1.034***	0.948***	0.784***	0.761***	0.877***	0.800***	2.036***
Top Featured Lists	0.023	0.117***	0.063***	0.116***	0.093***	0.097***	0.087***	0.110***
Top Featured Lists × Time	0.038	−0.138***	−0.011	−0.024	−0.032	0.018	−0.017	0.034
Top Featured Lists × Time^2	0.172	0.024	0.208	−0.253*	−0.107	−0.048	−0.036	−0.198
Other Featured Lists	−0.045**	−0.088***	−0.045	−0.067***	−0.052***	−0.077***	−0.064***	−0.034
Other Featured Lists × Time	0.088***	0.035	0.321***	0.090***	−0.030	0.158***	0.027	−0.017
Other Featured Lists × Time^2	−0.240*	0.491***	0.909***	−0.004	0.165	0.051	0.148	−0.383**
Above-the-fold	0.662***	−0.076	−0.073	0.536***	−0.000	0.617***	0.296***	0.578***
Above-the-fold × Time	−0.217	−1.857***	−1.546***	−0.073	−1.016***	−0.100	−0.220*	−0.191
Above-the-fold × Time^2	−0.859	−0.764	−0.104	−0.054	0.540	−0.323	0.874**	−0.593
Below-the-fold	0.424***	0.102*	−0.142**	0.512***	0.178***	0.368***	0.247***	0.499***
Below-the-fold × Time	−0.046	−0.553***	0.094	−0.036	−0.101	−0.104	−0.121	−0.111
Below-the-fold × Time^2	0.570	0.690	3.512***	−0.315	1.448***	0.502	1.083***	−0.627*
Below-the-2nd-fold	0.393***	0.141***	0.206***	0.236***	0.218***	0.247***	0.230***	0.320***
Below-the-2nd-fold × Time	0.054	0.021	0.133**	0.148***	0.128***	−0.043	0.091**	0.069
Below-the-2nd-fold × Time^2	0.658***	1.086***	1.522***	1.066***	1.337***	0.783***	1.175***	0.030
ln(Valence)	−0.003	0.035***	−0.034***	0.018***	0.007**	0.011**	0.009***	−0.007
ln(Valence) × Time	0.069***	0.004	−0.017	0.059***	0.042***	0.045***	0.045***	−0.151***
ln(Valence) × Time^2	−0.119***	−0.130***	−0.089**	−0.131***	−0.126***	−0.077**	−0.119***	−0.099
ln(Volume)	0.018***	0.021***	0.014***	0.024***	0.020***	0.012***	0.018***	0.038***
ln(Volume) × Time	−0.004**	−0.005**	0.005*	−0.006***	−0.004**	−0.013***	−0.007***	0.017***
ln(Volume) × Time^2	−0.051***	−0.059***	−0.073***	−0.056***	−0.046***	−0.060***	−0.049***	−0.222***
Minor Update	0.038***	0.067***	0.067***	0.046***	0.049***	0.045***	0.048***	0.089***
Minor Update × Time	0.046***	0.077***	0.035	0.073***	0.059***	0.026	0.049***	0.117***
Minor Update × Time^2	−0.312***	−0.343***	−0.398***	−0.328***	−0.308***	−0.390***	−0.331***	−0.868***
Intermediate Update	0.052***	0.070***	0.010	0.074***	0.055***	0.061***	0.058***	0.105***
Intermediate Update × Time	0.107***	0.048**	0.070**	0.083***	0.081***	0.050*	0.074***	0.188***
Intermediate Update × Time^2	−0.506***	−0.313***	−0.083	−0.520***	−0.420***	−0.375***	−0.417***	−0.795***
Major Update	0.066	0.132	0.015	0.067	−0.000	0.072	0.021	0.096
Major Update × Time	0.736	0.206	1.265**	0.217	0.326	0.460	0.334*	0.756
Major Update × Time^2	1.161	0.270	2.820***	0.499	0.921**	1.109	0.905**	0.753
ln(Price)	–	−0.140***	−0.185***	−0.123***	−0.144***	−0.129***	−0.140***	−0.126***
ln(Price) × Time	–	0.029***	−0.026***	−0.016***	−0.021***	−0.012***	−0.019***	0.035***
ln(Price) × Time^2	–	−0.022**	0.050***	−0.015***	0.007*	0.007	0.007*	−0.069***
Discount Depth	–	1.394***	1.483***	1.291***	1.467***	0.997***	1.355***	1.145***
Discount Depth × Time	–	−0.389***	−0.626***	−0.177***	−0.350***	−0.482***	−0.409***	−0.348***
Discount Depth × Time^2	–	−1.694***	−2.272***	−1.124***	−1.938***	−0.626*	−1.660***	−2.157***
ln(Downloads$_{t-1}$)	0.737***	0.723***	0.720***	0.736***	0.735***	0.728***	0.734***	0.723***
Tuesday	0.038***	0.030***	0.043***	0.031***	0.035***	0.034***	0.035***	0.049***
Wednesday	0.034***	0.030***	0.051***	0.024***	0.031***	0.037***	0.032***	0.053***
Thursday	0.053***	0.064***	0.100***	0.038***	0.056***	0.060***	0.057***	0.077***
Friday	0.066***	0.079***	0.153***	0.036***	0.072***	0.069***	0.071***	0.102***
Saturday	0.142***	0.152***	0.257***	0.099***	0.144***	0.150***	0.146***	0.186***
Sunday	0.126***	0.122***	0.186***	0.099***	0.122***	0.129***	0.124***	0.158***
Days Since Last Update	−0.000***	−0.001***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.001***
Number of apps	602	377	285	694	707	272	979	99
Number of observations	219,730	137,605	104,025	253,310	258,055	99,280	357,335	36,135
R-Square	0.717	0.752	0.769	0.718	0.738	0.723	0.734	0.781
Average VIF	8.76	8.74	9.26	7.13	7.68	7.71	7.40	11.65

