Creating and capturing value from digital products : implications of business model choice and product positioning in the mobile app market

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Implications of Business Model Choice and Product Positioning in the Mobile App Market

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ter verkrijging van de graad van doctor aan de Technische Universiteit Eindhoven,
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"If I waited for perfection,
I would never write a word."
– Margaret Atwood

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Chapter 1

Introduction

A growing number of industries is dominated by platforms, and their associated marketplaces have concomitantly become increasingly prominent, but highly challenging, contexts of business activity. Near-zero marginal costs of production and distribution around platforms tremendously deepen the pool of would-be producers of complementary products. Consequently, those complementor firms have to position their complements relative to a multitude of complementors that address the same consumer needs, and they are compelled to choose for business models based on free distribution of which the performance implications are not yet well understood. This dissertation addresses these issues by investigating the performance implications of competitive position and business model choice for complements in Apple's iOS App Store through three independent empirical studies. In doing so, this dissertation adopts a multidisciplinary perspective to competition in platform marketplaces, drawing from extant theories and perspectives on platforms and their associated marketplaces from across the management disciplines of organization theory, information systems, and strategy. This chapter further explicates this dissertation's motivation and overarching research question. It also provides further details about the iOS App Store as a study context, and provides details on the three empirical studies that constitute this dissertation.

1.1 Background and Research Focus

Fueled by the fast-paced advent of digitization, an increasing number of industries is dominated by platforms. Notable examples include enterprise software (e.g., Salesforce, SAP), mobile phones and tablets (e.g., Android, iOS), online retail (e.g., Alibaba, Amazon), social networking (e.g., Facebook, Twitter), taxis (e.g., Lyft, Uber), video gaming (e.g. PlayStation, Xbox), and others. At root, platforms function as interfaces that connect two or more groups of actors, who may or may not have been able to transact otherwise (Gawer, 2009; McIntyre & Srinivasan, 2017).[1] That way, platforms mediate the exchange of third-parties' products and services, usually through an associated marketplace or store. For example, video gaming consoles connect producers of video games with gamers, and ride-hailing services such as Uber or Lyft connect drivers with riders. The success of platforms is largely predicated on the idea that actors place higher value on platforms adopted by a lot of other actors, a phenomenon more usually referred to as the network effect (Cennamo & Santalo, 2013; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003). Direct network effects occur when actors value the ability to interact with their peers, such as when video gamers value the ability to compete with other gamers. Importantly though, platforms also harness indirect network effects, because actors on one side of the platform benefit from an increasing volume of actors on the other side, and vice versa. Gamers favor video gaming consoles that offer many games, while video game producers target their titles at consoles with many gamers.

Platforms thus enjoy increasing returns to scale, making it progressively difficult for rival products or platforms to offset their advantage (Eisenmann, Parker, & Van Alstyne, 2006; Gawer & Cusumano, 2002). This provides platform provider firms with clear incentives and motivation to adopt strategies to entice and facilitate the product development efforts of a large number of third-party complementor firms.[2] Notably, platform provider firms frequently utilize boundary resources, such as application programming interfaces (APIs), software development kits (SDKs), and knowledge resources that enable complementary products (or simply, complements) to effectively call and build upon a platform's core functionalities (Boudreau, 2012, Eaton, Elaluf-Calderwood, Sorenson, & Yoo, 2015, Ghazawneh & Henfridsson, 2013). In that sense, platforms could be

1 The use of the term platform in this dissertation is consistent with what in literature is sometimes referred to as an external, or industry, platform. Such platforms stand in stark contrast with internal, or product, platforms from which a single firm develops a stable stream of derivative products that are prevalent in industries such as automotive, aviation, and consumer electronics (Gawer & Cusumano, 2014).

2 In the spirit of the platforms literature (e.g., Gawer & Cusumano, 2014; Kapoor & Agarwal, 2017; Rietveld & Eggers, 2018), in this dissertation the terms "complementor" or "third-party complementor firm" are used to refer to those firms that produce and distribute products, or complements, that enhance the value of another firm's product, in this particular case the platform.

conceived of as foundations upon which other firms build complementary offerings (Gawer, 2009). Similarly, platform provider firms may subsidize the complementors' side of their platform, essentially providing complementors with financial incentives to produce complements for the platform (Caillaud & Jullien, 2003; Eisenmann et al., 2006; Rochet & Tirole, 2003). In fact, inventorying these strategies and evaluating their consequences for the platform provider firm's ability to create and capture value has been the main thrust of concern for scholarship on platforms (e.g., Boudreau & Hagiu, 2009; Cennamo & Santalo, 2013; Claussen, Kretschmer, & Mayrhofer, 2013; Gawer & Henderson, 2007; Li & Agarwal, 2017).

While prior work on platforms has devoted substantial attention to the unitary actor that orchestrates the platform and its associated marketplace, there has been much less interest in how complementors create and capture value within this nascent business context (but see Eckhardt (2016), Kapoor and Agarwal (2017), and Yin, Davis, and Murzyrya (2014) for some notable exceptions). This is surprising for at least two reasons. First, platform marketplaces are prominent locations of business activity that are also of great economic significance. By 2017, a staggering number of 1.2 million complementors produced software applications (or simply, apps) for mobile platforms such as iOS or Google Play (Appfigures, 2017); their gross annual revenues amounting to roughly $60 billion (Sensor Tower, 2018), a figure that is projected to only grow further in years to come (International Data Corporation, 2016). Second, by rule of design complementors constitute the vast majority of actors in platform-dominated industries, and their contributions and business success are not only critical to the platform provider firm's ability to create, but also to capture value. Complementors are generally due royalty payments for distributing their product or service through the platform's marketplace. For example, Apple (2018) reported that it had paid its iOS-complementors more than $26 billion in revenues in 2017. Given that it incurs between fifteen and thirty percent in royalty fees depending on the app's business model, Apple itself by approximation earned between $5 and $11 billion from its platform marketplace, the iOS App Store, during the same period, where the upper number likely most closely approximates its true revenues.[3] These earnings are a substantial share of Apple's $229 billion annual revenue in 2017 (Statista, 2017a). Hence, developing an understanding of how complementors create and capture value in platform marketplaces is of interest to our understanding of both complementors' and platform provider firms' success.

3 Apple's iOS App Store is the exclusive distribution channels for iOS-apps. In principle, Apple incurs a royalty fee of thirty percent on all paid app downloads and in-app purchases that proceed through the App Store. The only exception to this rule are receipts from subscription services with contracts running for more than one year, which are charged with a royalty fee of fifteen percent.

As noted, platform provider firms are incentivized to add many complementors to their platform. However, one of the implications of doing so is that complementors have to survive and thrive in a hypercompetitive environment (Kapoor & Agarwal, 2017; Yin et al., 2014). As many complementors churn to address the same consumer needs, rivalry increases, poising the individual complement performance to spiral downwards (Arora, Ter Hofstede, & Mahajan, 2017; Bain, 1968; Cattani, Porac, & Thomas, 2017). In practice, many complements will also simply go unnoticed by consumers, as the number of potentially relevant product alternatives is simply beyond what they can cognitively or physically assess (Bowers, 2015). In some cases, this may give rise to competitive crowding, essentially stalling the product development efforts of complementors in some markets or niches altogether (Boudreau, 2012). This happens either because the supply of new complements outpaces the number of new consumers adopting the platform, or because at some point there are just too many complements addressing the exact same consumer need. Consequently, competitive positioning is of critical concern to complementors. At first sight, they have apparent incentives and motivations to differentiate. It allows their complements to stand out and be noticed, while simultaneously foregoing the most intense competition (Cennamo & Santalo, 2013; Ethiraj & Zhu, 2008; Shamsie, Phelps, & Kuperman, 2004). However, with differentiation also comes the risk of placing the complement outside of consumers' consideration sets, causing them to go virtually unnoticed (Hsu, 2006).

Another implication of platform provider firms facilitating the product development process on the part of complementors, is that complementors can produce new complements at marginal cost (Shapiro & Varian, 1999). Given that subsequent distribution generally proceeds through the platform's marketplace, complementors also do not incur any additional costs for the distribution of their complements to a large consumer audience. Marginal costs of production and distribution combined with mounting competition have compelled complementors to experiment with new business models for their complements. Platform marketplaces have notably boosted the prevalence of freemium, ad-supported, and other business models based on free product distribution that are somehow geared towards extracting revenues from free offerings (Clemons, 2009; Kumar, 2014; Lambrecht et al., 2014). Moreover, complementors also increasingly combine multiple value-capturing mechanisms, or sources of revenue, in their business models, simply because relying on a single source of revenue is no longer sufficient or sustainable (Teece, 2010). Even though such new business models are commonplace in platform marketplaces, their performance implications and boundary conditions are not yet understood.

Despite the fact that a prevailing body of research has already begun to grapple with the performance implications of competitive positioning and business model choice, most of those studies are set in more traditional business contexts (e.g., Askin & Mauskapf, 2017; Aversa, Furnari, & Haefliger 2015; Barroso, Giarratana, Reis, & Sorenson, 2016; Casadesus-Masanell & Zhu, 2013; Deephouse 1999; Zott & Amit, 2007). As such, it remains an open question as to whether those findings would generalize to platform marketplaces, and it is this knowledge gap that this dissertation attempts to address. More specifically, it poses the following question.

What are the implications of competitive positioning and business model choice for the performance of complements in platform marketplaces?

After all, platform marketplaces are characterized by some fundamentally different market conditions. By virtue of generativity and virtually unbridled innovation, platforms address a long tail of consumer needs (Brynjolfsson, Hu, & Simester, 2011; Brynjolfsson, Hu, & Smith, 2006). As a consequence, platform marketplaces constitute a vivid variety of markets, where complements are positioned to target mass or niche markets (Brynjolfsson, Yu, & Smith, 2010). Market outcomes are also shaped by several specific features of, and information sources available in, the platform marketplace. Oftentimes complements are digital products, which tend to be shrouded by uncertainty (Arora et al., 2017). Therefore, consumers strongly rely on other sources of information, such as product descriptions (Ghose & Han, 2014), consumer ratings and reviews (Zhu & Zhang, 2010), and in-store recommendations (Fleder & Hosanagar, 2009). To illustrate, Duan, Gu, and Whinston (2009) show that the demand for specific complements exhibits distinct jumps and drops with their ranking on sales leaderboards, because consumers disproportionally rely on the behavior of others in deciding which complements to acquire. Moreover, platform marketplaces constitute contexts where paid and free complements coexist (Arora et al., 2017; Mollick, 2016),[4] and where profit-seeking firms are pitted against amateurs and hobbyists, and vice versa (Boudreau & Jeppesen, 2015; Eckhardt, 2016).

1.2 Research Strategy

To arrive at an answer to the overarching research question, this dissertation consists of three independent empirical studies. Each study addresses its own respective research question, yet focuses firmly on either establishing the performance implications of competitive positioning or business model choice in platform marketplaces. As such, all

4 The term paid complement in this dissertation refers to any complementary product that requires consumers to pay a fee prior to acquiring it. By contrast, free complements are those complementary products that can be acquired free of charge that may or may not be monetized otherwise.

three studies have been motivated by the paucity of research on competitive positioning and the use of business models somehow based on free product distribution in platform marketplaces.

Platforms have drawn academic interest from researchers from across disparate disciplines of management scholarship, including economics (e.g., Caillaud & Jullien, 2003; Rochet & Tirole, 2006; Rysman, 2009), information systems (e.g., Eaton et al., 2015; Liu, Au, & Choi, 2014; Wang, Li, & Singh, 2018), organization theory (e.g., Leung & Sharkey, 2014; Wareham, Fox, & Giner, 2014; Zhao, Ishihara, Jennings, & Lounsbury, 2018), marketing (e.g., Arora et al., 2017; Binken & Stremersch, 2009; Landsman & Stremersch, 2011), and strategy (e.g., Boudreau, 2012; Cennamo & Santalo, 2013; Cennamo, 2016), that way emphasizing different aspects of platforms and their marketplaces. In kind, the three studies in this dissertation each adopt distinct theoretical lenses, building from existing theories and perspectives on platforms in organization theory, information systems, and strategy, respectively.

Empirically, all three studies address the consequences of competitive positioning and business model choice in the context of the U.S. storefront of Apple's iOS App Store. The three studies are all quantitative and longitudinal in nature, but their analyses derive from distinct samples of apps drawn from the iOS App Store. Because the data collection remained ongoing throughout much of this dissertation's research trajectory, the observational period also differs from study to study.

Mobile app marketplaces were chosen as an empirical context for three main reasons. First, the smartphone industry is heralded as one of the hallmarks of a context that over the last decade has quickly become dominated by platforms. To illustrate, shortly after introducing the first iPhone and the iOS mobile operating system in 2007, Apple opened up its platform for complementary products by third-party complementor firms in June 2008 (Ghazawneh & Henfridsson, 2013). Harnessing network effects, the iOS App Store then witnessed unprecedented growth; it grew to contain from 500 apps in 2008 to over 2.2 million applications in 2017 (Statista, 2017b). The growth of the mobile app marketplace of iOS' main competitor, the Google Play Store, displayed a similar trend, as it came to contain more than 2.8 million apps (Statista, 2017c). By now, consumers that possessing mobile devices running on either Apple's iOS or Google's Android operating system can acquire apps to perform a palpable variety of tasks, including editing pictures, reading the news, measuring vital bodily functions, playing games, and maintaining to-do lists. In each market or niche, they have plenty of alternatives from which to choose, often adopting different business models. For this reason, mobile app marketplaces frequently serve as an empirical study context for research on platforms (e.g., Eaton et al., 2015; Kapoor & Agarwal, 2017; Wang et al., 2018; Yin et al., 2014). Second, owing to their widespread adoption by complementors and consumers, mobile app marketplaces now resemble many markets that until recently only existed in isolation, and therefore also had to be examined as such. Hence, this study context provides fruitful opportunities to observe competition across a wide variety of markets and niches. Third, as a storefront, mobile app marketplaces provide a comparably rich overview of apps and their characteristics that can be collected using automated data collection methods. For every app, this data among others encompasses a textual description of the app's attributes and how those create value for consumers, consumers' rating volume and valence, initial release dates, update histories, and details pertaining to app's business model, such as its price and whether it sells in-app purchases. The iOS App Store had preference over Google Play for a number of reasons. First, whereas the iOS App Store is the exclusive distribution platform for apps that are compatible with Apple's mobile devices, there exist multiple rivalling mobile app marketplaces for devices operating on Google's Android operating system. This is the case because there are several handset manufacturers, including Samsung, LG, Huawei, and HTC, producing mobile devices running Android. Most of those manufacturers, also maintain their own mobile app marketplaces. Moreover, Amazon also operates a relatively successful mobile app marketplace for Android that contained more than 600,000 distinct apps in 2017 (Statista, 2017b). Hence, by focusing on the iOS App Store, needing to control for complement competition across multiple mobile app marketplaces is avoided. Second, the entry barriers to producing and selling apps in the iOS App Store are somewhat more stringent compared to Google Play. Perhaps most importantly, apps in the iOS App Store have been subjected to a review process by Apple, whereas apps in Google Play are not.[5] Consequently, analyses performed in the context of the iOS App Store are less likely to be distorted by a rampant influx of low-quality or malicious apps. Third, the iOS App Store provides comparably richer information on apps' business models. For example, for those apps selling in-app purchases, the iOS App Store provides a detailed breakdown of up to ten in-app purchase items. By contrast, Google Play merely indicates whether an app does or does not sell in-app purchases.

In order to study the performance implications of competitive positioning and business model choice in the context of the iOS App Store, detailed information on indicators of app performance, such as periodic downloads or revenues, is required. Unfortunately, such information is not readily available from the App Store, nor is it publicly disclosed by Apple. Prior research has typically dealt with this limitation by merely analyzing the performance of the subset of apps for which sales rankings on store-wide sales

5 The review process of prospective iOS apps among others serve to verify apps' technical performance, trustworthiness, and whether their textual descriptions and screenshots adequately convey their main attributes.

leaderboards are available (Kapoor & Agarwal, 2017; Wang et al., 2018; Yin et al., 2014). However, this raises concerns about sample selection and other biases as those analyses are constrained to consider merely the most successful apps. For example, games are often overrepresented in those studies (Liu et al., 2014; Yin et al., 2014). Resorting to the number of submitted user ratings or reviews as a proxy measure for app performance may alleviate those concerns, but would still be problematic because user ratings and reviews are known to also affect app performance (Chevalier & Mayzlin, 2006).

Therefore, publicly available data from the iOS App Store is complemented with a proprietary dataset on app performance by app market analytics firm Apptopia (https://www.apptopia.com), one of the market leaders in this domain. Similar to its competitors, Apptopia calibrates apps' sales ranks on store-wide and category-specific sales leaderboards to estimate their downloads, revenues, and others, following a procedure similar to what is often described and applied in academic literature (Carare, 2012; Garg & Telang, 2013; Wang et al., 2018). They subsequently amend those predictions with true performance figures of iOS complementors that share their information in return for free market intelligence. Thus, the accuracy of Apptopia's predictions are directly contingent on the number and variety of complementors that share their data with them. According to Apptopia (2017a), over 50 percent of the top fifteen percent of ranked apps and over 80 percent of the bottom ten percent of ranked apps from the iOS App Store had shared data with them in the summer of 2017.

1.3 Research Studies

As noted, this dissertation consists of three empirical studies that may be read as standalone research papers, though together working towards providing an answer to the overarching research question. This section provides an overview of the three studies, including their respective research question, theory development, and research methods. This information is also summarized in Table 1.1 to highlight some of their key commonalities and differences.

1.3.1 Study 1: Combining Multiple Value-Capturing Mechanisms: Implications for Consumer Appeal in the Mobile App Market

Product classification systems reflecting consumer value propositions, such as film genres or product categories and labels, are instrumental to consumers in navigating contexts with many products (Hsu, 2006; Hsu, Hannan, & Kocak, 2009; Zuckerman, 1999). They help consumers to construct their initial consideration set, by distinguishing offerings worthy of further consideration from irrelevant ones, and consumers subsequently benchmark the products in their initial consideration set to choose the offering best fitting their needs (Haubl & Trifts, 2000; Leung & Sharkey, 2014; Payne, 1976). However, in most platform marketplaces the volume of available complements has grown so substantial that cues from product classification systems alone are insufficient to adequately constrain consumers' initial consideration sets (Bowers, 2015). It thus follows that consumers apply secondary selection criteria, and developing an understanding of those criteria is important because different compositions of their initial consideration set will by extension also lead consumers to make

different choices (Sevdalis & Harvey, 2006). In this study, the idea is advanced that the value-capturing portion of complements' business models, referred to as logics for value capture, is one such criterion. Logics for value capture are highly diverse because complementors often combine multiple value-capturing mechanisms (Clemons, 2009; Teece, 2010), are generally known to consumers screening the platform marketplace (Arora et al., 2017; Ghose & Han, 2014), and constitute points of common understanding among consumers concerning which they hold strong preferences (Alexy & George, 2013; Weijters, Goedertier, & Verstreken, 2014). To further explore this idea and its implications, this study asks the following research question.

What are the implications of combining multiple value-capturing mechanisms for the downloads of free complements?