Notes: *indicates $p < .1$, ** indicates $p < .05$ and *** indicates $p < .01$. We use Monday as the baseline while dummy-coding days of the week variable. All models include other controls, which are not shown here to conserve space.

(major) in response to free-app updates and by 3.78% (minor), 4.35% (intermediate), and 17.18% (major) for paid apps.[20]

The evolution patterns of the update semi-elasticities are similar across update types and app business models, and the order of magnitude is mostly preserved. As expected, the effect of an update increases moving from minor to intermediate updates and this increase is larger for paid apps. Interestingly, minor updates released shortly after the launch of free/paid apps lower the demand (Fig. 4, Panel A). We observe a similar pattern for intermediate updates of free apps. This result may suggest that having to offer a minor update (i.e., bug fixes and development tweaks) or an intermediate update (i.e., improvements to existing features of an app) shortly after an app's release signals low app quality (i.e., not ready for the market). However, approximately three months into an app's existence, the effects are reversed, and updates start to boost downloads as expected.

Panel D in Fig. 4 displays the evolution of *price* elasticity over time. Consistent with the low-price elasticities reported for US Apple App Store (e.g., Ghose & Han, 2014; Kübler et al., 2018), we find that a 10% increase in price lowers downloads by 1.41% on average. The magnitude of price elasticity declines with the passage of time: downloads become less sensitive to price changes as the app matures. As to the effect of *discounting* on downloads, displayed in Fig. 4 Panel E, we find a 13.20% increase in app demand in response to a 10% temporary reduction in price. The increase in app demand in response to a discount is more than double what has been reported in other studies (e.g., Ghose & Han,

[20] Though major updates findings are consistent with expectations directionally and magnitude wise, there is substantial uncertainty around the estimates – due to the scarcity of major updates released in the last half of the data. Hence, we refrain from drawing strong conclusions about their effects.