Because logics for value capture may constitute multiple value-capturing mechanisms, it is argued that they could be conceived of as code-preserving or code-violating, depending on whether the combined mechanisms together constitute a coherent approach to the extraction of economic value (Durand, Rao, & Monin, 2007; Ruef & Patterson, 2009). In the iOS App Store, for example, value-capturing mechanisms are either based on charging consumers or subsidizing consumers' complement usage with income incurred from other parties, such as advertisers. Combining subscriptions with product upgrades that can be purchases separately yields logics for value capture that are code-preserving, because the combined value-capturing mechanisms together represent a coherent approach to value capture that is based on charging consumers. By contrast, combining subscriptions with advertisements, two value-capturing mechanisms entailing distinct approaches to value capture, results in logics for value capture that are code-violating. Whether logics for value-capture are code-preserving or code-violating matters because of the strong preferences that consumers hold towards particular ways of paying for products. Complements with code-violating logics for value capture defy strong boundaries in such consumer product-payment preferences and are, alternative offerings abound, more likely to be overlooked by consumers with

Table 1.1. Overview of the studies in this dissertation

	Study 1	Study 2	Study 3
Title	Combining Multiple Value-Capturing Mechanisms: Implications for Consumer Appeal in the Mobile App Market	The Performance Implications of Freemium and Ad-Supported Freemium Business Models in the Apple App Store	Differentiation in Platform Marketplaces: An Entrant's Perspective
Focus	Business model	Business model; positioning	Positioning
Research question	What are the implications of combining multiple value-capturing mechanisms for the downloads of free complements?	What are the performance implications of freemium and ad-supported freemium business models?	What are the performance implications of differentiation for complements in platform marketplaces?
Discipline	Organization theory	Information systems	Strategy
Literature base	Business models; categories and categorization; demand-based perspectives	Business models; long-tail markets; sampling and versioning of information goods	Competitive strategy; information economics; platforms
Sample	Newly introduced and incumbent free apps with business model striving for direct economic returns from the iOS App Store	Newly introduced and incumbent free and paid apps with a business model striving for direct economic returns from the iOS App Store	Newly introduced paid apps
Observation period	Between May 2016 and April 2017	Between May 2016 and December, 2016	Between May 2016 and June 2017
Outcome variable	Downloads	Downloads; revenue	Revenue
Operationalization of key variables	Automated content analysis; text similarity analysis	Text similarity analysis	Topic modeling; Gaussian mixture model clustering
Data analysis	Conditional fixed-effects negative binomial regressions with control functions	Instrumental variables quantile regression; zero-inflated negative binomial regressions	Random effects regressions with control functions
Theoretical contributions towards	Business models; categories and categorization; demand-based perspectives	Business models; long-tail markets; role of product information	Complementors' performance; demand-based perspectives; optimal distinctiveness

specific product-payment preferences. Consequently code-violating logics for value capture are hypothesized to be negatively associated with complement downloads. As long as the combined value-capturing mechanisms are mutually coherent though, it is argued that increasing the number of value-capturing mechanisms in complements' logics for value capture favorably affects their downloads. Not defying strong boundaries in consumer preferences, adding value-capturing mechanisms may actually increase the size of the potential consumer audience that complements may appeal to.

These predictions are tested by examining how the changing composition of the logics for value capture of 24,194 free apps in the iOS App Store influence their downloads between May 2016 and April 2017. After all, in the absence of an up-front download price barriers to download should not differ from one app to another, all else equal. Apps' enacted value-capturing mechanisms are measured using an automated content analysis of their textual information (Short, Broberg, Cogliser, & Bingham, 2010), and text similarity analysis between different apps of the same complementor (Salton & McGill, 1986). Correcting for the potential endogeneity of complements' logics for value capture, conditional fixed-effects negative binomial regressions yield support for the hypotheses. Supplementary analyses rule out some alternative explanations, including that the observed results are driven by operational difficulties associated with enacting certain combinations of value-capturing mechanisms.

1.3.2 Study 2: The Performance Implications of Freemium and Ad-Supported Freemium Business Models in the Apple App Store

Freemium business models have become increasingly viable alternatives to simply distributing complements for-a-fee (Kumar, 2014). That is, complementors offer two versions of the same complement: a basic version that is free of charge and that can be used indefinitely, and a premium version that is made available as a separate complement or in-product purchase and that can be accessed by paying a fee. However, despite its widespread prevalence, the performance implications of the freemium business model are not yet well understood, and the work that exists has remained largely equivocal. For example, some scholars have documented that freemium is favorably associated with indicators of complement performance, such as downloads or revenue (Boudreau, Jeppesen, & Miric, 2017; Liu et al., 2014), while others document adverse effects (Arora et al., 2017; Rietveld, 2018). One explanation for these inconsistent findings is that prior research has typically overlooked the role of contingent effects, such as market characteristics. After all, the long-tailed nature of platform marketplaces implies that complements positioned to target mass and niche markets coexist (Brynjolfsson et al., 2010). In addition, freemium is often combined with advertising as a way to monetize those consumers that only use the free basic version of the offering (Niculescu

& Wu, 2014). Consumers remain skeptical of advertisements though (Goldfarb & Tucker, 2012), and it remains unclear whether this benefits or hinders the performance of freemium complements. This study grapples with these issues, as captured by the following research question.

What are the performance implications of freemium and ad-supported freemium business models?

This study advances the baseline expectations that, when pitted against paid complements, freemium complements yield relatively more downloads, but that this association should be weaker for ad-supported freemium apps. However, when considering the implications of freemium for complements' revenues, it is argued that the effect is contingent on whether complements are positioned to target mass or niche markets. Because conversion and retention rates for freemium complements are generally low (Datta, Foubert, & Van Heerde, 2015; Kumar, 2014), for them to appeal to a large consumer audience is of critical importance. Hence, the anticipation is that freemium complements' revenues exceed paid complements' revenues for mass market complements, while yielding inferior results for niche complements. The effects of combining freemium with advertising should work in the exact opposite direction, as the negative effects of advertising are particularly paramount under the relatively lower uncertainty associated with mass market complements.

The empirical part of this study regards how freemium complements perform vis-à-vis premium complements in a sample of 76,057 apps from the iOS App Store. The baseline association between freemium, ad-supported freemium, and downloads is tested by means of zero-inflated negative binomial regressions, because most apps are not downloaded during a certain month. The estimation results are in accordance with expectations. The revenue implications of freemium and ad-supported freemium are explored by examining the changing effect of those business models along the conditional distribution of revenue using quantile regressions (Koenker & Basett, 1978), conceiving of mass market and niche apps as those observations situated at the opposite ends of the distribution (Brynjolfsson et al., 2010). Doing so, this study documents shifts in the optimal business model along the conditional distribution of revenue that are in line with those theoretically predicted.

1.3.3 Study 3: Differentiation in Platform Marketplaces: An Entrant's Perspective

There is a mounting literature on the interface between organization theory and strategy that strongly informs our understanding of the performance implications of product positioning. It asserts that firms should aim to position their products at intermediate levels of differentiation, referred to as a point of optimal distinctiveness, because of facing opposing forces to differentiate and conform (Durand & Calori, 2006; Porac, Thomas, & Baden-Fuller, 1989; Zhao, Fisher, Lounsbury, & Miller, 2017; Zuckermann, 2016). Product market competition compels firms to differentiate (Cennamo & Santalo, 2013; Ethiraj & Zhu, 2008; Shamsie et al., 2004), while at least one of two forces may prompt them to conform. In rigid contexts such as banking, institutional pressures strongly dictate what is to be expected of products, therewith specifying the confines within which profitable differentiation may take place (Deephouse, 1999; DiMaggio & Powell, 1987; Hsu, 2006). In cultural contexts such as popular music, the attention of firms and consumers strongly coalesces around widely known highly successful hit products, providing other firms clear incentives to more closely adhere to those offerings (Askin & Mauskapf, 2017; Zhao et al., 2018). As such, the presence of either strong institutional pressures or widespread knowledge of hit products represents a critical boundary condition underpinning the current optimal distinctiveness hypothesis. However, these forces are less salient in platform marketplaces. The continuous arrival and retraction of complements causes market boundaries to be in flux so that they do not fully institutionalize (Navis & Glynn, 2010), while the long-tailed nature of platform marketplaces implies that most complements are targeted at smaller pockets of consumers, making it unlikely that many hit products emerge (Brynjolfsson et al., 2010). This raises questions about the performance implications of differentiation in platform marketplaces, and therefore this study's research question is as follows.

What are the performance implications of differentiation for complements in platform marketplaces?

In theorizing about this question, the idea is advanced that in the absence of strong institutional pressures and widespread knowledge of hit complements, conformity forces may also stem from demand conditions (Rietveld & Eggers, 2018). There exists an information asymmetry between complementors, who know the true value of their complement, and consumers, who do not. Because consumers reduce this informational disadvantage by drawing upon their knowledge of other comparable complements (Eckhardt, 2016), fearsome of settling for an inferior offering (Simonson, 1992), it is suggested that this information asymmetry provides complementors apparent incentives to more closely conform to the confines of their competitors. To probe the theoretical validity of this idea, this study also considers the moderating effect of two salient market characteristics that affect the strength of the opposing forces of market information and competition. The share of apps with consumer ratings or reviews affects the relative strength of market information over competition, while the share of paid apps in the market works in the opposite direction. Consequently, optimal distinctiveness is argued to favor greater conformity and differentiation, respectively.

Analyses are based on an assessment of how differentiation shapes the performance of 6,984 newly introduced paid apps between May 2016 and June 2017. Focusing on paid apps is consistent with prior work, and allows for examining the performance implications of differentiation net of the complexity of business models of free apps. Each newly introduced paid app is associated with a specific set of incumbent competitors by drawing on methods from computer science (Blei, Ng, & Jordan, 2003; McLachlan & Basford, 1988). Random effects regressions, correcting for the potential endogeneity of differentiation, provide support for the theoretically advanced predictions. Differentiation exhibits an inverted U-shaped relationship with complement performance. Moreover, peak performance occurs at lower levels of differentiation in markets with a large share of rated complements, while manifesting at higher levels of differentiation in markets with a large share of paid complements.

1.4 Authors' Contributions

This dissertation is the product of collaborations between doctoral candidate Joey van Angeren, supervisors, and co-authors. Table 1.2 provides a detailed breakdown of their contributions.

1.5 Dissertation Outline

The remainder of this dissertation is organized as follows. Chapter 2 presents the first study of this dissertation, which investigates the role that complements' value-capturing portions of their business models play in consumer decision-making processes by analyzing empirically how code-preserving and code-violating business models of free complements shape their downloads. Chapter 3 lays out this dissertation's second study, which explores the performance implications of freemium and ad-supported freemium business models, as well as how those implications might differ for complements positioned to target mass and niche markets. Chapter 4 then, outlines the third study of this dissertation. It considers the relationship between newly introduced paid complements' positioning and performance, as well as how this relationship is moderated by two salient market characteristics in platform marketplaces; the share of rival rated and paid complements in the market. Chapter 5 concludes this dissertation. It provides a summary of the main research findings, discusses their implications for scholarly theory and managerial practice, reflects upon potential limitations, and outlines avenues for future research.

Table 1.2. Contributions of authors

		Joey van Angeren	Fred Langerak	Ksenia Podoynitsyna	Govert Vroom
Chapter 1	Writing main text	•			
	Corrections and feedback	•	•	•	
Chapter 2	Design of study	•		•	
	Literature review	•			
	Data collection	•			
	Data analysis	•		•	
	Interpretation of results	•		•	
	Writing main text	•			
	Corrections and feedback	•	•	•	
Chapter 3	Design of study	•		•	
	Literature review	•			
	Data collection	•			
	Data analysis	•		•	
	Interpretation of results	•			
	Writing main text	•			
	Corrections and feedback	•	•	•	
Chapter 4	Design of study	•		•	•
	Literature review	•			
	Data collection	•			
	Data analysis	•			
	Interpretation of results	•			•
	Writing main text	•			
	Corrections and feedback	•	•	•	•
Chapter 5	Writing main text	•			
	Corrections and feedback	•	•	•	

2

Chapter 2

Products' Logics for Value Capture as Salient Markers for Consumers:

The Effect of Combining Multiple Value-Capturing Mechanisms for Downloads in the Mobile App Market*

* Earlier versions of this chapter were presented at the Annual Meeting of the Academy of Management, Virtual Entrepreneurship Research Center Seminar, and Eindhoven University of Technology. An earlier version of this chapter was a Finalist for the Best Student Paper Award of the Technology and Innovation Management Division at the 2016 Annual Meeting of the Academy of Management. This chapter is co-authored by Joey van Angeren, Ksenia Podoynitsyna, and Fred Langerak.

Product classification systems reflecting value propositions are instrumental to consumers in distinguishing offerings worthy of consideration from irrelevant ones. Observing digital markets though, the number of products per category is too large for consumers to assess and they thus also apply other criteria to screen out alternatives from consideration. This chapter advances that products' logics for value capture, their approach to extracting economic value, represent a salient criterion in this screening process, as digitization has enabled organizations to charge for their offerings in various ways. Logics for value capture are also apparent to consumers and represent points of common understanding concerning which they hold strong preferences. In considering the implications of this idea, it is argued that offerings with code-violating logics for value capture—constituting value-capturing mechanisms with distinct approaches to extracting economic value—and offerings with code-preserving logics for value capture—constituting value-capturing mechanisms together representing a coherent approach to extracting economic value—should be associated differently with downloads. Code-violating logics for value capture defy boundaries in consumer product-payment preferences and are overlooked, while code-preserving logics for value capture are more likely to be considered by consumers with specific product-payment preferences. It is also argued that increasing the number of value-capturing mechanisms constituting offerings' logics for value capture increases downloads, as it enlarges the consumer audience they appeal to. Analyzing monthly download data on 24,194 mobile apps from the Apple App Store provides support for these predictions, suggesting that logics for value capture and their categorizations play an important role in consumer decision-making processes, beyond classification systems reflecting consumer value propositions.

2.1 Introduction

Observing digital markets, technological advances have made it easier for organizations to introduce new products (Yoo, Boland, Lyytinen, & Maichrzak, 2012). This has led to a proliferation in the amount of organizations and their offerings that jointly vie for consumers' limited attention. Faced with multiple alternatives of which the inherent quality is usually unclear, consumers rely on product classification systems that lump together similar products, clearly demarcating them from distinctly different ones, in order to simplify thought and focus attention (DiMaggio, 1987). For example, feature films are organized by genre (Hsu, 2006), auction items on eBay are presented in categories (Hsu, Hannan, & Kocak, 2009), and software products are typified and labeled based on their core functionalities (Pontikes, 2012). That way, product classification systems provide structure to markets. They help define what consumers can expect from products (Rosa, Porac, Runser-Spanjol, & Saxon, 1999), and therefore play a crucial role in the demarcation of consumers' initial consideration sets (Haubl and Trifts, 2000; Leung & Sharkey, 2014; Payne, 1976).

In some digital markets though, the volume of available offerings has grown so substantial that cues from product classification systems alone are insufficient to adequately constrain consumers' initial consideration sets (Bowers, 2015). The number of offerings in any single product category is simply beyond what consumers can cognitively nor physically assess. For example, if consumers were to constrain their initial consideration set from the over 2.2 million available mobile software applications (apps) in the Apple App Store to those offerings categorized as productivity apps, they would be left with a choice from over 40,000 offerings. This is even true if they would narrow their search upfront to task management or expenditure tracking applications, because such a query would still return hundreds of comparable offerings. It follows that consumers in practice consider merely a subset of all products in a category, and thus apply additional selection criteria to adequately constrain their initial consideration set (Bronnenberg & Vanhonacker, 1996; Bowers, 2015; Urban, Hulland, & Weinberg, 1993). This is important, because consumers subsequently benchmark the products in their initial consideration set to select the offering that best suits their needs (Haubl & Trifts, 2000; Leung & Sharkey, 2014; Payne, 1976), and different compositions of consumers' initial consideration sets will therefore also lead them to make different choices (Bowers, 2015; Sevdalis & Harvey, 2006). Hence, gaining insight into other selection criteria that consumers apply in screening out offerings from further consideration may enhance our understanding of the origins of different download or sales levels for offerings from the same category. So what other selection criteria could consumers apply in filtering out organizations' offerings from further consideration? In this chapter, we argue that offerings' logics for value capture, defined as the approach to the extraction of economic value enveloped within the product, might be particularly salient markers for consumers in digital markets. From their perspective, offerings' logics for value capture represent the way in which they are ought to pay organizations for using a product, to which they may hold strong preferences (Weijters, Goedertier, & Verstreken, 2014), and the near-zero marginal costs of production and distribution of digital products have greatly enriched the variety of ways in which they may be asked to do so (Bresnahan, Davis, & Yin, 2015; Clemons, 2009; McGrath, 2010; Teece, 2010), as for example illustrated by the rapidly increasing prevalence of freemium and ad-supported products in various markets (Casadesus-Masanell & Zhu, 2010; Kumar, 2014). Consumers are also generally aware of offerings' logics for value capture upon initially screening the product space, for instance from their viewing of product descriptions or in-product purchase menus (Arora et al., 2017; Ghose & Han, 2014; Liu et al., 2014). Given the vast number of competing offerings in a category, consumers can in turn afford to accept or reject a product's logic for value capture in demarcating their initial consideration set (Priem, 2007).

To test this idea, we adopt a consumer-centric perspective as we examine empirically how logics for value capture of free apps shape downloads in the U.S. Apple App Store between May 2016 and April 2017. The App Store is the distribution platform wherefrom consumers with mobile devices operating on Apple's iOS operating system acquire their apps. The majority of those apps is distributed for free, though frequently with the intention of extracting economic value (Arora et al., 2017; Bresnahan et al., 2015; Flurry, 2013; Ghose & Han, 2014). This makes for an appealing study context because in the absence of an up-front download price, consumers' barriers to consider and download offerings should not differ across offerings with distinct logics for value capture, ceteris paribus. Downloads then, reflect the extent to which consumers as an audience accept or reject an offering's logic for value capture, by considering and acquiring a focal app as opposed to other offerings from the same category (Pontikes, 2012; Priem, 2007). Downloads are also instrumental to the financial prosperity of free apps, as the consumers that adopted the offering constitute the population that an organization may attempt to solicit its income from (Kumar, 2014).

Similar to contexts such as digital music streaming (Lin, Ke, & Whinston, 2012) and software (Niculescu & Wu, 2014), the App Store presents a setting where comparable products are countless and where those offerings' logics for value capture often constitute multiple value-capturing mechanisms (International Data Corporation & App Annie, 2014). That is, organizations for example combine subscriptions and advertising, rather than simply selling subscriptions, giving rise to a palpable variety of logics for value capture. Because logics for value capture may constitute multiple value-capturing mechanisms, we propose that they can be conceived of as either code-preserving or code-violating, depending on whether the combined mechanisms together constitute a coherent approach to the extraction of economic value—in our empirical context either based on charging consumers or subsidizing consumers' product usage with income incurred from other parties, such as advertisers (Durand et al., 2007; Ruef & Patterson, 2009). Logics for value capture are code-preserving if the combined value-capturing mechanisms together represent a coherent approach to the extraction of economic value, such as when they are exclusively based on charging consumers through subscriptions and product upgrades that can be purchased separately. By contrast, logics for value capture are code-violating when they constitute value-capturing mechanisms that each follow different approaches to the extraction of economic value, for instance when consumers are asked to pay for a product through subscriptions while their usage is simultaneously paid for with income from advertisers.

Whether offerings' logics for value capture are code-violating or code-preserving matters because consumers in digital markets are typically heterogeneous, and thus also hold particular preferences concerning how to pay organizations for using their product (Adner & Levinthal, 2001; Rietveld & Eggers, 2018; Weijters et al., 2014). Offerings with code-violating logics for value capture defy strong boundaries in consumer product-payment preferences, making them less likely to be considered by consumers with particular preferences and confusing them concerning how exactly they are ought to pay organizations for using their offering (Hsu, 2006; Zuckerman, 1999). By contrast, code-preserving logics for value capture do not violate strong boundaries in consumer preferences and thus should be more likely to be considered by consumers with specific product-payment preferences. Hence, in the presence of offerings with code-preserving logics for value capture, at least some consumers are likely to overlook offerings with code-violating logics for value capture in the process of demarcating their initial consideration set, which given subsequent benchmarking by consumers results in an inferior number of downloads for offerings with code-violating logics for value capture (Bowers, 2015). Moreover, we argue that increasing the number of value-capturing mechanisms constituting offerings' logics for value capture should increase the size of the consumer audience that will include them in their initial consideration set (Teece, 2010), which in turn should be reflected in greater download volumes. We find robust evidence for these predictions in our empirical data.

2.2 Theory and Hypotheses

2.2.1 Markets, Product Classification Systems, and Violating Category Boundaries

Markets can be conceived of as interfaces between organizations and external audiences (Hannan, Polos, & Carroll, 2007; Zuckerman, 1999). In a product market, for example, organizations present offerings to appeal to consumers who evaluate them. Because the volume of offerings in a market vying for the same consumers' attention is usually substantial and highly diverse, evaluating each one individually and along the same assessment criteria is unfeasible, both in terms of the time needed and cognitive ability required to complete such a daunting task. Hence, standard models of consumer decision-making posit a two-stage selection process by which consumers arrive at the offering of their liking (Haubl & Trifts, 2000; Leung & Sharkey, 2014; Payne, 1976). In the first stage, consumers identify an initial consideration set consisting of some reasonable alternatives given their search criteria, essentially eliminating any irrelevant offering from further consideration. In the second stage, they evaluate and choose between this smaller and therefore more manageable set of alternatives. Because the alternatives in the initial consideration set are deemed similar to one another, consumers are then able to apply the same set of assessment criteria to all those offerings (Bowers, 2015).

Product classification systems are instrumental in circumscribing the boundaries of the initial consideration set. They forge socio-cognitive partitions in a market, by grouping products considered similar along some dimensions together into one overarching category, thereby clearly demarcating them from offerings that are perceived distinctly different (DiMaggio, 1987; Rosa et al., 1999). In this sense, categories reflect shared understandings among consumers as to how similar products can be categorized, and sometimes labeled. For example, feature films classified under the genre "western" share common features including that they are set in the past and somehow deal with the ethics of violence, while the label "electronic design automation" is used for software products that design and test electronic systems such as integrated circuits (Hsu, 2006; Pontikes, 2012). Thus, categories provide a highly salient marker for consumers to distinguish offerings worthy of further consideration from irrelevant ones, eventually leading to a consideration set consisting of commensurable alternatives.

Exactly because consumers rely on product classification systems in the demarcation of their initial consideration set, categorical boundaries matter. A stream of prior literature suggests that adopting attributes from multiple categories is problematic, as it follows that such offerings do no longer neatly fit within category boundaries (Hsu, 2006; Pontikes, 2012; Zuckerman, 1999). Consumers tend to exclude products that violate category boundaries from further consideration, instead focusing their limited attention to the evaluation of category-focused products. This might happen because consumers find it difficult to make sense of offerings that violate category boundaries and therefore tend to overlook them (Hsu, 2006; Zuckerman, 1999), or because they perceive offerings' lack of focus on a single category as something negative, such as a lack of commitment to, or ability in, either one (Hsu et al., 2009; Zuckerman and Kim, 2003;). Though, violating categorical boundaries may in some cases also have positive effects. Organizations that operate in stigmatized categories receive less negative press coverage when they do also participate in less controversial categories (Vergne, 2012), and similarly they may benefit from presence in two adjacent categories of which the boundaries are not yet clearly defined (Kovacs & Hannan, 2010; Ruef & Patterson, 2009).

2.2.2 Logics for Value Capture as Salient Markers for Consumers

When the number of offerings in a market is large, though not excessive, product classification systems may adequately constrain consumers' initial consideration sets. It is reasonable to assume that consumers are able to, and will, evaluate all possible offerings in a single category to arrive at the offering that best suits their needs. For example, consumers looking to buy a car may narrow their search to minivans, subsequently benchmarking all vehicles in this category along the same set of assessment criteria for them to choose the car of their liking (Rosa et al., 1999).

However, the volume of offerings in some digital markets tends to be much larger. Near-zero marginal costs of production and distribution have greatly facilitated broad entry of organizations and their offerings (Shapiro & Varian, 1999). Technological advances have also permeated reuse and recombination as legitimate processes by which organizations develop new products (Yoo et al., 2012), essentially reducing the time needed and effort required to introduce offerings into the market, therewith contributing to an even more dense product space. In such markets, cues from product classification systems alone are unlikely to adequately constrain consumers' initial consideration sets (Bowers, 2015). Most categories contain dozens or hundreds of comparable offerings, which is simply beyond what consumers can cognitively nor physically assess. In reality, consumers are thus prone to consider merely a subset of the offerings in a certain category (Bowers, 2015; Urban et al., 1993). This is important, because consumers subsequently benchmark the products in their initial consideration set along a set of assessment criteria for them to arrive at the offering that best suits their needs; simply by considering different subsets of offerings from the same category, consumers' eventual choices can vary (Bowers, 2015; Sevdalis & Harvey, 2006).

Because consumers end up considering a subset of offerings in a category, it follows that they apply other selection criteria in screening out offerings from further consideration (Bowers, 2015; Bronnenberg & Vanhonacker, 1996; Urban et al., 1993). We argue that offerings' logic for value capture, their approach to the extraction of economic value, might be particularly salient markers in this screening process (Alexy & George, 2013; Ghose & Han, 2014). They represent the way in which consumers are ought to pay organizations for using their offering, and the near-zero marginal costs of production and distribution of digital products have greatly enriched the variety of ways in which consumers may be asked to do so (Bresnahan et al., 2015; Clemons, 2009; McGrath, 2010; Teece, 2010). Offerings' logics for value capture are also generally apparent to consumers from product descriptions or in-product purchase menus when screening the product space (Arora et al., 2017; Ghose & Han, 2014; Liu et al., 2014). For instance, if the textual description accompanying an offering stipulates subscription terms and tariffs, it is apparent that consumers' payment for the product will proceed along repeated installments of a given amount. Because consumers are aware of offerings' logics for value capture, they are able to weigh in this information in the demarcation of their initial consideration set.

Moreover, logics for value capture represent points of common understanding among consumers (Alexy & George, 2013). Products are frequently typified or labeled in accordance with their approach to the extraction of economic value. To illustrate, prior literature casually refers to products as "freemium" or "sponsor-based" (Casadesus-Masanell & Zhu, 2010; Kumar, 2014; Niculescu & Wu, 2014), clearly reflecting that their producing organizations are financing themselves by charging consumers for paid product upgrades or by incurring income from third parties such as advertisers or content providers, respectively. Because this is common not only in scientific discourse but also in the popular press, a shared understanding concerning what certain logics for value capture entail spreads among consumers (Rosa et al., 1999), enabling them to further partition the offerings in a certain category based on their approach to the extraction of economic value.

Because logics for value capture represent points of common understanding, consumers may hold priors towards particular approaches to the extraction of economic value. Indeed, consumers tend to have strong preferences regarding how, or how not to pay organizations for using their offering (Goldfarb & Tucker, 2011; 2012; Sutanto, Palme, Tang, & Phang, 2013). For example, in the context of digital music streaming services, Weijters et al. (2014) used a conjoint analysis to uncover systematic and persistent patterns in how consumers like, and refuse to pay for music, illustrating that consumers' disliking of a product's logic for value capture alone may be reason enough for them to altogether reject the offering from further consideration. This does not imply though, that all consumers share the same product-payment preferences. Prior literature in digital markets underscores that consumers constitute a highly diverse audience (Adner & Levinthal, 2001; Pontikes, 2012; Rietveld & Eggers, 2018). They range from young to old, from early to late adopters of technologies, and from experts to novices that tend to substantially differ in their requirements, willingness to pay, and importantly, their preferences regarding how to pay organizations (Sutanto et al, 2013).

To summarize, we thus argue for the following. Offerings' logics for value capture are salient markers for consumers in the demarcation of their initial consideration sets because: (1) there is a palpable diversity of ways in which consumers may be asked to pay for offerings; (2) logics for value capture are generally apparent to consumers upon initially screening the product space; (3) logics for value capture represent points of common understanding among consumers allowing them to partition offerings accordingly; and (4) consumers tend to hold strong preferences towards certain logics for value capture. Given that categories in digital markets generally harbor numerous offerings from which to choose, likely with different logics for value capture, consumers can afford to act upon their preferences regarding logics for value capture and include or exclude offerings from their initial consideration set accordingly (Priem, 2007).

2.2.3 Code-Violating and Code-Preserving Logics for Value Capture, and Consumer Appeal

If offerings' logics for value capture are indeed salient markers for consumers in the demarcation of their initial consideration set, then offerings with different logics for value capture should also be associated with different levels of downloads or sales, ceteris paribus. We expect this to be particularly apparent in digital markets such as video games, software, and digital music streaming services, where combining multiple value-capturing mechanisms, including advertising, subscriptions, and separate paid product upgrades is commonplace (Lin et al., 2012; Niculescu & Wu, 2014). An abundance of offerings from which to choose, and the palpable variety of these offerings' logics for value capture that results from being able to combine multiple value-capturing mechanisms, should afford consumers substantial discretion in accepting or rejecting offerings' with certain logics for value capture.

Different value-capturing mechanisms may represent distinct approaches to the exaction of economic value. Most notably, in the context of free products, prior research has implicitly or explicitly distinguished between two categories of value-capturing mechanisms: (1) those that are based on charging consumers such as through subscriptions or separate paid product updates; and (2) those that ensue income from third parties, for instance by means of advertising, essentially subsidizing consumers' product usage altogether (Casadesus-Masanell & Zhu, 2010; Clemons, 2009; Lin et al., 2012; Teece, 2010). Because offerings' logics for value capture may consist of multiple value-capturing mechanisms, we argue that logics for value capture could be conceived of as either code-preserving or code-violating depending on the value-capturing mechanisms they constitute (Durand et al., 2007; Ruef & Patterson, 2009). Code-preserving logics for value capture are combinations of value-capturing mechanisms that together represent a coherent approach to the extraction of economic value—that is, they constitute value-capturing mechanisms from the same overarching category so that they are either exclusively based on charging consumers or ensuing income from third parties. By contrast, code-violating logics for value capture constitute value-capturing mechanisms from across multiple categories and thus follow distinctly different approaches to the extraction of economic value. An example of a code-violating logic for value capture would be when an organization asks consumers to pay for product upgrades while their product usage is simultaneously subsidized with income from advertisers.

Whether offerings' logics for value capture are code-preserving or code-violating matters because consumers hold preferences concerning product payment. By combining value-capturing mechanisms from different categories, code-violating logics for value capture defy strong boundaries in those preferences. Analogous to the traditional argument in the categories literature regarding the inferior appeal of offerings that violate category boundaries (Hsu, 2006; Zuckerman, 1999), this may well lead to confusion with consumers concerning how exactly they are ought to pay for using the product. For instance, returning to the delineation between value-capturing mechanisms that charge consumers and those that ensue income from third parties, combining mechanisms from both categories could make it unclear for consumers for what and when they are supposed to pay directly, through product upgrades or subscriptions, as opposed to indirectly, through their exposure to advertising or other third-party materials, for using the offering. Prior research suggests that the negative effects of violating category boundaries are most eminent when the differences in consumer preferences towards certain approaches to the extraction of economic value are strong (Kovacs & Hannan, 2010; Ruef & Patterson, 2009).

What is more, because consumers hold strong but generally heterogeneous preferences concerning particular ways of paying for offerings, enacting code-violating logics for value capture may actually make offerings less likely a contender to consumers in any segment. To illustrate, consider the following stylized example. Imagine that three consumers, consumer A, B, and C, are looking to acquire a product from the same product category. Consumer A, B, and C differ in their preferences concerning product payment: consumer A prefers paying herself over having her product usage subsidized by third parties such as advertisers; consumer B refuses to pay herself; while consumer C is indifferent to any approach. They have four free products from which to choose, each with a different logic for value capture. Product 1, 2, and 3 have a code-preserving logic for value capture, based on charging for separate paid product upgrades, charging for separate paid product upgrades and subscriptions, and advertising, respectively. Meanwhile, product 4 has a code-violating logic for value capture, as it charges for subscriptions but also includes advertising. All else equal, given their product-payment preferences, it follows that consumer A is most likely to consider acquiring products 1 and 2, consumer B presumably only considers product 3, and consumer C may include all four products in her initial consideration set. Put differently, when compared to offerings with code-preserving logics for value capture, offerings with code-violating logics for value capture are less likely to be considered by consumers with particular product-payment preferences, while equally likely to be considered by all others. This matters, because consumers subsequently benchmark the products in their initial consideration set to arrive at the offering of their liking. A greater prevalence in consumers' initial consideration sets should thus eventually also result in a greater likelihood that consumers will settle for an offering with a code-preserving logic for value capture vis-à-vis an offering with a code-violating logic for value capture. It is not that consumers will never consider, or end up downloading, offerings with code-violating logics for value capture, but in the presence of comparable offerings with code-preserving logics for value capture, it just does not make such offerings more appealing to consumers. Therefore, we propose the following:

Hypothesis 1: *Code-violating logics for value capture will be negatively associated with downloads.*

As noted, apart from their preferences concerning product payment, consumers also differ in other ways, such as concerning their requirements for a particular offering or their usage intensity (Adner & Levinthal, 2001; Rietveld & Eggers, 2018). Consequently, some value-capturing mechanisms are per definition more suiting to some consumers than they are to others. For example, separate paid product upgrades allow consumers to upgrade to premium functionalities on-the-spot or whenever they see fit, and as such offer particular merit for incidental or casual users of an offering. Meanwhile, more frequent users would put less value on such a way of product payment. Instead, subscriptions should perhaps better cater to their needs. For this reason, online dating services and mobile voice communication products frequently combine paid product upgrades and subscriptions in their logics for value capture (Teece, 2010).

Because some value-capturing mechanisms are more suiting to some consumers than they are to others, increasing the number of value-capturing mechanisms that constitute offerings' logics for value capture may increase their downloads. It simply expands the size of the consumer audience that will consider such offerings worthy of further consideration. Given subsequent benchmarking by consumers as before, it follows that increased frequency with which an offering is considered should also be associated with greater downloads, as it increases the likelihood that consumers will settle for that offering as the one that best suits their needs. Formally:

Hypothesis 2: *Increasing the number of value-capturing mechanisms constituting a logic for value capture will be positively associated with downloads.*

2.3 Data and Methods

2.3.1 Study Context and Data

To test our hypotheses, we constructed a unique unbalanced panel data set with 216,064 monthly observations on 24,194 distinct free apps that at some point strive for the extraction of economic value from the U.S. Apple App Store between May 2016 and April 2017.[6] The App Store is the exclusive distribution platform for mobile apps that operate on Apple's iOS operating system. The operating system constitutes the backbone for mobile devices such as iPhone, iPad, iPod, and Apple Watch. Consumers turn to the App Store to download apps for a multitude of purposes, including education, gaming, and navigation, and are organized in categories accordingly. We considered the apps listed under the categories entertainment, productivity, and utilities. The Apple App Store represents a canonical example of a digital market. It harbors a massive volume of distinct offerings, and many of those envelop distinct logics for value capture (International Data Corporation & App Annie, 2014). The majority of apps can be acquired without paying an up-front download price though (Arora et al., 2017; Bresnahan et al., 2015; Flurry, 2013; Ghose & Han, 2014), making for an attractive study context. In the absence of an up-front download price, consumers' barriers to consider and download apps should not differ across offerings and their logics for value capture, ceteris paribus.

To construct our data set, we used machine collection methods to observe the apps in the App Store at the beginning of each month. Each app in the App Store has an information

6 We dropped apps with a non-English textual description because we rely on automated content analysis in the operationalization of some of our variables (Short et al., 2010). To this purpose, we used a simple procedure that determines the language of the textual description based on determiner words, which are unique to a language.

page (i.e., web site) that provides consumers with an overview of contemporaneous app-specific information. For each app, we collected all information that consumers could access from the app information page, among others including the app's categorization, the description and screenshots on the app information page, and the app's ratings submitted by consumers. We complemented this data set with hand-collected data on all the app-related news articles and expert reviews published by a select number of traditional media and technology blogs to control for the potential reinforcing effect of recognitions by expert critics for apps' appeal with consumers (Gemser, Leenders, & Wijnberg, 2008).[7] Data on monthly app downloads were obtained from an app market analytics firm; Apptopia (http://www.apptopia.com).

2.3.2 Code-Violating and Code-Preserving Logics for Value Capture in the Apple App Store

In our empirical setting, offerings with logics for value capture constituting multiple value-capturing mechanisms are commonplace. Returns to any individual value-capturing mechanism are usually marginal (Vision Mobile, 2015) and value-capturing mechanisms may freely be combined (International Data Corporation & App Annie, 2014). This provides app-producing organizations clear incentives and discretion to enact multiple value-capturing mechanisms, and gives rise to a palpable variety of logics for value capture. In turn, the ubiquitous availability of app descriptions and in-app purchase menus make those decisions tractable for consumers.

Figure 2.1 presents an overview of the value-capturing mechanisms that may be combined in the App Store. Analogous to the theory section, a distinction exists between two categories of value-capturing mechanisms: (1) those that are based on charging consumers; and (2) those that ensue income from third parties (Casadesus-Masanell & Zhu, 2010; Clemons, 2009; Liu et al., 2012; Teece, 2010). By extension, an offering's logic for value capture is code-preserving if it exclusively constitutes value-capturing mechanisms from within a single category, while a code-violating logic for value capture constitutes value-capturing mechanisms from across categories.

There are four value-capturing mechanisms based on charging consumers. Organizations may: (1) sell in-app items that might be purchased repetitively (i.e., consumables), for example, matching puzzle game Candy Crush Saga allows consumers to keep playing despite surpassing the maximum number of free games after paying a small premium; (2) offer paid app upgrades (i.e., durables) that may be used perpetually, such as custom keyboard skins in the SwiftKey Keyboard app; (3) transfer the temporal right to use their offering (i.e., subscriptions) for instance for unlimited music streaming on Spotify;

7 We selected the most influential sources as reflected by their Alexa page rank, an indicator of a website's popularity.

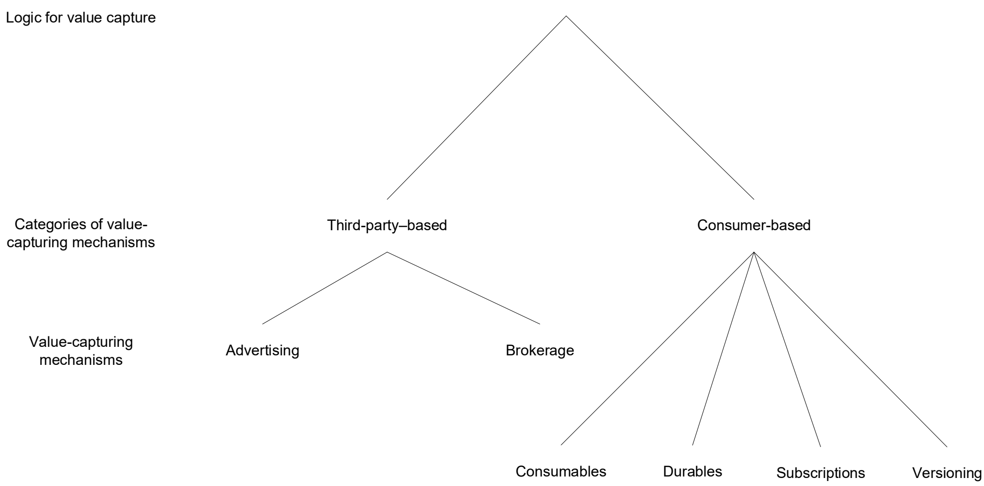

Figure 2.1. Value-capturing mechanisms in the Apple App Store

and (4) offer multiple versions of their app, one free and one paid (i.e., versioning), such as NOAA Weather Radar and NOAA Radar Pro.