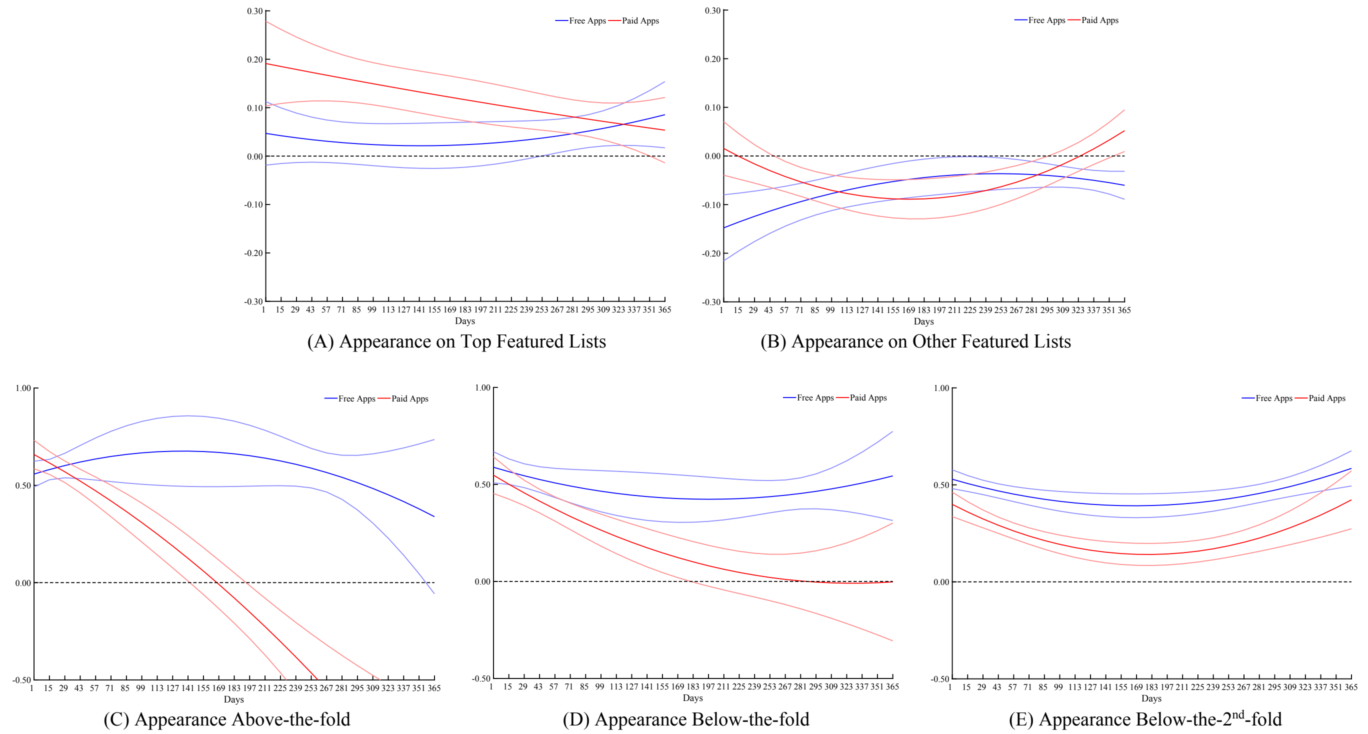


Fig. 2. Effectiveness of Platform-controlled Variables over Time. *Notes:* Blue represents free apps and red represents paid apps. The solid lines are average marginal effects and the shaded areas show 95% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

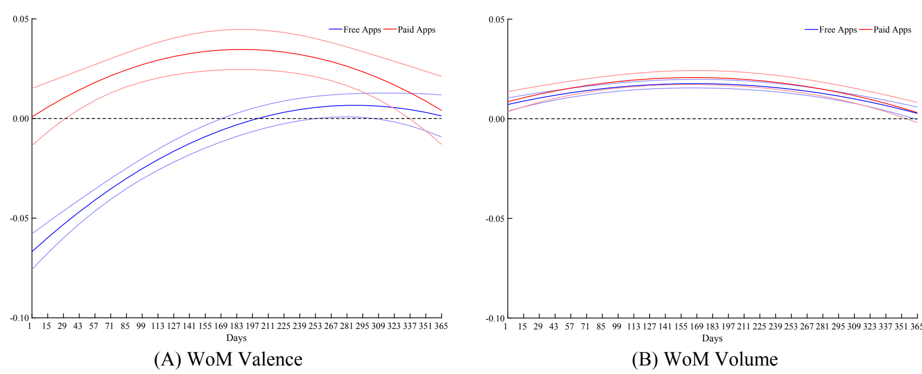


Fig. 3. Effectiveness of User-side Variables over Time. *Notes:* Blue represents free apps and red represents paid apps. The solid lines are average marginal effects and the shaded areas show 95% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