Alternatively, there are two value-capturing mechanisms by which organizations can ensue income from third parties. They may (1) bundle their offering with advertising (i.e. advertising) such as in avatar-creation app Bitmoji; (2) or they may act as a broker between their consumers and content providers (i.e., brokerage), for example, Shazam allows consumers to identify songs and subsequently buy or stream those songs on iTunes, Rdio, or Spotify.

2.3.3 Variable Specifications

Independent variables. Because apps' logics for value capture are apparent to consumers from the app description or in-app purchase menu (Arora et al., 2017; Ghose & Han, 2014), we chose to utilize computer aided text analysis to operationalize our independent variables, a method that has recently been applied to such organizational narratives as annual reports, mission statements, and press releases (Duriau, Reger, & Pfarrer, 2007; Short et al., 2010). More specifically, we devised a list of words for each constituent of apps' logics for value capture, consumables, durables, subscriptions, versioning, advertising, and brokerage, from which its presence becomes apparent to consumers. To arrive at the word lists, two of the authors randomly sampled 400 apps from the store-wide leaderboard with the most popular free apps and independently coded the presence or absence of each value-capturing mechanism (Krippendorff, 2004). They reached substantial agreement in their responses, yielding a Cohen's kappa of 0.806 (Cohen, 1960); disagreements were resolved based on discussion. Then, we compiled an initial list with the most frequently occurring words per value-capturing mechanism, subsequently adding and removing words based on iterative rebuttal between the same two authors. Thereafter, we augmented these word lists with synonyms and words that are per definition associated with a certain value-capturing mechanism (Short et al., 2010). For example, in-app purchases containing the words "pro," "premium," or "full" can univocally be associated with versioning because they connote an upgrade to an app version of superior quality (Shapiro & Varian, 1999). Similarly, we extended the advertising word list with the names of the most prevalent mobile advertising networks in the Apple App Store (Apptopia, 2017b). An overview of the word lists for each value-capturing mechanism is provided in Table 2.1. Illustrative examples of our operationalization are presented in Table 2.2.

Because app-producing organizations may also version their offering through standalone free and paid versions of the same app (Arora et al., 2017; Liu et al., 2014), we also devised a simple procedure to automatically pair such cross-listed offerings. Our approach is predicated on the premise that a free and paid version of the same app can be identified through similar titles and descriptions; they essentially describe the same offering, and otherwise consumers would not be aware of their option to upgrade. Thus, we quantified the similarity of the titles and descriptions of free and out-of-sample paid apps from the same app category by the same organization based on the words they have in common. We do this by computing cosine similarity (Salton & McGill, 1986):

$$similarity(f,p) = \frac{W_f \cdot W_p}{||W_f||\,||W_p||} = \frac{\sum_{k=1}^{K} W_{f,k} W_{p,k}}{\sqrt{\sum_{k=1}^{K}(W_{f,k})^2}\sqrt{\sum_{k=1}^{K}(W_{p,k})^2}}. \tag{2.1}$$

where W^f and W^p represent the word frequency distributions of the title and description of a free and an out-of-sample paid app, and K denotes the sum of distinct words in either of those word frequency distributions. The measure ranges between 0 and 1, where higher values represent greater similarity. Because organizations usually use the titles and descriptions of versioned apps to make consumers aware of their option to upgrade, for instance by referencing the additional functionalities of the paid app in the description of the free app, we allow for some dissimilarity in the texts associated with those apps. We set a threshold at 0.7 and also consider a free app versioned if we were able to identify an out-of-sample paid app by the same organization in the same category for which the cosine similarity, for both the title and description, equals or exceeds the similarity threshold.

To ensure that our text analyses were actually capturing the constituents of apps' logics for value capture, two of the authors manually examined two separate random samples of

300 apps (McKenny, Aguinis, Short, Anglin, 2017; Short et al., 2010). The first sample contained 50 apps per value-capturing mechanism for which its presence was identified; the second sample instead consisted of 50 apps per value-capturing mechanism where it was deemed absent. We independently coded the apps' logics for value capture and subsequently

compared these results to the codes as produced by our computer-aided text analysis. The two authors were well in agreement, yielding a Cohen's kappa of 0.881. The average Pearson correlation coefficients between the coding by the two authors and our algorithm equaled 0.792, 0.837, 0.883, 0.896, 0.880, and 0.779 for consumables, durables, subscriptions, versioning, advertising, and brokerage, respectively (McKenny et al., 2017).

Relating the outlined operationalization back to our hypotheses, we constructed the following variables. In interpreting these variables, it is important to note that we use the monthly observations on apps whose logics for value capture did not yet constitute any value-capturing mechanism as the reference group. To test our first hypothesis that predicts a negative association between code-violating logics for value capture and downloads, we created two indicator variables denoting whether apps' logics for value capture constitute consumer and third-party–based value-capturing mechanisms. The interaction term of those variables then, is included in our models to capture whether an offering's logic for value capture is code-violating (i.e., whether it constitutes both consumer and third-party–based value-capturing mechanisms). Assessing the size and magnitude of the interaction effect relative to the main effects allows us to test Hypothesis 1. To test our second hypothesis, which predicts that increasing the number of value-capturing mechanisms constituting a logic for value capture should be positively associated with downloads, we counted the number of consumer and third-party–based value-capturing mechanisms constituting apps' logics for value capture as independent variables. Thus, the variable for number of consumer-based value-capturing mechanisms takes a value between zero and four, reflecting the extent to which an app's logic for value capture constitutes any or a combination of consumables, durables, subscriptions, or versioning. Analogously, the variable for number of third-party–based value-capturing mechanisms equals the sum of the indicator variables for advertising and brokerage.

Dependent variable. Consumers endorse or reject a focal app's logic for value capture by choosing whether to consider and subsequently download that offering vis-à-vis other offerings in the same category (Priem, 2007). Because details on monthly download volumes for apps in the App Store are not publicly available from Apple or a sizeable population of app-producing organizations, we obtained proprietary download

Table 2.1. Dictionaries per value-capturing mechanism in apps' logics for value capture

Value-capturing mechanism	Keywords
Advertising[a, b]	"ad", "ad-sponsored", "ad-supported", "adcolony", "admob", "ads", "ads-sponsored", "ads-supported", "adsmogo", "advert", "adverts", "advertise", "advertised", "advertisement", "advertisements", "advertising", "advertise", "advertised", "advertisement", "advertizements", "advertising", "adwhirl", "applovin", "chartboost", "fyber", "iad", "iads", "inmobi", "mobfax", "mopub", "nend", "revmob", "tapjoy", "unityads", "vungle"
Brokerage[a, c]	("auction", "auctioning", "auctions", "broker", "brokers", "brokerage", "marketplace", "marketplaces") OR ("acquire", "acquiring", "bid", "bidding", "buy", "buyer", "buying", "find", "finding", "get", "getting", "obtain", "obtaining", "purchase", "purchasing") AND ("compare", "comparing", "exchange", "exchanging", "offer", "offering", "sell", "seller", "selling", "trade", "trading")) OR (("acquire", "buy", "find", "get', "listen", "obtain", "purchase", "stream", "view", "watch") AND [name of other app])
Consumables[b]	("buck", "bucket", "bucketful", "bucks", "bux", "bag", "bagful", "boost", "booster", "box", "cash", "call", "calls", "candies", "candy", "coin", "coins", "copies", "copy", "crate", "crateful", "credit", "credits", "currency", "diamond", "diamonds", "dollar", "dollars", "double", "doubler", "fax", "faxes", "gem", "gems", "gold", "handful", "hint", "hints", "jewel", "jewels", "key", "keys", "large", "life", "lives", "loot", "medium", "mega", "mini", "minute", "minutes", "money", "page", "pages", "pearl", "pearls", "pile", "point", "points", "potion", "potions", "pouch", "power", "power-up", "recharge", "refill", "reload", "role", "rubies", "ruby", "sack", "scan", "scans", "second", "seconds", "skip", "skips", "small", "spin", "spins", "stack", "stamina", "stardust", "stash", "token", "tokens") OR [any number in absence of keywords associated with any other value-capturing mechanism]
Durables[b]	"accessories", "accessory", "avatar", "avatars", "background", "backgrounds", "bonus", "card", "cards", "catalog", "catalogs", "chapter", "chapters", "character", "characters", "course", "courses", "cover", "covers", "deck", "decks", "doodle", "doodles", "e-card", "e-cards", "ecard", "ecards", "effect", "effects", "emoji", "emojis", "emoticon", "emoticons", "episode", "episodes", "filter", "filters", "font", "fonts", "game", "games", "guide", "guides", "instruction", "instructions", "keyboard", "keyboards", "lesson", "lessons", "level", "levels", "mode", "modes", "pack", "package", "packages", "packs", "phrase", "phrases", "record", "records", "set", "sets", "sticker", "stickers", "theme", "themes", "tip", "tips", "tool", "tools", "track", "tracks", "training", "trainings", "video", "videos", "wallpaper", "wallpapers", "watermark", "watermarks", "workout", "workouts"
Value-capturing mechanism	Keywords
Subscription[a, b]	"annual", "annually", "auto-renew", "auto-renewal", "auto-renewable", "auto-renewing", "day", "daily", "dues", "member", "membership", "memberships", "month", "monthly", "quarter", "quarterly", "renew", "subscribe", "subscriber", "subscription", "subscriptions", "year", "yearly"
Versioning[b, d]	("advanced", "complete", "deluxe", "expert", "full", "plus", "premium", "pro", "professional", "unlock", "update", "upgrade", "ultimate", "version") AND [absence of keywords associated with any other value-capturing mechanism]

[a] Keywords are applied to app descriptions while controlling for negations (e.g., "without ads" or "no subscriptions").

[b] Keywords are applied to in-app purchase menus.

[c] Keywords that are separated by the "AND" operator have to be used in the same sentence or single in-app purchase menu item.

[d] Versioning is also operationalized through a text similarity search that for a focal free app identifies an associated out-of-sample paid app that is listed in the same app category and produced by the same app-producing organization.

Table 2.2. Illustrative applications of automated content analysis to identify value-capturing mechanisms in apps'

Value-capturing mechanism	Title	Description
Advertising	Disney Emoji Blitz	Before you download this app, please consider that this app includes **advertising**, some of which may be targeted to your interests. You may choose to control targeted **advertising** within our applications by using your mobile device settings (for example, by re-setting your device's **advertising** identifier and/or opting out of interest based **ads**).
Brokerage	Barcos - Barcode Scanner	Barcos is a Barcode scanner for iPhone, iPad and iPod Touch. Its main purpose is to scan and parse the contents of Barcode & QR Codes. It can also generate QR Codes. 3. Shop Right in the App After scanning any product code you can **buy** that product from **Amazon** or **eBay** just right in the app. You don't even need to exit from the app to buy a product! Check the Product price & other info, buy if you wish! This app is not just your scanner but also your e-commerce shopping assistant.
Consumables	PrankDial - #1 Prank Call App	
Durables	25 Days of Christmas 2016	
Subscription	Budge World - Kids Games & Fun	
Versioning	QR Reader for iPhone	
	I'd Cap That® - Add Funny Captions and Text to Photos	I'd Cap That takes your normal photo and selects the perfect, most hysterically crude caption and slaps it on top. If you don't LOL right away, refresh the caption for optimal hilarity. You and your friends will have an absolute blast capping your pics. Never before has anything ever made you laugh this hard.
	I'd Cap That® PRO - Add Funny Captions and Text to Photo	I'd Cap That+ takes your normal photo and selects the perfect, most hysterically crude caption and slaps it on top. If you don't LOL right away, refresh the caption for optimal hilarity. You and your friends will have an absolute blast capping your pics. Never before has anything ever made you laugh this hard.

information for the app categories entertainment, productivity, and utilities from Apptopia, an app market analytics firm. Apptopia infers an app's number of downloads from its daily rank on store-wide and category-specific download leaderboards in the App Store, using an estimation procedure similar to that outlined in extant literature (Carare, 2012; Garg & Telang, 2013). Subsequently, it combines this baseline estimation with proprietary data, including true download figures for a subset of apps in the App Store, to arrive at its final estimations.

Drawing from this proprietary data, we were thus able to observe apps' monthly number of downloads. As a dependent variable, it reflects the extent to which consumers as an audience are acquiring an offering (Pontikes, 2012). From the perspective of organizations that produce a free offering with the aim of extracting of economic value, the amount of downloads that it garners is equally meaningful. Accumulating a large consumer base is a critical precursor for successful value capture from a free app, because it is those consumers that adopt the offering that organizations may try to solicit direct or indirect income from (Kumar, 2014).

Control variables. We included a number of control variables to account for other app-specific factors that may affect their number of downloads. The app information page contains a wealth of information about the offering, including a description of its functionalities and a number of screenshots of its user interface. As prior research suggests that consumers tend to prefer apps for which they have more information (Ghose & Han, 2014), our models included both a count of the number of words in the description and the number of screenshots on the information page. Ghose and Han (2014) further found that an app's file size is a significant predictor of its popularity with consumers. Therefore, in all our models we controlled for apps' file size measured in megabytes. The potential audience size for apps may equally depend on the iOS-devices that they are compatible with, and thus we introduced indicator variables that denote whether apps were compatible with Apple's iPhone, iPad, iPod, and Watch.

Apps tend to attract most attention and visibility in the first months after their introduction into the App Store (Trusov, Rand, & Joshi, 2013). Hence, in all our models we controlled for the number of months apps have been on the market. The visibility of apps is also affected by the release of new updates. To control for this effect, we included a count of the number of months since the most recent update for an app has been released.

As is common in digital markets, consumers can rate apps with scores between one and five stars after downloading them. The volume and valence of such ratings are visible to prospective consumers when they browse the App Store and are thus instrumental in their decisions. Indeed, prior research indicates that the volume and valence of consumers' ratings are likely associated with offerings' number of downloads (Chevalier & Mayzlin, 2006). Accordingly, our models included a count of the number submitted ratings and the average valence of those submitted ratings, where a value of zero denotes that ratings are absent.

We also accounted for the various mechanisms by which Apple directs consumers' attention to particular apps. First, on a focal app's information page, under the headers "Consumers also Bought…" and "More by this Developer…," Apple prominently displays a list with hyperlinks to the apps that have most frequently been downloaded together with that app, either store-wide or from the same organization. Because prior research suggests that such recommendations may positively influence downloads (Fleder & Hosanagar, 2009), we included monthly counts of the frequency at which an app appeared under either header on the information pages of other apps. Second, Apple promotes a small subset of apps as their editors' choice. Thus, we incorporated an indicator variable denoting whether an app was editors' choice.

Prior research suggests that appraisals by expert critics also influence consumers' download decisions (Gemser et al., 2008). Therefore, we included two indicator variables. The first indicator variable denotes whether a review attributing a quality appraisal to the offering was published by 148Apps, AppAdvice, CNET, MacWorld, Mashable, or *The New York Times*. The second indicator variable captures whether an app received regular media coverage in any of the preceding sources.

3.3.4 Statistical Analysis

We had to consider several characteristics of our data in deciding upon an appropriate method of statistical analysis. We constructed a data set with repeated observations on a sizeable number of apps characterized by substantive time-invariant heterogeneity. Our dependent variable, the number of monthly downloads, is a non-negative and highly dispersed count. That is, the variance is substantially larger than the mean, making Poisson regression inappropriate. Therefore, we chose to analyze our data using a conditional fixed-effects negative binomial regression model that also includes time fixed effects (Hausman, Hall, & Griliches, 1984).

Moreover, because an app's logic for value capture signifies a conscious choice on behalf of the app-producing organization (Arora et al., 2017; Liu et al., 2014), it is susceptible to endogeneity concerns. More specifically, it is likely that an app's logic for value capture reflects factors unobserved in our data, possibly resulting in a correlation between our independent variables and the error term. This would violate one of the assumptions of our regression model and could bias our estimation results (Wooldridge, 2002).

We chose to address this endogeneity concern through two-stage residual inclusion (2SRI) because it is one of the few approaches suited to address endogeneity in nonlinear panel data (Terza, Basu, & Rathouz, 2008). For this reason, 2SRI has recently been applied to analyze data sets comparable to ours (Beaudry & Allaoui, 2012; Alvarez-Garrido & Dushnitsky, 2016). Similar to traditional two-stage instrumental variables approaches, the 2SRI approach relies on the identification of instruments that are correlated with the endogenous independent variables, though unrelated to the dependent variable. Hence, 2SRI encompasses a first stage in which the instruments and exogenous control variables are regressed on the endogenous independent variables. However, instead of substituting predicted values from this first-stage regression into a second-stage regression model, 2SRI involves including first-stage residuals as additional explanatory variables to represent the component of the error term that is correlated with the endogenous independent variables. As such, the 2SRI approach is comparable to addressing endogeneity through control functions (Wooldridge, 2015).

To identify instruments for apps' logics for value capture, as described by their reliance on, or number of, consumer and third-party–based value-capturing mechanisms, we drew from recent literature. Following Arora et al. (2017), who addressed endogeneity concerns in a research setting similar to ours, we used the time-varying average proportion of apps enacting consumer and third-party–based value-capturing mechanisms in an app category as instruments for the composition of apps' logics for value capture. As such, we exploit the prevalence of bandwagon effects in the mobile app market (Bresnahan et al., 2015; Bryce, Dyer, & Hatch, 2011; Kumar, 2014). App-producing organizations frequently make decisions, such as when choosing their offering's logic for value capture, by simply following what is common among their competitors (Arora et al., 2017). Hence, the rationale here is that as the prevalence of a certain category of value-capturing mechanisms increases within an app category, app-producing organizations with offerings in this app category will be more inclined to adopt this category of value-capturing mechanisms themselves as well. This app category-level trend is beyond the control of individual app-producing organizations though. Moreover, due to the rough and encompassing product categorizations in the App Store, small fluctuations in the prevalence of a certain category of value-capturing mechanisms are also unlikely to directly affect the downloads of individual apps. Indeed, we found that our instruments were not significantly correlated with apps' number of downloads. Because we address endogeneity by means of 2SRI, tackling the endogeneity of the main effects is sufficient to obtain consistent estimates of associated interaction effects (Wooldridge, 2015, p. 428). We thus did not have to identify an additional instrument for the interaction between the variables denoting the reliance on, or number of, consumer and third-party–based value-capturing mechanisms of apps' logics for value capture.

To summarize, we thus estimated the following nonlinear structural model. In the first stage, we estimate whether apps' logics for value capture constitute consumer and third-party–based value-capturing mechanisms, or the number of each category of mechanisms that logics for value capture envelop, as a function of our instruments and control variables, using logit or Poisson regressions, respectively.[8] We then used the residuals from these regressions as additional variables in a second-stage conditional fixed-effects negative binomial regression model. All second-stage standard errors are corrected by means of bootstrapping (Cameron & Trivedi, 2013; Terza et al., 2008; Wooldridge, 2002).

2.4 Results

Descriptive statistics and bivariate correlations for the variables in our main analyses are presented in Table 2.3. Apps in our sample accumulated an average of 7,764 monthly downloads, though as noted earlier download volumes are highly dispersed. The standard deviation of app downloads equals roughly eleven times its mean, with minimum and maximum values ranging from 0 to 12,000,000. We observe that correlations among variables are low to moderate, with the obvious exception of the indicator and count variable for consumer-based value capturing mechanisms and that between the indicator and count variable for third-party–based value-capturing mechanisms. None of our models did simultaneously include these variables. We also estimated variance inflation factors (VIFs) to further evaluate the possibility of collinearity. The highest VIF is equal to 2.01, well below the oft-cited ceiling of 10 (Cohen, Cohen, West, & Aiken, 2003).