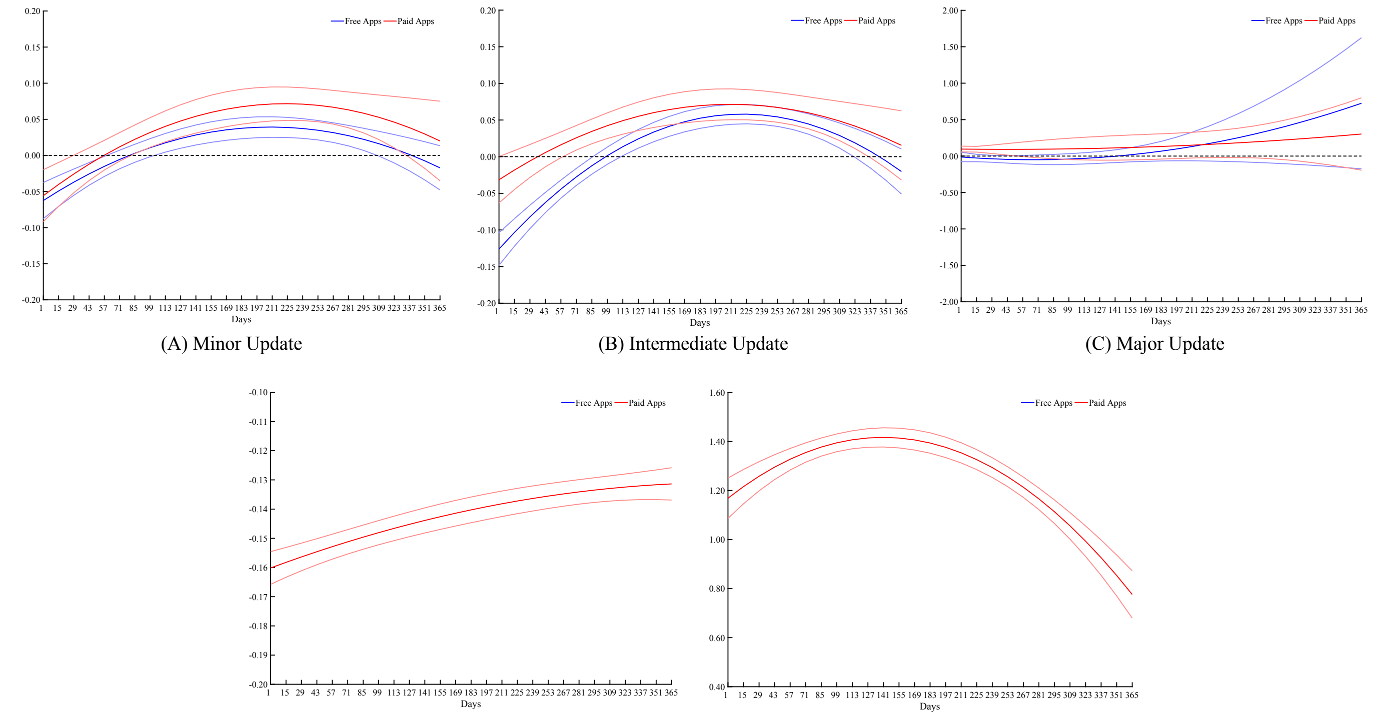
2014), indicating that users are more discount sensitive shortly after the launch of an app and discounts lose their power to boost downloads with maturity. Supporting this conclusion, we observe that offering discounts increases downloads more and more as time passes, reaching peak effectiveness mid-year, declines from then on to a level lower than its initial effectiveness.

5.4. Sensitivity checks

To explore the sensitivity of our findings, we re-estimate the models with different sub-groups of apps in our data. Specifically, we compared the results from (1) games (fun-oriented and hedonic) to non-games (task-oriented and utilitarian), (2) new apps (no history or customer base to rely on, mobile first) to apps by existing businesses (with a customer base that can readily be activated, not necessarily mobile first), and (3) all apps in the sample (current study's setting) to apps ranked at least 120 days (mimicking previous studies' settings). As the data exhibits a tendency to crumble, we refrain from further breaking these sub-samples down to free and paid apps. The coefficient estimates obtained from these sub-samples are presented in Table 5.

Noting that the over-time behavior of a given variable associated with downloads is fairly similar across different sub-samples within a grouping (e.g., games vs. non-games), unless otherwise mentioned, we observe the following structural differences. First, appearing on other featured lists, which had a deleterious effect on downloads, starts to work for games but only later in the first year of a game's existence. Second, the effectiveness of appearance in top app charts varies substantially across sub-samples. Appearing above (below) the fold is much more (more) strongly associated with downloads of games (vs. non-games), apps by existing businesses (vs. new apps), and apps ranked at least 120 days (vs. all apps).

Third, ratings and, more importantly, the number of reviews appear



(A) Minor Update (B) Intermediate Update (C) Major Update

(D) Price Elasticity (E) Discount Depth

Fig. 4. Effectiveness of Developer-controlled Variables over Time. *Notes:* Blue represents free apps and red represents paid apps. The solid lines are average marginal effects and the shaded areas show 95% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

to have a stronger impact on downloads of non-games (vs. games) and new apps (vs. apps of existing businesses). Comparison of the user-side variables' effects of all apps vs. apps ranked at least 120 days shows that both over-time behavior and strength of associations exhibit substantial differences. Fourth, minor updates bring in slightly more users to games (vs. non-games). Intermediate updates, on the other hand, are more strongly associated with the downloads of non-games (vs. games). Though they follow a similar over-time pattern, the relationships between minor and intermediate updates and downloads observed in the apps ranked at least 120 days sub-sample (vs. all apps) are accentuated.

Finally, potential adopters of games (vs. non-games), new apps (vs. apps by existing businesses), and apps ranked at least 120 days (vs. all apps) are more sensitive to price changes independent of the direction of change. We also observe a change in the over-time behavior of price elasticity when comparing all apps to ranked apps.

6. Conclusions, implications and avenues for future research

In this paper, we explore factors that are related to app downloads and how these relationships may develop during the first year after an app's release. Our access to a rich database with download numbers enables us to include newly released apps in the sample independent of their ranking status and explore the effects of a broader set of variables to develop a more generalized understanding. *Time-varying* results from separate analyses for *free* and *paid* apps add interesting insights to the existing literature and suggest valuable implications for app developers.

Overall, our results suggest that the decisions and the actions of all three players in the app market – developers, users, and platform owners – seem critical for improving app performance at least at some point in the year following an app's release. The effects of platform-controlled variables, explored for the first time in this stream of the literature, dwarf those of variables shaping an app's relevance (i.e., developer-controlled factors) and variables reflecting current users' views about an app (i.e., user-side factors), highlighting the power app platform has on users' adoption decisions. Among these platform-controlled variables, the impact of appearance in top apps charts stands out, especially early on in a paid app's lifecycle and throughout a free app's. Featuring works when and where it benefits the platform owner the most: early on in the case of paid apps, which are featured almost twice as much, and only after gaining some traction with the users in the case of free apps, which experience a twofold increase in top feature placements over time. For an app platform that generates its revenues from paid app downloads and in-app purchases, most of which comes from free apps, our results have face validity.

The sheer size of platform-controlled variables' effects begs the question is this merely an awareness effect? Though it is without a doubt that the platform's decision to give apps a prominent position in the store aids app discovery, it is likely that potential adopters use this to infer additional information about apps. This is especially the case early on in an app's lifecycle, when relying on others' opinions is not an option either because the information is limited, or they think it is unreliable – evidenced by the deleterious effect of WoM valence on free app downloads shortly after release. Equipped with the common knowledge that an app's position in a top chart is determined by a combination of (i) a few unknown proprietary factors, (ii) previous updates, ratings, reviews, and downloads of the app – whose effects are controlled for in our analyses –, and (iii) user engagement, retention, and revenues from in-app purchases, one may argue that what this variable also captures is the effect current users' repeated interactions have on download decisions. This can be considered as a signal of app's quality based on others' actions. Likewise, a "feature" can also be considered as a signal of quality that reflects the platform's "seal of approval". Users looking to download an app may infer that the featured app must be of high quality because the platform owner has no incentive to feature an app with a low likelihood success. Independent of whether the actions of the platform owner merely aids app discovery or are used as quality signals that facilitate app evaluations or downloads, the app platform is powerful.