Table 2.4 reports the results from our first-stage regressions. Model 1 and 2 estimate whether apps' logics for value capture constitute consumer and third-party–based value-capturing mechanisms. Model 3 and 4 present the first-stage regressions for the number of consumer and third-party–based value-capturing mechanisms. The first stage estimation results show that our instruments are significant predictors of the composition of apps' logics for value capture. The instruments are significant and positively associated with the endogenous independent variables. Highly significant (p < 0.001) likelihood ratio tests across Models 1 to 4 also indicate that our instruments are strong.

2.4.1 Hypotheses Tests

Second-stage regression results testing our hypotheses are reported in Table 2.5. We report standard conditional fixed-effects negative binomial regression coefficients, which when exponentiated can be interpreted as elasticities associated with a one unit change

8 We used Poisson rather than negative binomial regressions in the first-stage because there was no evidence of overdispersion. In supplementary analyses, we reran our analyses using negative binomial regressions in the first stage obtaining results nearly identical to the ones reported here.

Table 2.3. Descriptive statistics and pairwise correlations

Variable	Mean	S.D.	Min	Max	1	2	3	4	5
1. Downloads	7,763.56	84,199,15	0.00	12,000,000.00					
2. Consumer-based value- capturing mechanisms	0.64	0.48	0.00	1.00	0.01				
3. Third-party–based value-capturing mechanisms	0.51	0.50	0.00	1.00	0.02	-0.58			
4. Number of consumer-based value-capturing mechanisms	0.75	0.65	0.00	4.00	0.01	0.86	-0.46		
5. Number of third-party–based value-capturing mechanisms	0.52	0.51	0.00	2.00	0.02	-0.57	0.94	-0.46	
6. Co-download "Consumers also Bought"	0.23	3.07	0.00	204.00	0.18	0.00	0.01	0.00	0.02
7. Co-download "More by this Developer"	0.11	0.66	0.00	53.00	0.00	0.01	-0.02	0.02	-0.01
8. Description length	184.15	134.77	1.00	804.00	0.04	0.16	-0.06	0.15	-0.05
9. Editors' choice	0.01	0.02	0.00	1.00	0.03	0.00	0.00	0.00	0.01
10. File size	32.75	67.68	0.00	3,399.68	0.06	0.05	-0.02	0.07	-0.01
11. Media coverage	0.01	0.01	0.00	1.00	0.05	0.00	0.00	0.00	0.00
12. Months since introduction	35.21	24.14	0.00	106.00	0.01	0.04	-0.05	0.01	-0.05
13. Months since update	17.59	19.36	0.00	104.00	-0.06	0.03	-0.06	-0.01	0.07
14. Number of ratings	971.65	9,092.92	0.00	486,010	0.22	0.02	0.00	0.04	0.00
15. Number of screenshots	4.12	1.18	1.00	6.00	0.03	0.11	-0.06	0.12	-0.05
16. Rating valence	2.47	1.82	0.00	5.00	0.07	-0.09	0.09	-0.03	0.09
17. Reviewed by experts	0.01	0.10	0.00	1.00	0.22	0.01	0.00	0.02	0.01

Variable	6	7	8	9	10	11	12	13	14	15	16
7. Co-download “More by this Developer”	0.00										
8. Description length	0.04	0.02									
9. Editors’ choice	0.00	0.00	0.03								
10. File size	0.04	-0.01	0.11	0.01							
11. Media coverage	0.03	0.00	0.01	0.06	0.01						
12. Months since introduction	0.04	0.02	0.07	0.00	-0.10	0.00					
13. Months since update	-0.04	-0.01	-0.11	-0.01	-0.11	-0.01	0.58				
14. Number of ratings	0.10	0.00	0.06	0.01	0.02	0.01	0.14	0.00			
15. Number of screenshots	0.03	0.00	0.27	0.02	0.10	0.01	-0.02	-0.09	0.03		
16. Rating valence	0.17	0.09	0.09	0.02	0.04	0.01	0.26	0.09	0.07	0.04	
17. Reviewed by experts	0.06	0.01	0.08	0.07	0.06	0.02	0.05	-0.04	0.24	0.05	0.08

in the explanatory variable. Model 5 only contains control variables. As expected, we observe that apps are downloaded more frequently when app-producing organizations recently released a new version of their offering. Downloads also increase with the valence of consumer ratings, while the number of screenshots of the user interface on the app information page have a negative effect.

In Model 6, we add the indicator variables for consumer and third-party–based value-capturing mechanisms constituting apps' logics for value capture and their associated residuals from the first-stage regressions. The coefficients for both first-stage residuals are significant at $p < 0.01$ and $p < 0.001$, respectively. Controlling for these effects, any remaining association between the indicator variables for consumer and third-party–based value-capturing mechanisms and monthly download volumes is likely due to consumers actively accepting or rejecting apps' logics for value capture in their considerations. We observe that the coefficients for the indicator variables for consumer and third-party–based value-capturing mechanisms are positive and significant at $p < 0.01$ and $p < 0.001$, respectively.

We focus on Model 7, which introduces the interaction between the indicator variables for consumer and third-party–based value-capturing mechanisms, for interpretation and to test Hypothesis 1. We find that the coefficients for both consumer and third-party–based value-capturing mechanisms indicator variables remain positive and significant (consumer-based value-capturing mechanisms: $\beta = 0.766$, $p < 0.001$; third-party–based value-capturing mechanisms: $\beta = 0.886$, $p < 0.001$). The effect of the composition of apps' logics for value capture on monthly download volumes is substantial. For one, the effects are appreciably larger than the effect sizes of most control variables.

In the first hypothesis, we predicted that code-violating logics for value capture, which constitute both consumer and third-party–based value-capturing mechanisms, should be negatively associated with downloads. In Model 7, we find support for this hypothesis. The interaction term between consumer and third-party–based value-capturing mechanisms is negative and significant ($\beta = -0.792$, $p < 0.001$). To get a better sense of the impact of this effect, an additional simple slope test reveals that the effect of logics for value capture constituting third-party–based value-capturing mechanisms is negative if they also constitute consumer-based value-capturing mechanisms ($\beta = -0.0260$, $p < 0.05$), reducing downloads by about 3% (Aiken & West, 1991). Figure 2.2 provides further details about this negative effect, by graphically representing the effect of logics for value capture constituting consumer-based value-capturing mechanisms in the presence, and absence, of third-party–based value-capturing mechanisms.

Table 2.4. First-stage regressions predicting the number of consumer and third-Party–based value-capturing mechanisms constituting apps' logics for value capture

Variable	Model 1	Model 2	Model 3	Model 4
Proportion of apps with consumer–based value-capturing mechanisms in category	3.519*** (0.467)	0.797 (0.457)	1.278*** (0.134)	0.298* (0.138)
Proportion of apps with third-party–based value-capturing mechanisms in category	-0.501 (0.541)	4.621*** (0.516)	0.344* (0.158)	2.366*** (0.205)
Co-download "Consumers also Bought"	-0.003 (0.004)	0.006 (0.004)	-0.001 (0.002)	0.003 (0.002)
Co-download "More by this Developer"	0.020 (0.023)	-0.035 (0.025)	0.018* (0.008)	-0.016 (0.013)
Description length	0.002*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)	-0.001** (0.000)
Editors' choice	-0.736 (0.599)	0.281 (0.587)	-0.344 (0.233)	0.340 (0.304)
File size	0.001*** (0.000)	-0.001*** (0.000)	0.001** (0.000)	-0.001* (0.000)
Media coverage	-0.283 (0.495)	0.073 (0.607)	-0.145 (0.179)	-0.029 (0.291)
Months since introduction	0.003*** (0.000)	-0.002** (0.000)	0.001 (0.001)	-0.001** (0.000)
Months since update	0.004*** (0.000)	-0.007*** (0.000)	0.001* (0.000)	-0.004*** (0.001)
Number of ratings	0.001 (0.001)	-0.001 (0.001)	0.001** (0.000)	-0.001 (0.001)
Number of screenshots	0.112*** (0.012)	-0.071*** (0.012)	0.060*** (0.005)	-0.030*** (0.005)
Rating valence	-0.140*** (0.008)	0.118*** (0.008)	-0.024*** (0.003)	0.055*** (0.004)
Reviews by experts	-0.247 (0.156)	0.183 (0.147)	0.005 (0.062)	0.089 (0.068)
Constant	-1.340* (0.636)	-2.885*** (0.623)	-1.573*** (0.228)	-2.300*** (0.236)
Compatibility effects	Included	Included	Included	Included
Time fixed effects	Included	Included	Included	Included
Number of apps	24,194	24,194	24,194	24,194
Number of observations	216,064	216,064	216,064	216,064
Log pseudo-likelihood	-132,642	-144,492	-221,841	-183,906

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.
Model 1 and 2 are logistic regressions of apps' logics for value capture constituting consumer or third-party–based value-capturing mechanisms, respectively. Model 3 and 4 are Poisson regressions on the number of consumer and third-party–based value-capturing mechanisms. Coefficients are reported. Robust standard errors clustered by app are in parentheses.

Table 2.5. The effect of logics for value capture on app downloads

Variable	Model 5	Model 6	Model 7	Model 8	Model 9
Consumer-based value-capturing mechanisms		0.112** (0.039)	0.766*** (0.062)		
Third-party–based value-capturing mechanisms		0.247*** (0.029)	0.886*** (0.058)		
Consumer-based value-capturing mechanisms x third-party–based value-capturing mechanisms			-0.792*** (0.066)		
Number of consumer-based value-capturing mechanisms				0.128** (0.023)	0.241*** (0.039)
Number of third-party–based value-capturing mechanisms				0.264*** (0.028)	0.429*** (0.048)
Number of consumer-based value-capturing mechanisms x number of third-party–based value-capturing mechanisms					-0.231*** (0.045)
Co-download "Consumers also Bought"	0.001 (0.006)	-0.001 (0.006)	-0.001 (0.006)	-0.001 (0.006)	-0.001 (0.006)
Co-download "More by this Developer"	-0.043 (0.031)	-0.043 (0.031)	-0.046 (0.032)	-0.042 (0.031)	-0.043 (0.033)
Description length	0.001** (0.000)	0.001* (0.000)	0.001** (0.000)	0.001* (0.000)	0.001** (0.000)
Editors' choice	0.840 (0.455)	0.763 (0.472)	0.715 (0.442)	0.773 (0.470)	0.711 (0.449)
File size	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)
Media coverage	-0.403 (0.445)	-0.372 (0.459)	-0.384 (0.474)	-0.365 (0.462)	-0.363 (0.440)
Months since introduction	0.016*** (0.001)	0.016*** (0.001)	0.016*** (0.001)	0.016*** (0.001)	0.016*** (0.001)
Months since update	-0.032*** (0.001)	-0.031*** (0.001)	-0.031*** (0.001)	-0.031*** (0.001)	-0.031*** (0.001)
Number of ratings	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Number of screenshots	-0.053*** (0.009)	-0.048*** (0.009)	-0.047*** (0.009)	-0.050*** (0.009)	-0.050*** (0.009)
Rating valence	0.474*** (0.006)	0.471*** (0.006)	0.464*** (0.006)	0.470*** (0.006)	0.465*** (0.006)
Reviews by experts	-0.350 (0.234)	-0.384 (0.235)	-0.386 (0.206)	-0.368 (0.223)	-0.355 (0.231)
First-stage residual consumer-based value-capturing mechanisms		-0.287** (0.103)	-0.104** (0.104)	-0.051** (0.018)	-0.098*** (0.020)
First-stage residual third-party–based value-capturing mechanisms		-0.520*** (0.124)	-0.541*** (0.125)	-0.207*** (0.058)	-0.244*** (0.056)
Constant	-2.274 *** (0.252)	-2.851*** (0.264)	-3.444*** (0.265)	-2.998*** (0.258)	-3.170*** (0.259)
Compatibility effects	Included	Included	Included	Included	Included

Time fixed effects	Included	Included	Included	Included	Included
Number of apps	24,194	24,194	24,194	24,194	24,194
Number of observations	216,064	216,064	216,064	216,064	216,064
Log likelihood	-1,067,377	-1,065,991	-1,065,822	-1,066,731	-1,066,624

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.
Conditional fixed-effects negative binomial regressions on monthly app downloads. Coefficients are reported. Bootstrapped standard errors based on 1,000 replications are in parentheses.

We examine the association between the number value-capturing mechanisms constituting apps' logics for value capture and downloads in Model 8 and 9. In our second hypothesis, we predicted that the number of value-capturing mechanisms constituting apps' logics for value capture should be positively associated with app downloads. Model 8 reports support for this hypothesis, we observe that the coefficients for the number of consumer and third-party–based value-capturing mechanisms constituting apps' logics for value capture are positive and significant (number of consumer-based value-capturing mechanisms: β = 0.128, p < 0.001; number of third-party–based value-capturing mechanisms: β = 0.264, p < 0.001). Adding a consumer-based value-capturing mechanism is associated with an increase in downloads of 14%; following the addition of a third-party–based value-capturing mechanism downloads rise by 30%. For the sake of completeness, Model 9 introduces the interaction between the number of consumer and third-party–based value-capturing mechanisms. These estimations are broadly consistent with our preceding findings. Increasing the number of value-capturing mechanisms in apps' logics for value capture is favorably associated with download volumes, though this effect is attenuated if doing so yields code-violating logics for value capture.

2.4.2 Robustness Checks

Alternative Model Specifications. Besides the main models reported in Table 2.5, we performed several additional analyses to further assess the validity of our findings. We present the results of those alternative model specifications in Table 2.6. Conditional fixed-effects negative binomial regressions only account for all time-invariant app-specific heterogeneity under rather stringent assumptions and rely on some non-zero variation in an apps' downloads over time for identification (Allison & Waterman, 2002; Hausman et al., 1984). Hence, some remaining time-invariant heterogeneity and apps not downloaded during our observation window dropping out of our sample may influence our results.[9] To address this concern, we also estimated our models using an unconditional fixed-effects negative binomial estimator that approximated fixed effects by including dummy variables for each app (Allison & Waterman, 2002). Because the estimation of unconditional fixed-effects negative binomial regressions is mathematically and computationally demanding on relatively large samples such as ours, we ran the

9 A total of 10,780 free apps striving for the extraction of economic value was not downloaded during our observation window.

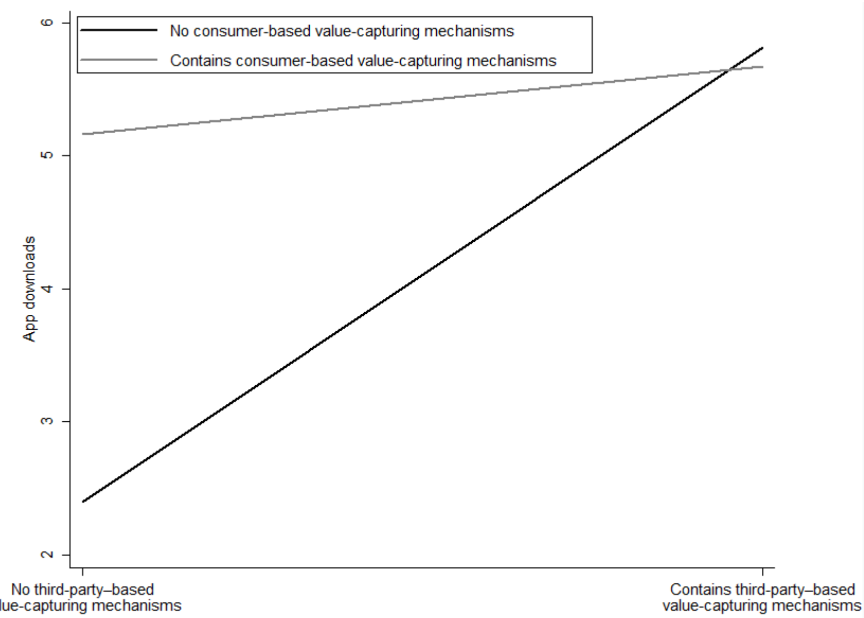

Figure 2.2. The effect of enacting code-violating logics for value capture on app downloads

estimations per app category and only for apps that were updated in the last four years.[10] The estimation results for the utilities app category are presented under Model 10 and 11, and are similar to the results obtained for the other app categories. We observe that the estimation results are qualitatively similar to the estimation results from our conditional fixed-effects negative binomial regressions.

As described in our Methods section, our download estimates were partially derived from leaderboards in the App Store. We thus chose to not control for apps' leaderboard appearance in any of our main models. Leaderboards are instrumental to consumers in discovering new offerings though (Duan et al., 2009), and failing to account for this may bias our results. To evaluate this concern, we estimated models introducing apps' appearance on store-wide top free and top grossing leaderboards as additional control variables. The estimation results are reported under Model 12 and 13, and exhibit similar patterns as our main results; the coefficients for apps' appearance on leaderboards are

10 We ran our estimations using Stata 14, which is able to handle models with up to roughly 11,000 explanatory variables. However, the number apps from the utilities app category in our sample for example equals 11,687, essentially keeping us from approximating fixed effects by including dummy variables for each app. Therefore, we focused our estimations only on those apps that were updated in the last four years. Being somewhat actively maintained, those apps are more likely to display within variance in the composition of their logic for value capture. This reduced our estimation sample to monthly observations on 10,146 distinct utility apps. Given the mathematical and computational complexity associated with estimating unconditional fixed-effects negative binomial regressions, we report conventional, rather than bootstrapped, standard errors.

Table 2.6. Robustness checks by means of alternative model specifications

Variable	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Consumer-based value-capturing mechanisms	0.120* (0.056)		0.761*** (0.062)		0.762*** (0.062)	
Third-party–based value-capturing mechanisms	0.248*** (0.069)		0.881*** (0.058)		0.882*** (0.058)	
Consumer-based value-capturing mechanisms x third-party–based value-capturing mechanisms	-0.167* (0.065)		-0.785*** (0.066)		-0.785*** (0.066)	
Number of consumer-based value-capturing mechanisms		0.125*** (0.026)		0.127*** (0.023)		0.127*** (0.023)
Number of third-party–based value-capturing mechanisms		0.168** (0.052)		0.265*** (0.028)		0.266*** (0.028)
Co-download "Consumers also Bought"	0.091*** (0.024)	0.092*** (0.024)	-0.004 (0.007)	-0.003 (0.007)	-0.004 (0.007)	-0.003 (0.007)
Co-download "More by this Developer"	-0.034 (0.043)	-0.050 (0.043)	-0.047 (0.032)	-0.043 (0.032)	-0.048 (0.032)	-0.043 (0.032)
Description length	0.001*** (0.000)	0.001*** (0.000)	0.001* (0.000)	0.001* (0.001)	0.001* (0.000)	0.001* (0.000)
Editors' choice	0.151 (1.113)	0.298 (1.112)	0.708 (0.404)	0.763 (0.441)	0.708 (0.405)	0.764 (0.440)
File size	1.067*** (0.023)	1.063*** (0.023)	0.001** (0.000)	0.001* (0.000)	0.001** (0.000)	0.001** (0.000)
Media coverage	0.205 (0.324)	0.198 (0.323)	-0.297 (0.434)	-0.291 (0.333)	-0.297 (0.418)	-0.292 (0.331)
Months since introduction	-0.403*** (0.015)	-0.403*** (0.015)	0.016*** (0.001)	0.016*** (0.001)	0.016*** (0.001)	0.016*** (0.001)
Months since update	0.010 (0.031)	0.009 (0.031)	-0.031*** (0.001)	-0.031*** (0.001)	-0.031*** (0.001)	-0.031*** (0.001)
Number of new apps in category					-0.001 (0.001)	-0.001 (0.001)
Number of ratings	0.748*** (0.023)	0.735*** (0.023)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Number of screenshots	-0.093*** (0.018)	-0.094*** (0.018)	-0.046*** (0.009)	-0.049*** (0.009)	-0.046*** (0.009)	-0.049*** (0.009)
Rating valence	0.268*** (0.022)	0.269*** (0.023)	0.463*** (0.009)	0.469*** (0.006)	0.463*** (0.006)	0.469*** (0.006)
Reviews by experts	-0.530 (0.669)	-0.543 (0.669)	-0.460* (0.231)	-0.445 (0.229)	-0.462* (0.231)	-0.447 (0.229)
Top 1,000 free app			0.428*** (0.077)	0.438*** (0.076)	0.428*** (0.077)	0.438*** (0.076)
Top 1,000 grossing app			0.254*** (0.069)	0.247*** (0.071)	0.253*** (0.064)	0.246*** (0.071)
First-stage residual consumer-based value-capturing mechanisms	-0.007 (0.021)	0.080** (0.024)	-0.101 (0.105)	-0.051** (0.019)	-0.100 (0.105)	-0.051** (0.019)

First-stage residual third-party–based value-capturing mechanisms	-0.156** (0.047)	-0.035 (0.070)	-0.555*** (0.126)	-0.211*** (0.058)	-0.554*** (0.127)	-0.211*** (0.058)
Constant	0.763 (0.442)	0.660 (0.439)	-3.454*** (0.264)	-2.980*** (0.257)	-3.436*** (0.264)	-2.958*** (0.256)
Compatibility effects	Included	Included	Included	Included	Included	Included
Time fixed effects	Included	Included	Included	Included	Included	Included
Number of apps	38,794	38,794	24,194	24,194	24,194	24,194
Number of observations	335,117	335,117	216,064	216,064	216,064	216,064
Log likelihood			-1,065,549	-1,066,450	-1,065,548	-1,066,448
R^2	0.233	0.231				

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.
Model 10 and 11 are unconditional fixed-effects regressions on monthly app downloads. Model 12 to 15 are conditional fixed-effects negative binomial regressions on monthly app downloads. Coefficients are reported. Bootstrapped standard errors based on 1,000 replications are in parentheses.

positive and significant. Because apps' visibility with consumers may decrease with the amount of new offerings that are introduced into a certain category, we incorporated the number of new app introductions in a category as an additional control variable in Model 14 and 15. The results remain similar to our main results.

Alternative Explanations. We also attempted to rule out some alternative explanations for our findings. We present the results in Table 2.7. While our argument takes a consumer-centric perspective, our findings regarding the negative association between code-violating logics for value capture and downloads could theoretically also be explained from an organization-centric perspective. We advance the idea that offerings' logics for value capture are salient markers for consumers in partitioning markets and circumscribing the boundaries of their initial consideration set. It is because of this that the composition of logics for value capture matter. Offerings enveloping logics for value capture that defy strong boundaries in consumer product-payment preferences tend to be overlooked, either because they confuse consumers or because they become less likely a contender to consumers with particular product-payment preferences. However, adopting an organizations-centric perspective instead, code-violating logics for value capture might also be deemed problematic because of the operational difficulties that they might engender. Niche-width theory for instance would dictate that if organizations combine multiple value-capturing mechanisms, they would have less resources to dedicate to mastering either one (Dobrev, Kim, & Hannan, 2003; Freeman & Hannan, 1983). Alternatively, one could simply argue that different value-capturing mechanisms have to be underpinned by different—and usually inconsistent—organizational activities (Lambrecht et al., 2014; Siggelkow, 2002). Either might lead to inferior offerings, in turn also likely leading to less downloads.

If operational difficulties on behalf of the app-producing organization would indeed drive our results, we would expect the negative effect of enacting code-violating logics for value capture to be less pronounced for those offerings of organizations that have prior experience with such logics. Having gained experience with offerings with code-violating logics for value capture in the past, they are likely better at managing the associated operational difficulties as opposed to organizations that choose to enact a code-violating logic for value capture for the very first time. Hence, we performed a supplementary analysis on those apps whose producing organizations already had experience with code-violating logics of value capture in the same category prior to the start of the observation window of our data analysis. In this analysis, we also controlled for the number of code-violating apps that the organization produced. The results are presented in Model 16 and suggest that the penalty that offerings enveloping code-violating logics for value capture suffer is not substantially weaker for app-producing organizations with experience with such logics. This finding offers further support for our consumer-centric account of the effect. In Model 17, we introduce a three-way interaction between the indicator variables for consumer and third-party–based value-capturing mechanisms and the number of apps with code-violating logics for value capture that an organization has in the same app category to further explore whether the negative effect of enacting code-violating logics for value capture does erode with experience. We find no evidence for such an attenuating effect; even though the coefficient for the three-way interaction is positive, it is not statistically significant.

We also explored other possible explanations with respect to different types of organizations. Organizations in the App Store are highly diverse, they range from profit-seeking firms to indie developers, and from open source collectives to hobbyists. To check if there are any systematic differences between these organizations driving our results, we estimated separate models for profit-seeking app-producing organizations (Model 18 and 19) and others (Model 20 and 21). To delineate profit-seeking and other organizations based on their names and websites, we trained a naïve Bayes classifier based on a manually coded training set of organizations (Das & Chen, 2007). When validating the accuracy of the classifier against the details of a further 300 organizations, we found that the classifier labeled 90% of organizations correctly. The estimation results in Models 3-6 are not different from our main results.

Model 22 and 23 evaluate the possibility of reverse causality, implying that apps' download volumes would influence their enacted logic for value capture, rather than the other way around. In our main analyses, we tried to address this by measuring all our independent variables at the beginning of each month. As an additional check, we reran our main analyses lagging our dependent variable by another month. The results

Table 2.7. Robustness checks addressing alternative explanations

Variable	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23
Consumer-based value-capturing mechanisms	0.663**	0.571**	0.713***		0.832***		0.645***	
	(0.206)	(0.202)	(0.105)		(0.090)		(0.064)	
Third-party–based value-capturing mechanisms	0.794***	0.642**	0.785***		0.984***		0.715***	
	(0.224)	(0.223)	(0.102)		(0.079)		(0.056)	
Consumer-based value-capturing mechanisms x third-party–based value-capturing mechanisms	-0.802**	-0.747**	-0.674***		-0.903***		-0.672***	
	(0.232)	(0.231)	(0.108)		(0.090)		(0.062)	
Number of apps with violating logics by organization	0.015***	-0.022						
	(0.002)	(0.021)						
Consumer-based value-capturing mechanisms x number of apps with violating logics by organization		0.015						
		(0.022)						
Third-party–based value-capturing mechanisms x number of apps with violating logics by organization		0.035						
		(0.022)						
Consumer-based value-capturing mechanisms x third-party–based value-capturing mechanisms x number of apps with violating logics for value capture by organization		-0.009						
		(0.023)						
Number of consumer-based value-capturing mechanisms				0.166***		0.104***		0.146***
				(0.035)		(0.028)		(0.022)
Number of third-party–based value-capturing mechanisms				0.259***		0.274***		0.213***
				(0.042)		(0.034)		(0.029)
Co-download "Consumers also Bought"	0.008	0.008	0.005**	0.015**	-0.006	-0.006	-0.002	-0.002
	(0.005)	(0.004)	(0.002)	(0.002)	(0.012)	(0.011)	(0.006)	(0.006)
Co-download "More by this Developer"	-0.004	-0.003	0.003	0.006	-0.099*	-0.090	-0.071	-0.068
	(0.030)	(0.029)	(0.018)	(0.019)	(0.048)	(0.047)	(0.039)	(0.038)
Description length	0.001	0.001	0.001*	0.001*	0.001	0.001	0.001*	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Editors' choice	-0.104	-0.135	0.778	0.842	0.228	0.245	0.921*	1.014
	(2.097)	(2.173)	(0.485)	(0.477)	(1.593)	(1.727)	(0.527)	(0.545)

File size	0.001	0.001	0.001*	0.001*	0.001	0.001	0.001***	0.001**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Media coverage	0.315	0.335	-0.053	-0.106	-0.396	-0.349	-0.536	-0.524
	(0.396)	(0.418)	(0.372)	(0.364)	(0.693)	(0.620)	(0.421)	(0.394)
Months since introduction	0.014***	0.013**	0.017***	0.016***	0.015***	0.015***	0.017***	0.017***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Months since update	-0.030***	-0.030***	-0.031***	-0.031***	-0.032***	-0.032***	-0.028***	-0.028***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of ratings	0.001	0.001	0.001**	0.001**	-0.001	-0.001*	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Number of screenshots	-0.050*	-0.053**	-0.064***	-0.066***	-0.035**	-0.037**	-0.055***	-0.057***
	(0.020)	(0.020)	(0.013)	(0.013)	(0.012)	(0.012)	(0.009)	(0.009)
Rating valence	0.504***	0.506***	0.484***	0.488***	0.450***	0.457***	0.579***	0.583***
	(0.013)	(0.013)	(0.009)	(0.009)	(0.008)	(0.008)	(0.006)	(0.006)
Reviews by experts	-0.191	-0.179	0.243	0.263	-0.725*	-0.697	-0.476	-0.448
	(0.428)	(0.427)	(0.213)	(0.211)	(0.337)	(0.329)	(0.276)	(0.269)
First-stage residual consumer-based value-	-0.403	-0.405	-0.092	-0.105**	-0.111	-0.026	-0.099	-0.051**
capturing mechanisms[b]	(0.223)	(0.230)	(0.164)	(0.032)	(0.142)	(0.022)	(0.110)	(0.018)
First-stage residual third-party–based value-	-0.298	-0.225	-0.568**	-0.172*	-0.533**	-0.243**	-0.400**	-0.101
capturing mechanisms[b]	(0.212)	(0.212)	(0.183)	(0.067)	(0.170)	(0.091)	(0.125)	(0.053)
Constant	-3.569***	-3.410***	-3.582***	-3.142***	-3.259***	-2.749***	-4.311***	-3.918***
	(0.490)	(0.479)	(0.377)	(0.364)	(0.410)	(0.420)	(0.293)	(0.288)
Compatibility effects	Included	Included	Included	Included	Included	Included	Included	Included
Time fixed effects	Included	Included	Included	Included	Included	Included	Included	Included
Number of apps	8,201	8,201	10,223	10,223	13,961	13,961	21,867	21,867
Number of observations	65,530	65,530	93,350	93,350	122,714	122,714	181,793	181,793
Log likelihood	-315,616	-315,556	-473,479	-473,788	-591,390	-591,991	-895,964	-896,442

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.

Conditional fixed-effects negative binomial regressions on monthly app downloads. Coefficients are reported. Bootstrapped standard errors based on 1,000 replications are in parentheses.

reported under Model 7 and 8 are invariant to the use of this longer lag.

2.5 Discussion

In this chapter, we started from the observation that in some digital markets the volume of available offerings has become so substantial that product classification systems alone do not adequately constrain consumers' initial consideration sets. The number of offerings in any single category is simply beyond what consumers can cognitively or physically assess. Consequently, consumers are likely to consider merely a subset of offerings from a certain category, thus applying additional selection criteria to screen out offerings from further consideration (Bowers, 2015; Bronnenberg & Vanhonacker, 1996; Urban et al., 1993). This study submits the idea that offerings' logics for value capture, defined as their approach to the extraction of economic value, might be particularly salient markers for consumers in this screening process. Logics for value capture in digital markets tend to be highly diverse, are generally apparent to consumers upon their initial screening of the product space, represent points of common understanding among consumers allowing them to partition offerings accordingly, and signify markers concerning which consumers hold strong preferences. Given the large volume of offerings that is available to them, consumers can afford to act upon their preferences regarding logics for value capture and include or exclude offerings from their initial consideration set accordingly. This is important, because consumers subsequently benchmark the products in their initial consideration along a set of assessment criteria. Merely by considering different subsets of offerings, consumers' eventual choices may vary (Sevdalis & Harvey, 2006).

We tested this idea by adopting a consumer-centric perspective in regarding how logics for value capture of free mobile software applications striving for the extraction of economic value shape downloads in the U.S. Apple App Store between May 2016 and April 2017. Because app-producing organizations frequently combine multiple value-capturing mechanisms in their offerings' logics for value capture, we argued that these logics could be conceived of as either code-violating or code-preserving, depending on whether the combined value-capturing mechanisms together represent a coherent approach to the extraction of economic value. Code-violating logics for value capture should be negatively associated with downloads because they defy strong boundaries in consumer product-payment preferences, leading to confusion with consumers, as opposed to offerings with code-preserving logics for value capture that are more likely to be considered by consumers with particular product-payment preferences. Consequently, in the presence of offerings with code-preserving logics for value capture, at least some consumers will end up overlooking offerings with code-violating logics for value capture. Moreover, we argued that increasing the number of value-capturing mechanisms constituting offerings' logics for value capture should increase the size of the consumer audience taking them into consideration, eventually leading to more downloads. Analyzing a data set with monthly observations on 24,194 free apps and addressing endogeneity concerns, we find robust support for these predictions. By showing that the negative effect of enacting code-violating logics for value capture also persists for organizations having prior experience with enacting such logics, we are more confident in suggesting that it is consumers using logics for value capture as important markers in screening out offerings from further consideration and not potential operational difficulties associated with certain logics for value capture that drive the observed empirical results.

The findings of our study contribute to the literatures on market categories, business models, and demand, or consumer-centric, perspectives in management research. Foremost, our findings speak to prior literature on market categories that has thoroughly established the important role of product classification systems in consumer decision-making processes, most notably by providing empirical evidence that violating categorical boundaries affects the identities of organizations and their offerings (Vergne, 2012; Zuckerman, 1999). This effect has been shown to persist across an array of classification systems, including feature film genres (Hsu, 2006), labels of software products (Pontikes, 2012), auction categories on eBay (Hsu et al., 2009), and producing styles in winery (Negro & Leung, 2013), though all ostensibly reflecting some form of consumer value proposition (Priem, 2007). Notwithstanding the importance of classification systems that reflect such product-level value creation, we provide evidence that in digital markets where the number of offerings in a single category is simply beyond what consumers are able to assess, products' downloads or sales levels are also shaped by their logic for value capture. Consumers tend to hold strong preferences towards particular ways of paying for product usage. Given the large volume of offerings that is available to them, they can afford to act upon those preferences by shortlisting or neglecting offerings with particular logics for value capture in their considerations. Our empirical results suggest that categorization of logics for value capture plays an important role in this process. We find that consumers tend to disproportionally overlook offerings with code-violating logics for value capture defying strong boundaries in consumers' product-payment preferences in favor of offerings with code-preserving logics for value capture. Our findings seem to suggest that the identities of offerings in digital markets are established or muddied along multiple dimensions, at a minimum including their consumer value proposition and logic for value capture, encouraging us to take a closer look at processes within product categories.

Our study holds additional implications for the business model literature, where the way in which organizations and their offerings create and capture value is a principal concern (Zott, Amit, & Massa, 2011). In this stream of literature, the fact that offerings' logics for value capture may constitute multiple value-capturing mechanisms has been duly noted (Casadesus-Masanell & Zhu, 2010; Clemons, 2009; Teece, 2010). However, in grappling with its intricacies, prior research has by and large focused on the operational difficulties that may emanate from combining multiple value-capturing mechanisms (Aversa, Haefliger, and Reza, 2017; Casadesus-Masanell & Zhu, 2010; Markides, 2013), essentially leaving the consumers that eventually evaluate these choices in the product market out of consideration. Our study illustrates that also taking consumers into account can lead to new insights. Contrary to the conventional wisdom that combining multiple value-capturing mechanisms should per definition be intricate because the operations of one value-capturing mechanism detract from the operations of another value-capturing mechanism and vice versa (Lambrecht et al., 2014), our findings suggest that organizations may actually benefit from combining multiple value-capturing mechanisms in their offering's logic for value capture, as long as the combined approaches to economic value extraction do not defy strong boundaries in consumer product-payment preferences. This is an important insight, because it may help explain why organizations continue combining multiple value-capturing mechanisms in their offerings, even if prior research seems to generally strongly advocate against it. That way, our findings also clearly demonstrate the merits of adopting a demand, or consumer-centric, view in empirical management research as a complement to more conventional supply, or organization-centric, perspectives (Adner & Levinthal, 2001; Priem, 2007; Rietveld & Eggers, 2018).

The findings and inferences from our study are subject to a number of caveats that offer opportunities for future research. First, our findings are limited to a single empirical context, and their validity needs to be established across other settings. It would seem that our findings are perhaps most readily generalizable to densely populated digital or platform-mediated markets (Boudreau, 2012), such as software, music streaming, and video games. However, digitization is also rapidly changing the ways in which consumers may be asked to pay for other products such as cars or digital media (Lin et al., 2012), and it would thus be interesting to explore whether offerings' logics for value capture will play similar roles in consumer decision-making processes in such settings. Second, inherent limitations in our empirical data warrant some caution in interpreting our results. Our data constitute secondary aggregate-level observations of apps over time, implying that we are only able to observe the app downloading behavior of consumers at the level of the entire consumer audience. Data availability issues prohibit us from directly observing individual consumers in constructing their initial consideration sets, or from determining whether consumers actually actively use the offerings they download. Future research could use individual-level data or field experiments to develop a more fine-grained understanding of how consumers make sense of and choose between offerings in digital markets that harbor a colossal volume and variety of products. This could also provide further insight into how an offering's value proposition and its logic for value capture work together in shaping its identity. It might for instance be that an offering's value proposition supersedes its logic for value capture in establishing or muddying its identity, as we have implicitly assumed in this chapter.

Despite these limitations, this study advances our understanding of how offerings' logics for value capture influence downloads or sales in densely populated digital markets, where the number of offerings in any single category is simply beyond what consumers can assess. We propose and test the idea that consumers, next to relying on product categorization systems, also screen out offerings from further consideration based on their enveloped logic for value capture, as consumers tend to hold strong preferences concerning the way in which they are ought to pay for products. It is exactly because of this that the findings of our study also hold strong implications for organizations. In deciding upon their offering's logic for value capture, organizations do not merely have to be wary of the operational difficulties that may emanate from enacting certain combinations of value-capturing mechanisms, they also have to carefully consider the characteristics of the demand environment in which their offering will be set.

3

Chapter 3

The Performance Implications of Freemium and Ad-Supported Freemium Business Models in the Apple App Store*

* Earlier versions of this chapter have been presented at the Annual Meeting of the Academy of Management, Beta Conference, Munich Summer Institute, and Cass Business School. This chapter is co-authored by Joey van Angeren, Ksenia Podoynitsyna, and Fred Langerak.

Noting intense competition and low consumers' willingness to pay, app developers increasingly operate freemium rather than premium business models: they distribute a version of their app for free, then charge for premium content or features instead of simply selling the app. Despite the increasing popularity of this business model, its implications are not well understood. This chapter therefore considers how the freemium business model influences app downloads and revenue, as well as whether it might be complemented with additional income from advertising to compensate for the costs of supporting an abundance of nonpaying consumers. The dataset contains longitudinal information on 76,057 distinct apps in Apple's U.S. App Store. The results show that the freemium business model yields more downloads on average than the premium business model, but combining a freemium business model with advertising attenuates this effect. Furthermore, the revenue implications differ across app market types: compared with a premium business model, the freemium approach yields more revenue for mass market apps but less revenue for niche apps. Conversely, combining freemium business models with advertising attenuates revenues for mass market apps but improves revenues for niche apps, even if the total effect of ad-supported freemium business models tends to remain negative.