What can developers do given the influence app platforms have on

Table 6
Summary of results for the effects of external and internal factors on downloads for Free vs. Paid Apps.

Variable	Free Apps		Paid Apps	
	Direction	Evolution over time	Direction	Evolution over time
Platform Controlled Variables				
Appearance on Top Featured Lists	+	Flat U shape	++	Decrease
Appearance on Other Featured Lists	–	Flat Inverse U shape	–	U shape
Appearance Above-the-fold	++	Flat Inverse U shape	–	Decrease
Appearance Below-the-fold	++	Flat U shape	+	Decrease
Appearance Below-the-2nd-fold	++	U shape	+	U shape
User-side Variables				
Valence of WOM	–	Decrease in magnitude	+	Inverse U shape
Volume of WOM	+	Inverse U shape	+	Inverse U shape
Developer Controlled Variables				
Minor Update	+	Inverse U shape	++	Inverse U shape
Intermediate Update	+	Inverse U shape	++	Inverse U shape
Major Update	+	Flat U shape	+	Flat U shape
Price	NA	NA	–	Decrease in magnitude
Discount	NA	NA	+	Inverse U shape

Notes: Directions are based on the sign of the average effect over time and does not necessarily imply that the effect stays in that region throughout. ++ indicates that the association between a variable and downloads is stronger for a specific app type compared to the other.

users' adoption decisions? The pattern of results observed for free apps suggests that potential adopters are cautious early on. They are mainly swayed by the platform-controlled variable of appearance in top apps charts and the number of reviews the app has garnered (i.e., WoM volume), which signal how large and engaged the current user base is. Subjective evaluations of others (i.e., WoM valence) and developers' attempts to fix or improve apps (i.e., minor and intermediate updates) are either seen as signals that cannot be trusted or that the app is of inferior quality. As free apps mature, potential adopters start to rely more on what others say in addition to what others do. Yet, others' opinions never exceed the influence that (signals of) their actions have.

The only thing that is fully under the free-app developer's control is the app's value proposition; what unique need it satisfies and how effectively and efficiently it does so. The observation that intermediate updates appearing in the early days of a free app have a stronger deleterious effect on downloads than minor updates, which quickly recover, suggests that developers are better off releasing almost-ready-for-the-market apps. Though potential adopters may palate inefficiencies (i.e., bugs) early on, they are unforgiving when it comes to ineffectiveness (i.e., subpar content, functionality). This is especially important considering most free app developers launch minimum-viable-products and fix the issues along the way. As updates released later in a free app's lifecycle have a larger effect on downloads, especially when the changes between two consecutive versions of the app are more than minor, the developer can aim to increase the relevance of the app in the eyes of a larger pool of users and maintain or improve engagement of the current user base. This, in turn, may generate positive word-of-mouth on the platform and increase the chances that the free app gets a prominent position on the platform.

The pattern of results observed for paid apps suggests that potential adopters are even more cautious than those of free apps, especially early on. They combine signals from multiple sources (i.e., what others before them have said and done, whether the platform owner thinks the app is worthy of a prominent display in the store, how much they have to part with to acquire the app). However, as the paid app matures, the signals emanating from platform-controlled variables lose their relative power over those from app users and app developers.