3.1 Introduction

The market for mobile devices has grown at astounding rates, with recent estimates suggesting that around 200 million people in the United States own smartphones (ComScore, 2016). This growth has been greatly enhanced by the ubiquitous availability of mobile software applications (apps). The two largest app stores, Apple's App Store and Google Play, each contain more than 2 million distinct apps, and the International Data Corporation (2016) predicts that annual app downloads will increase globally from almost 156 billion in 2015 to 210 billion in 2020, with global annual app revenues jumping from $34.2 billion to $57 billion in the same time frame.

Clearly, the apparent viability of app stores has found favor with developers. In most app categories, consumers have dozens or hundreds of competing apps from which to choose, and every day, more new apps arrive. For example, in May 2016 over 48,000 apps debuted in the Apple App Store (Sensor Tower, 2016). App stores have become markets where large, heterogeneous pools of profit-seeking firms, open source collectives, and hobbyists vie for consumers' limited attention (Eckhardt, 2016). As long-tail and superstar literatures predict though (Brynjolfsson et al., 2010; Garg & Telang, 2013), app downloads concentrate around a small number of mass market apps, that appeal to the majority of consumers, with a thick tail of specialized, obscure, niche apps that attract smaller audiences. In such markets, developers must invest their resources wisely to achieve positive returns.

So what are the best approaches to recover investments in app development once the app has been introduced? Generally, developers contemplate over the common trade-off between charging a fee, or providing indefinite access to the app for free. Intense competition and low willingness to pay in app markets have prompted the growth of the freemium business model, in which the developer provides access to its app free of charge, but it charges for additional content or features (Anderson, 2009). In most app stores, developers can do so in two ways: they can offer separate lite (free) and full-functionality (paid) versions of the same app, or they can offer the app for free but charge for in-app purchases. In either case, the business model is apparent to potential consumers, whether in the app description or through the availability of an in-app purchase menu, so it can influence their decision to download the app (Ghose & Han 2014; Liu et al., 2014).

A freemium business model likely fosters app downloads better than a conventional, premium business model that charges for access, but its influence on revenues is less clear. Average conversion rates of freemium apps (i.e., the percentage of consumers that upgrade from the lite to the full-functionality version) appear to range somewhere between 2–5% (Kumar, 2014), which means that developers confront the significant costs required to support the abundance of nonpaying consumers (Niculescu & Wu, 2014). Some developers may thus be tempted to complement their freemium business model with advertising as an additional source of revenue. The performance implications of this strategy have not been specified to date either. Yet insight into how a freemium business model affects app downloads and revenue is of critical importance to enable developers to formulate a viable digital business strategy (Bharadwaj El Sawy, Pavlou, & Venkatraman, 2013). Therefore, the objective of this study is to examine empirically the performance implications of the freemium business model. To do this, we develop and test relevant hypotheses using a unique data set that contains monthly observations of download frequency and revenue for apps in the entertainment, productivity, and utilities categories of Apple's U.S. App Store between May and December 2016.

The findings show that apps with a freemium business model get downloaded more frequently than apps with a premium business model, but this relationship is attenuated by the use of advertising as an additional source of revenue. Furthermore, the implications of the freemium business model for revenues differ for mass market versus niche apps, such that the freemium approach, compared with the premium business model, yields more revenue for mass market apps but less revenue for niche apps. In addition, when freemium apps include advertising, it results in attenuated revenues for mass market apps. Analogously, the total effect of ad-supported freemium business models remains negative for niche apps, yet in this case some synergies arise between the freemium business model and advertising.

With these findings, this study makes several contributions. First, it adds to literature on business models (Zott et al., 2011), by advancing both conceptual and empirical understanding of how different configurations of freemium business models relate to app downloads and revenues. Second, our research can inform research on long-tail markets; specifically, it represents a response to calls for more fine-grained understanding of the optimal strategy for mass market as opposed to niche apps (Brynjolfsson et al., 2010). We explicitly delineate the distinct implications of operating a freemium business model for both types of apps. Third, for literature pertaining to how product information influences adoption decisions, we show how a consumer's knowledge of an app's business model affects downloads. Fourth, we complement recent research in the app industry that focuses on antecedents of app downloads or usage (Han, Park, & Oh, 2016), by including both downloads and revenue as dependent variables. Fifth, for developers our study offers guidelines about the performance implications of different configurations of the freemium business model.

3.2 Theory and Hypotheses

In a common consumption scenario, a consumer chooses among multiple competing apps (Haubl & Trifts 2000), with a clear sense of the functionalities that the app should possess. Therefore, the apps in the initial consideration set tend to be comparable in terms of their functionality, such that they are listed in the same app category. These apps might be produced by developers who may, or may not, strive for some form of direct economic returns from their applications.

Typically, most consumers possess some information about each app, obtained from the app store and other sources such as the product information page in the app store (Ghose & Han, 2014), screenshots (Ghose, Ipeirotis, & Li, 2012), consumer reviews (Chevalier & Mayzlin 2006,), recommendations provided by the app store's recommender system (Oestreicher-Singer & Sundararajan, 2012), download behaviors indicated in the app store's sales leaderboards (Duan et al., 2009), or awards and reviews from expert critics (Wijnberg & Gemser, 2000). Consumers also have general knowledge of the app's business model, inasmuch as they know if it uses a freemium or premium business model, as well as whether it contains advertising in some cases. The availability of a free and paid version of the same app or references to in-app purchases in the app description are indicative of a freemium business model; the use of a premium business model is apparent from the upfront download price. Despite the availability of this information, the complexity of most such software products makes consumers' value assessments difficult (Bakos, 1991), such that they often possess limited or imperfect information and struggle with some uncertainty regarding the merits of each app, prior to the download decision.

3.2.1 Freemium Business Models

Consumers can resolve uncertainty fully only by experiencing the app's functionality firsthand (Shapiro & Varian, 1999). Developers therefore turn to sampling and versioning strategies, such as time-locked trials that help consumers determine their value assessments by experiencing the full functionality of the offering for a limited time, until the free trial ends. Research documents the viability of such time-restricted trials in various market conditions, including settings marked by consumers' uncertainty and network effects, as are typical in software-based industries (Cheng & Liu, 2012). Versioning also can facilitate value assessments by enabling consumers to choose, and subsequently upgrade, among multiple, vertically differentiated versions of the same product that differ in quality (Bhargava & Choudhary, 2008).

In a similar spirit, the freemium business model achieves vertical differentiation by offering indefinite access to a limited or lower quality version of the app, along with the option to upgrade to gain access to additional content or features for a fee (Baird, Miller, Raghu, & Sinha, 2016). The beneficial effects of sampling or versioning strategies thus might extend to the free app embedded in the freemium business model. In addition, these apps may benefit from consumers' tendencies to evaluate apps without upfront costs differently from paid apps. According to Shampanier, Mazar, and Ariely (2007), consumers often attach disproportionate valuations to free apps, likely due to the positive affect that zero-priced apps evoke in consumers, compared with apps with some non-zero price.

Apps with a freemium business model also might benefit from favorable perceptions associated with the availability of in-app purchases, which increase downloads. Because in-app purchase menus typically contain a variety of items, consumers may anticipate their ability to extend the functionality of the free app as they see fit (Ghose & Han, 2014) or self-select into a type of in-app purchase, depending on their usage intensity (Hui, Yoo, & Tam, 2007). For example, popular dating services typically allow consumers either to purchase credits or to subscribe to a premium service. The subscriptions should appeal to frequent users; an incidental consumer may be more inclined to upgrade by purchasing a batch of credits to use to occasionally send messages to peers. Research in games and virtual worlds similarly demonstrates the positive effects of rich in-app purchase menus that consumers can use to make their in-game characters resemble themselves (Suh, Kim, & Suh, 2011). Therefore, we anticipate that consumers are more likely to download an app with a freemium, as opposed to a premium, business model from the initial consideration set.

Hypothesis 1: *Apps with a freemium business model will yield more downloads than apps with a premium business model.*

As its underlying assumption, the freemium business model seeks to encourage downloads of the free app, in the hope that a sufficient number of consumers eventually will invest in additional content or features. Because upgrades often come in the form of subscriptions or repetitively purchased digital goods, the resulting revenues could be greater and more sustainable than one-time revenues associated with simply selling the app. Indeed, anecdotal evidence suggests that an app with a freemium business model may yield greater revenues than one with a premium business model, as signaled by the success of mass market freemium apps such as FarmVille (Baden-Fuller & Haefliger, 2013), Flickr (Teece, 2010), and Spotify (Wagner, Belian, & Hess, 2014).

Yet not all developers have been able to unlock this potential. Publishers such as The

New York Times grapple with how to configure a freemium business model, prompting many changes in how it charges for its content and how much it gives away for free (Oh, Animesh, & Pinsonneault, 2015). The configuration of freemium business models is a complex and multifaceted process. Prior studies highlight the importance of finding the right balance between what is given away for free and what is charged for in a freemium app (Kumar, 2014; Wagner et al., 2014). Research in this area also shows that a consumer's willingness to pay for an upgrade increases with community participation, underlining the importance of managing consumer communities around apps with freemium business models (Oestreicher-Singer & Zalmanson, 2013). Along similar lines, studies underscore the importance of referrals by peers, in that social contagion and word-of-mouth significantly affect consumers' decisions to upgrade (Bapna & Umyarov, 2015; Niculescu & Wu, 2014).

The characteristics of most app stores also complicate the successful operation of a freemium business model. Low search costs and the availability of many competing apps make it easy for consumers to switch, especially because they did not pay upfront and thus do not feel committed to any particular app (Bar-Isaac, Caruna, & Cunat, 2010). An app with a freemium business model thus might become a device for consumers to resolve their uncertainty about the merits of the various apps within a consideration set (Eckhardt, 2016), such that they can try out the different apps, then select a preferred option once they have better information, long before they spend anything inside the freemium app. Consequently, conversion and retention rates for freemium apps generally are low (Kumar, 2014), so accumulating a substantive consumer base appears to be a crucial precursor of unlocking the potential of the freemium business model.
Echoing the intricacy of configuring freemium business models, related findings from extant research are mixed. With an analysis of apps from sales leaderboards in Google Play, Liu et al. (2014) find that providing a free version enhances sales of a paid app. With their empirical study, Gallaugher and Wang (2002) suggest that developers that offer a free trial app can command higher prices. Yet Datta, Foubert, and Van Heerde (2015) illustrate that consumer retention rates and thus opportunities for monetization are lower among those acquired through free trials, and Niculescu and Wu (2014) analytically show that premium business models might outperform freemium ones, contingent on market conditions such as consumer priors and the strength of word-of-mouth effects.

This mixed evidence might stem from a common implicit assumption in prior research that all apps have equal market potential. In reality though, apps differ in the number of consumers who are likely to consider downloading them. As such, prior research has implicitly shied away from the important role that an app's potential to garner a large consumer base has in enabling a developer to unlock the potential of the freemium business model. Weighing in apps' market potential is particularly salient in Internet markets such as app stores, where mass market and niche apps often viably coexist (Brynjolfsson et al., 2010). That is, while these markets still tend to be dominated by a relatively small number of mass market apps that appeal to the majority of consumers (Garg & Telang, 2013), low search costs and ever-increasing variety of available applications are simultaneously conducive to more downloads of specialized, obscure, niche apps—a phenomenon more commonly referred to as the emergence of the long tail (Brynjolfsson et al., 2011).

Some recent research has explicitly discerned the consequences of such factors as word-of-mouth (Dellarocas, Gao, & Narayan, 2010; Gu, Tang, & Whinston, 2013) and recommender systems (Fleder and Hosanagar, 2009; Oestreicher-Singer and Sundararajan, 2012) for mass market and niche apps. Along similar lines, it is conceivable that the implications of app-level strategies might differ for mass market as opposed to niche apps as well (Brynjolfsson et al., 2010), and we accordingly postulate that the optimal business model, in terms of app revenue, varies across app market types. Specifically, mass market apps may be well suited to unlock the potential of the freemium business model, because they appeal to a broad audience, such that they are more widely present in consumers' consideration sets. By garnering a relatively larger number of downloads, these mass market apps should initiate a positive feedback loop, as informational cascades unleash a rich-get-richer effect. As Duan et al. (2009) illustrate, an app's appearance on sales leaderboards often prompts further periods of app download growth. Therefore, mass market apps have the potential to attract a consumer base that is large enough to mitigate the inhibiting effects of low conversion and retention rates. Thus, they should be able to accumulate more revenues from upgrades than mass market apps earn with a premium business model, because the freemium business model unlocks the potential of recurring revenue or else can command a higher price for upgrades.

Conversely, with their specialized scope and limited visibility, niche apps appeal to a subset of consumers. They are comparatively less frequently part of consumers' consideration sets and are downloaded relatively less frequently than mass market apps. In turn, niche apps with a freemium business model are unlikely to accumulate a sufficiently large consumer base to offset the inhibiting effects of low conversion and retention rates. Therefore, we expect that the revenues of niche apps with a freemium business model generally do not surpass the revenues of niche apps with a premium business model.

Hypothesis 2a: *Mass market apps with a freemium business model will yield more revenue than mass market apps with a premium business model.*

Hypothesis 2b: *Niche apps with a freemium business model will yield less revenue than niche apps with a premium business model.*

3.2.2 Ad-Supported Freemium

A developer incurs costs with each additional consumer it acquires. At a minimum, each consumer requires some server capacity or access to customer service (Kumar, 2014). As a consequence, costs may quickly rise for developers, especially if they operate a freemium business model, because consumers tend to adopt a free app quickly. For example, Spotify must pay royalties for each streamed song, regardless of whether it has been requested by a free or paying consumer. Similarly, FarmVille's gaming servers remain online for consumers that spend on digital fertilizers that expedite their progress in the game as well as for those that do not. Even though an assumption of the freemium business model is that the revenues from the fraction of paying consumers are sufficient to subsidize the costs of operating a free service for everyone else (Anderson, 2009), by now many freemium business models also rely on advertising as an additional source of revenue (Niculescu & Wu, 2014). Consumers remain skeptical of advertisements though. Targeted advertisements, in which the promotional material being displayed is contingent on consumers' prior behavior can prompt concerns about privacy. Accordingly, consumers express an increasing unwillingness to share sensitive information (Goldfarb & Tucker, 2012) and a preference for privacy-safer applications (Sutanto et al., 2013). In general, advertising also may feel intrusive or annoying, especially if developers and advertisers deliberately make it prominent by using pop-ups, animation, or other audiovisual features that make the ads hard to ignore (Goldfarb & Tucker, 2011).

Consumers can generally learn whether an app contains advertisements prior to the download decision by finding disclaimers on the app information page, noting the availability of in-app purchases that disable ads, reviewing app screenshots, or reading complaints in consumer reviews. Congruent with Ghose and Han (2014), who find that app downloads decrease with the inclusion of advertisements in both the Apple App Store and Google Play, we postulate that downloads of an app with a freemium business model will be attenuated by the inclusion of advertising that functions as an additional source of revenue, because the advertising reduces consumers' value assessments. Given the vast number of competing apps within consideration sets, at least some consumers will actively switch their attention to competing apps without advertising, once they learn that a freemium app contains advertising. Hence, we postulate the following.

Hypothesis 3: *The positive association between a freemium business model and downloads will be attenuated by the inclusion of advertising as an additional source of revenue.*

Similarly, including advertisements may attenuate the association between operating a freemium business model and revenue for mass market apps. Consumers rely on the free app embedded in the freemium business model to reduce their uncertainty, but their firsthand experiences with the app's functionality are not always positive (Sriram, Chintagunta, & Manchanda, 2015), especially if it contains annoying or intrusive advertising that negatively affects the free trial experience (Foubert & Gijsbrechts, 2016). Thus, at least some consumers who would have converted into paying consumers may prematurely back out of using the app before ever upgrading, thereby limiting the pay-offs of the freemium business model. Meanwhile, each additional free consumer provides only marginal advertising income; revenues per click or impression are generally low. Even if the advertising revenue earned by mass market apps eventually becomes relatively large given the size of their potential consumer base, we expect that it generally is insufficient to offset the revenue lost from a lack of upgrades.

Because niche apps generally have a smaller potential market, they usually generate fewer downloads, such that the loss of consumer revenues due to the inclusion of advertisements might be smaller than that for mass market apps. The additional revenue from advertising analogously will be smaller for niche apps, but it still might in this case be sufficient to offset the lost revenue from upgrades. Put differently, niche apps with a freemium business model may partially compensate for their relatively few paying consumers with additional income from advertising. We therefore expect that niche apps with a freemium business model might partially, additively, benefit from the inclusion of advertising as an additional source of revenue.

Hypothesis 4a: *For mass market apps, the interaction between the freemium business model and the inclusion of advertising as an additional source of revenue will be negatively associated with app revenue.*

Hypothesis 4b: *For niche apps, the interaction between the freemium business model and the inclusion of advertising as an additional source of revenue will be positively associated with app revenue.*

3.3 Data and Methods

3.3.1 Research Context

We explore our theoretical propositions in the context of the U.S. market of Apple's App Store. It offers an attractive research setting for this empirical study for three main reasons. First, it is economically significant. According to Gartner (2016), mobile devices that run on Apple's iOS mobile operating system account for approximately 13% of the entire mobile industry. To date, Apple has paid out more than $40 billion to developers (Apple, 2016), and industry reports suggest that mobile users spend twice as much in Apple's App Store than in Google Play (Appsflyer, 2016). Second, iOS users can only download apps through the App Store, whereas Android users may turn to either Google Play or third-party app stores.[11] So by focusing on Apple's platform, we avoid needing to account for the potentially confounding effects of downloads that originate from other app stores for the same operating system. Third, the App Store typically resembles other product repositories on the Internet, with various categories that present consumers with a wide variety of competing apps. It also offers access to information, in the form of app information pages, consumer reviews, sales leaderboards, and recommendations from recommender systems, to aid consumers' decision making.

3.3.2 Data

We test our hypotheses with a unique longitudinal dataset, featuring monthly observations of apps listed within the entertainment, productivity, or utilities categories in the U.S. Apple App Store between May and December 2016. For our research purposes, we include only those apps whose business model seeks direct economic returns from the App Store. The U.S. market contains apps in languages other than English, but because we rely on an automated content analysis in the operationalization of some of our variables (Short et al., 2010), we dropped non-English language apps, resulting in a data set of 463,474 observations on 76,057 distinct apps. At the start of each month, we used the App Store's application programming interface (API) to determine what information would be available to consumers browsing the App Store. Thus we constructed a longitudinal data set with an extensive list of app characteristics, consumer reviews, daily sales leaderboards, selective app promotions by Apple (e.g., "Editors' Choice"), and recommendations from its recommender system.

Apple does not disclose download or revenue information for apps in its App Store. To overcome this limitation, scholars have either attempted to estimate these figures using inferences from rankings on sales leaderboards (Garg & Telang, 2013) or relied on readily-supplied estimates from companies within the industry (Ghose & Han, 2014). We followed the latter approach and obtained proprietary download and revenue estimations from Apptopia (http://www.apptopia.com), a mobile app analytics firm. Further, we hand-collected daily data about app discounting campaigns (e.g., App of the Day, App of the Week, AppAdvice, AppGratis), expert app awards (e.g., Apple Design Awards, Appy Awards, Global Mobile Awards), and expert app reviews (published by

11 For example, Android users might download apps from the Amazon Appstore, Samsung Galaxy Apps, or SlideME.

148Apps, AppAdvice, CNET, MacWorld, Mashable, and The New York Times).[12]

3.3.3 Dependent Variables

Downloads. Because we cannot observe each consumer's individual decision making, we measure *Downloads* at the collective level, consistent with much of extant empirical research in similar research settings (Duan et al., 2009; Eckhardt, 2016). We thus measure *Downloads* per app-month. Because we observe each app at the beginning of a given month, *Downloads* reflects the number of consumers that opted to download the app during this month.