Because getting the paid app in a top featured list as early as possible in the lifecycle helps with the discoverability problem and boosts downloads, the developer's actions that affect the curators' decisions to feature an app assumes great importance. These decisions are based on, among other factors, the app's content and functionalities (i.e., the value proposition) as well as user-experience and user-interface design (i.e., how effectively and efficiently the value proposition is delivered). Therefore, developers of paid apps should aim to launch a ready-for-the-market app that (better) satisfies a unique need and find ways of encouraging the users to rate and review the application. With the initial boost they can get from being featured in a top list and, possibly sometime later a prominent position in the top apps charts, they can attract more users who not only engage with the app but also generate the much needed positive word-of-mouth for even more downloads. As updates released later in the paid app's lifecycle are capable of generating additional downloads, the developer can mine the reviews accumulated over time and decide in what direction to improve the app in the next version, ensuring longevity and a steady stream of revenues for the developer as well as the platform owner. Considering the recent changes in Apple's revenue sharing model with developers of paid apps (i.e., a lower cut in the second year), survival has become more important than before.

Another decision variable at the disposal of a paid app developer is price. Developers should carefully determine their price points prior to release. As our results indicate that users are more price sensitive in the early phases of an app introduction and gradually become less concerned with price, penetration pricing seems to be the more meaningful choice. Yet, developers have room to set a slightly higher initial price and stimulate downloads and expand their user bases via promotions. Moreover, as discounting reaches its peak effectiveness several months into the app's first year of existence, developers also have the flexibility to gradually increase the app's price and encourage additional downloads occasionally by offering a discount.

Though our study adds interesting insights to the existing literature, there are several issues that may provide fruitful avenues for future research. First, given the nature of our data, we investigate the drivers of downloads at the aggregate level (i.e., number of downloads on a day). However, while conceptualizing, we rely on an individual's decision journey on the app platform and identify factors that may facilitate users' transitions from one journey stage to the next. Future research can enrich the insights by modeling at the individual level, provided these data exist and are accessible. Second, our findings on updates are particularly interesting, as this is the only variable that is completely under the app developer's control independent of the business model. In this paper, we inferred the nature of updates from the change in version numbers. Future research should consider the nature of these updates by analyzing the verbal descriptions of the improvements that accompany new version releases. Third, our analyses do not provide detailed insights into several systematic differences across apps. Although we provide initial insights on how the effects change across games vs. non-games or branded vs. non-branded developers, future research may contribute to an even more enriched understanding of these categorical differences. Finally, another growing area of research includes business model type as an important driver of app sales and performance. Especially for digital platforms, freemium business models are of increasing interest. Though extant work in this domain sheds some light on the effectiveness of freemium/paymium business model, our study could be extended to investigate the performance of apps following different business models.

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Zeynep Aydin Gokgoz is a PhD candidate in Rotterdam School of Management, Erasmus University. She received her Bachelors' with honors in Statistics from Middle East Technical University and her Master's degree in Industrial Engineering from Bilkent University. Her research interests include Bayesian Modeling, Time Series Models and Text Analysis with applications on mobile marketing and user generated content. She presents her work at leading international conferences such as European Marketing Academy Conference and Marketing Science Conference.

M. Berk Ataman is an Associate Professor of Marketing at Koç University Faculty of Economics and Administrative Sciences. Assoc. Prof. Ataman received his B.Sc. and M.Sc. degrees in Management Engineering from Istanbul Technical University and his Ph.D. from Tilburg University. He held research positions at Rotterdam School of Management, (Erasmus University, 2006-2013), Tilburg University (2002-2006), and Istanbul Technical University (1999-2002). Assoc. Prof. Ataman's work has appeared in journals such as Journal of Marketing Research, Marketing Science, Journal of Product and Brand Management, and Social Indicators Research. Assoc. Prof. Ataman's research focuses on developing quantitative models to support marketing decision making and seeks to help managers better understand how marketing affects performance specifically in the long run.

Gerrit Van Bruggen Professor van Bruggen's primary research interest lies in strategic marketing issues and the impact of information technology and information systems on marketing strategy and decision making. His research has been published in the field's leading scientific journals including Marketing Science, the Journal of Marketing, the Journal of Marketing Research, Management Science, MIS Quarterly, Information Systems Research and Interfaces. He is a regular speaker at international management conferences and an experienced teacher at the executive level. He is a former visiting scholar at the Smeal College of Business Administration at Pennsylvania State University in the US.