Revenue. To test the association of freemium and ad-supported freemium business models with app revenue, we use revenue measured in rounded U.S. dollars, prior to deducting Apple's royalty fee[13] per app-month. Thus, the *Revenue* dependent variable reflects the sum of net direct earnings of an app from the App Store in a certain month. Because app revenue is highly skewed, we take the natural logarithm of this variable, such that it better satisfies the normal distribution assumption of most regression models (Greene, 2002).

3.3.4 Independent Variables

Freemium. The independent variable of interest is whether an app operates a freemium business model in a given month. In the App Store, developers may operate such a business model in two ways: offer separate lite (free) and full-functionality (paid) versions of the same app or else provide their application for free with in-app purchases. Prior research has typically relied on manual coding procedures to pair cross-listed lite and full-functionality versions of the same app (Ghose & Han, 2014; Liu et al., 2014), which is possible because their titles and descriptions are usually comparable; otherwise, consumers would not be able to identify the option to upgrade. However, the size of our data set made such a manual approach unfeasible. Therefore, we turned to text mining and devised an automated procedure to identify and aggregate observations of cross-listed freemium apps. Specifically, with a text similarity measure, we quantify the degree of overlap in texts (i.e., title or description) associated with two apps. Congruent with existing manual coding procedures, the premise here is that the lite and full-functionality versions will contain many words in common, not only to facilitate recognition by consumers but also because these app descriptions refer to essentially the same product. For each pair of free and paid apps by a certain developer, we define their degree of

12 We selected the most influential sources, on the basis of their Alexa page rank.

13 Because consumers pay upfront download fees or in-app purchase fees directly through the App Store, Apple collects payments on behalf of developers. Apple aggregates payments per app, deducts its own royalty fees of 15% (for revenue from subscriptions with durations of more than one year) or 30% (all other direct app revenue), and pays the remaining revenue to the developers.

overlap as the cosine similarity of their associated texts (Salton & McGill, 1986). If W_f and W_p represent the word frequency distributions of a text associated with a free and paid app, respectively, and K is the number of distinct words used in either text, their cosine similarity can be written as follows:

$$similarity(f,p) = \frac{w_f \cdot w_P}{||w_f||\ ||w_P||} = \frac{\sum_{k=1}^{K} w_{f,k} w_{p,k}}{\sqrt{\sum_{k=1}^{K}(w_{f,k})^2}\sqrt{\sum_{k=1}^{K}(w_{p,k})^2}} \tag{3.1}$$

The cosine similarity ranges from 0 to 1, where higher values represent more overlap. The measure equals 0 if and only if two texts do not share any common words; it is 1 if and only if two texts share the same words with the same frequency. To allow for some dissimilarity in the texts associated with cross-listed versions of the same app,[14] we set a threshold at 0.7 and aggregated observations of free and paid apps for which the cosine similarity value, for both titles and descriptions, was equal to or greater than this threshold. For example, in our data set the cross-listed freemium app Tiny Calendar by Appxy appears as two separate apps: "Tiny Calendar–Sync with Google Calendar" and "Tiny Calendar Pro–Sync with Google Calendar." In turn, the *Freemium* indicator variable is coded 1 if we detect and aggregate cross-listed lite and full-functionality versions of the same app, or if we identify an app that is free with in-app purchases, and 0 otherwise.

Advertising. The *Advertising* indicator variable was coded with an automated content analysis of the app title, description, and in-app purchase menu (Short et al., 2010). This, because consumers may infer the use of advertisements from the presence of disclaimers or the availability of upgrades in the in-app purchase menu that disable ads. Content analysis is well-suited to transform the meaning of text into objective data (Duriau et al., 2007), so we devised a dictionary of keywords that makes the inclusion of advertising apparent. We relied on both inductive and deductive procedures to craft these dictionaries (Krippendorff, 2004; Short et al., 2010). Specifically, we first randomly sampled 200 apps from the sales leaderboard that indicated the most popular free apps and manually coded whether each app included advertising. For those that did, we compiled a list of frequently occurring words that in some way related to the inclusion of advertising. Then we extended the dictionary with terms such as "iAd"[15] that by definition should be associated with the use of advertising. The resulting dictionary with

14 Developers often use terms such as "full," "premium," or "pro" in app titles to designate a full-functionality version of a cross-listed app. They also tend to use the description of the lite version of a cross-listed app to make consumers aware of the option to upgrade, by downloading the app's full-functionality counterpart.

15 Discontinued in July 2016, iAd previously was Apple's mobile advertising platform.

keywords looked as follows.
ad, ads, advert, adverts, advertise, advertised, advertisement, advertisements, advertising, advertize, advertized, advertizement, advertizements, advertizing, iad, iads, noad, noads**[16]

We took several steps to assess the validity of our dictionary. First, we performed a keyword-in-context analysis to evaluate the relevance of different keywords and their usefulness in the text corpus under study (Krippendorff, 2004). We randomly sampled 200 apps from our data set and manually recorded the occurrence of all keywords, along with their context (i.e., the sentence in which the keyword appeared). This analysis prompted us to control explicitly for negations (e.g., "no ads"). Second, we manually coded another random sample of 300 apps and computed the correlation between manual and computer-coded outcomes generated on the basis of our created dictionary. The correlation was 0.92 ($p < 0.001$), well above the commonly accepted reliability threshold (Short et al., 2010).

3.3.5 Control Variables

App characteristics. Downloads for apps in the same category likely correlate (Duan et al., 2009; Han et al., 2016). Generally, they provide similar functionalities and thus jointly vie for downloads from the same group of consumers. The revenue of apps in a category also might be correlated in the same way. Therefore, we created indicator variables (*Categories*) for the different app categories in our dataset. We also accounted for the content rating of apps (*ContentRating*) and their compatibility with iPad, iPod, iPhone, and Apple Watch devices (*Compatibility*). Apps vary in their file size and updates, and consumers likely prefer apps that are not excessive in size but that are well maintained. Therefore, we included two continuous variables, *FileSize* and *Update*, that capture the app's file size in megabytes and the number of days since its most recent version was released, respectively. Consumers could develop a preference for applications from a certain developer, so to account for the consequences of such spillovers for app downloads and revenue, we include *AppsByDeveloper* as a measure of the total number of apps produced by a developer. Because consumers might be more prone to consider downloading an app if it is discounted (Niculescu & Wu, 2014), we include an indicator variable *Discount* that captures whether an app was discounted on any day of a given month, as signaled by its identification as App of the Day, App of the Week, AppAdvice, or AppGratis. Bundling multiple apps and selling them together at a discount instead might adversely affect downloads and revenues of the individual apps, so the *Bundles* variable measures the number of bundles in which an app is included.

16 Keywords with an asterisk are only used when we identify cross-listed lite (free) and full-functionality (paid) versions of the same app. With cross-listed apps, an explicit mention that the full-functionality version does not contain advertising likely implies that the lite version does. For the same reason, we do not account for negations in the app descriptions of full-functionality app cross-listings.

App information. A developer provides textual and visual information about its apps through the app information page in the App Store. Providing extensive information tends to be positively associated with a consumer's download decision, because the developer can better convey the app's value proposition and thus aids consumers' value assessments (Ghose & Han, 2014; Ghose et al., 2012). With *AppDescription*, we capture the number of words in the app description; with *AppScreenshots*, we account for the number of screenshots displayed.

Word-of-mouth. Consistent with prior research (Eckhardt, 2016; Ghose & Han, 2014), we control for the volume and valence of consumer reviews. To this end, *ConsumerRatings* measures the cumulative number of consumer ratings. As is common online, consumers might rate apps with scores between one and five stars. Not all apps attract consumer ratings though, so we include a vector of indicator variables (*ConsumerRating*) for different app rating levels, rather than a continuous rating measure. In line with the word-of-mouth literature (Chevalier & Mayzlin, 2006), we expect both variables to enhance app downloads and revenue.

Recommender systems. The App Store uses a "co-purchase" network to direct consumers' attention to particular apps. On each app information page, Apple prominently displays hyperlinks to the apps most frequently downloaded with the focal app, under the title "Customers Also Bought…." Extant research conjectures that such peer-based recommendations in product repositories on the Internet benefit downloads and revenues of either mass market (Fleder & Hosanagar, 2009) or niche (Oestreicher-Singer & Sundararajan, 2012) apps. We use *TimesCoPurchase* to capture the number of times an app appeared as co-purchase in a given month.

Sales leaderboards. The App Store publishes Top Free, Top Grossing, and Top Paid leaderboards, with the most popular free, best earning, and paid apps, respectively. Consistent with prior work (Duan et al., 2009), we posit that consumers may observe their peers' download and spending behavior from these leaderboards, which then influences their decision to download or spend on an app themselves. Therefore, we include three dummy variables: *TopFree*, *TopGrossing*, and *TopPaid*. They denote whether an app was listed among the top 1000 free, best earning, or paid apps during a given month, respectively.

Recognition by expert critics. Consumers rely on expert judgements to make decisions (Wijnberg & Gemser, 2000). Developers thus seek to get their apps on the radars of the editors of the App Store, technology blogs, or traditional media to foster their apps' downloads or increase their revenue. The implications of various types of expert recognition might differ (Gemser et al., 2008), so we include multiple variables to account for this potential positive effect. To control for the potential reinforcing effect of selective promotion within the App Store, we create two indicator variables, *EditorsChoice* and *Essentials*, that denote whether an app appears as an Editors' Choice or an essential app, respectively. Analogously, with the indicator variables *Award*, *Feature*, or *Review*, we discern the effects of three distinct forms of expert recognition in technology blogs. An award is synonymous with recognition, in the form of an Apple Design Award, Appy Award, or Global Mobile Award, granted on the basis of an app's excellence. We code this variable as far back as May 2015, because receiving an award may have an enduring performance effect. For feature, we determine if an app appeared in an article, without explicit quantitative or qualitative quality appraisals, in 148Apps, AppAdvice, CNET, MacWorld, Mashable, or *The New York Times* during a given month. The indicator variable for review instead indicates whether the editors of any of these sources published an explicit quantitative or qualitative appraisal. Again, we code the indicator variable for reviews back to May 2015, because of the likely enduring effect of expert reviews

3.3.6 Estimation Approach

Downloads. The App Store includes a few mass market apps that are downloaded very frequently and a large number of niche apps. Thus, our data show evidence of overdispersion. The variance of *Downloads* is substantially greater than its mean (as shown in the descriptive statistics and pairwise correlations presented in Table 3.1). Our data are also characterized by an excessive amount of zeros: 143,947 observations of downloaded apps and 319,527 observations of no downloads. Simply estimating ordinary least squares (OLS) regression models thus would yield biased and inconsistent estimates (Cameron & Trivedi, 2013).

To counter the potential effects of overdispersion and excessive zeros in *Downloads*, we perform our estimations using zero-inflated negative binomial regression (Greene, 2002). This model anticipates that the App Store contains two groups of apps: those that that might be downloaded because they fall within consumers' consideration sets, and those that are outside of their initial scope of consideration to begin with. It thus explicitly accommodates for the low probability that any app gets downloaded, amid many substitutes. The zero-inflated negative binomial model relies on a joint estimation of both binary and negative binomial processes. Taken together, if we use ψ_{it} to denote the chance that app i is part of the group of apps that fall outside of a consumer's initial scope of consideration in month t, Z_{it} as the vector of variables that governs the assignment to this group, X_{it} as a vector of all independent and control variables, and β' as a vector of parameters to be estimated, the probability $\Pr(Y_{it} = y_{it} \mid X_{it}, Z_{it})$ can be

Table 3.1. Descriptive statistics and correlation matrix

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1. Downloads	1,458.63	37,896.45	0.00	1,160,000.00	1.00										
2. Revenue	621.10	56,753.06	0.00	1,870,000.00	0.44	1.00									
3. Freemium	0.26	0.44	0.00	1.00	0.05	0.01	1.00								
4. Advertising	0.11	0.32	0.00	1.00	0.03	0.00	0.32	1.00							
5. AppDescription	143.95	115.74	1.00	795.00	0.02	0.01	0.08	0.03	1.00						
6. AppsByDeveloper	61.35	181.17	1.00	2,932.00	-0.01	0.00	0.05	-0.01	-0.02	1.00					
7. AppScreenshots	3.90	1.32	1.00	6.00	0.02	0.01	0.09	0.01	0.24	0.02	1.00				
8. AppSize	33.49	111.41	0.00	3,952.64	0.01	0.00	-0.02	-0.02	-0.03	0.08	0.12	1.00			
9. Award	0.01	0.01	0.01	1.00	0.24	0.00	0.01	0.01	0.01	0.00	0.00	0.00	1.00		
10. Bundles	0.07	0.32	0.00	3.00	-0.01	0.00	-0.10	-0.05	0.01	0.01	0.04	0.05	0.00	1.00	
11. ConsumerRatings	204.34	3,611.29	0.00	329,532.00	0.28	0.34	0.06	0.03	0.03	0.01	0.02	0.00	0.02	-0.01	1.00
12. Discount	0.01	0.01	0.00	1.00	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.00
13. EditorsChoice	0.01	0.01	0.00	1.00	0.01	0.06	0.00	0.00	0.01	0.00	0.01	0.00	0.14	0.01	0.01
14. Essentials	0.01	0.02	0.00	1.00	0.18	0.26	0.01	0.00	0.02	0.00	0.01	0.01	0.08	0.01	0.18
15. Feature	0.01	0.01	0.00	1.00	0.04	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01
16. Review	0.01	0.04	0.00	1.00	0.16	0.10	0.03	0.02	0.05	-0.01	0.03	0.01	0.07	0.00	0.16
17. TimesCoPurchase	0.03	0.98	0.00	214.00	0.19	0.03	0.04	0.02	0.02	-0.01	0.02	0.01	0.10	-0.01	0.17
18. TopFree	0.01	0.05	0.00	1.00	0.34	0.12	0.06	0.04	0.03	-0.01	0.02	0.01	0.06	-0.01	0.20
19. TopGrossing	0.01	0.04	0.00	1.00	0.16	0.15	0.05	-0.01	0.05	-0.01	0.02	0.01	0.01	0.00	0.15
20. TopPaid	0.01	0.08	0.00	1.00	0.02	0.01	0.04	-0.01	0.05	-0.02	0.02	0.01	0.02	0.05	0.04
21. Update	817.15	718.57	0.00	3073.00	-0.04	-0.01	-0.23	-0.14	-0.06	0.00	-0.09	-0.07	-0.01	-0.06	-0.02

Variable	12	13	14	15	16	17	18	19	20	21
12. Discount	1.00									
13. EditorsChoice	0.00	1.00								
14. Essentials	0.00	0.00	1.00							
15. Feature	0.00	0.00	0.06	1.00						
16. Review	0.00	0.10	0.11	0.03	1.00					
17. TimesCoPurchase	0.00	0.01	0.22	0.03	0.16	1.00				
18. TopFree	0.03	0.03	0.11	0.03	0.15	0.27	1.00			
19. TopGrossing	0.00	0.04	0.15	0.06	0.06	0.09	0.21	1.00		
20. TopPaid	0.01	0.06	0.03	0.03	0.04	0.01	0.03	0.11	1.00	
21. Update	-0.01	-0.01	-0.02	-0.01	-0.03	-0.03	-0.05	-0.04	-0.06	1.00

expressed as:

$$\Pr(Y_{it} = y_{it} \mid X_{it}, Z_{it}) = \begin{cases} \psi(\beta' z_{it})[1-\psi(\beta' z_{it})]\, g(0 \mid x_{it}) & if\ y_{it}=0 \\ [1-\psi(\beta' z_{it})]\, g(y_{it} \mid x_{it}) & if\ y_{it}>0 \end{cases} \tag{3.2}$$

That is, we first estimate the probability that an app falls outside of consumers' consideration sets by means of a logit model, which is more conventionally called an inflation model. We model the probability that an app falls into the zero group as a function of several control variables that signal elements that might make an app unappealing for consumers.[17] Because consumers likely will not download apps that they have little information about, we include *AppDescription* and *AppScreenshots*. Another indicator variable, *NoRatings*, denotes whether an app received any consumer ratings, as consumers might be more skeptical of apps for which they cannot rely on word-of-mouth in their value assessments. Finally, *FileSize* and *Update* accommodate the potential influences of excessive app file sizes and a lack of app updates, respectively.

Next, we estimate the number of app downloads while taking the probable occurrence of zero counts into consideration in a full negative binomial model that contains all independent and control variables. We estimate our models with robust app-clustered standard errors to account for disturbances due to heteroscedasticity and autocorrelation (Cameron & Trivedi, 2013).

Revenue. Because we are interested in dissecting the distinct revenue implications of freemium and ad-supported freemium business models for mass market and niche apps, we perform a series of quantile regressions. Quantile regressions enable us to investigate how the effects of particular variables change along the conditional distribution of app revenue. Such analyses are common in economics and finance but rarely used by management or information systems scholars (e.g., Coad & Rao, 2008; Taylor & Bunn, 1999). In our quantile regression models, a specific conditional quantile of app revenue is expressed as a linear function of app-level independent and control variables (Koenker & Bassett, 1978). In contrast, OLS regressions consider the conditional mean of a continuous response variable as a linear function of independent and control variables. We estimate regression equations of the general form:

$$Q_\theta(\ln(y_{it}) \mid X_{it}) = \alpha_\theta\, \beta'_\theta X_{it} \tag{3.3}$$

where $ln(y_{it})$ is the natural logarithm of the revenue of app *i* in month *t*, α is the intercept,

17 We reran our zero-inflated negative binomial regressions with a full inflation model that includes all control variables as a robustness check. The estimation results are similar to those reported here.

X_{it} is a vector of independent and control variables, and β'_{θ} is the vector of parameters to be estimated at the θth percentile of the conditional distribution of app revenue, where $0 > \theta > 1$. By estimating a system of regression equations at various percentiles of app revenue, we can assess the varying impact of freemium and ad-supported freemium business models across the conditional distribution of app revenue (Koenker & Hallock, 2001). App revenue contains a lot of zeros, as the descriptive statistics in Table 3.1 reveal, so we consider the conditional distribution of app revenue only for values greater than zero, to ease the interpretation.[18] That is, due to this transformation, the 5th percentile of app revenue represents the bottom 5% of apps with revenue greater than zero. Consistent with extant work on the long tail (Brynjolfsson et al., 2010; Oestreicher-Singer & Sundararajan, 2012), we conceive of mass market and niche apps as observations that lie at opposite ends of the conditional distribution of app revenue. Mass market apps are in the upper tail; the lower tail of the distribution is populated by niche apps. Accordingly, we estimate quantile regression equations at the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of app revenue. We estimate the quantile regressions using app-clustered standard errors to account for disturbances due to autocorrelation in repeated observations on the same app (Parente & Santos Silva, 2016).

3.4 Results

3.4.1 Implications of Freemium and Ad-Supported Freemium for App Downloads

Table 3.2 contains the results for the zero-inflated negative binomial regressions with *Downloads* as the dependent variable. Variables are entered step-wise into the regressions. Model 1 presents the baseline model with control variables. Counterintuitively, the control variables in the inflation model function to identify apps that fall outside of consumers' initial scope of consideration. The large, positive coefficient for *NoRating* indicates that apps without consumer ratings are not likely to be considered, whereas apps with more screenshots and longer app descriptions have a greater likelihood of entering consumers' consideration set.

In Model 2 we add *Freemium* to test the first hypothesis, which suggests that apps with a freemium business model, on average, yield more downloads than apps with a premium business model. We use the premium business model as reference group and control for apps that rely on advertising. The positive, significant, coefficient for *Freemium* offers support for our first hypothesis ($\beta = 1.768$, $p < 0.001$). That is, on average, apps with a freemium business model yield more than six times ($e^{1.768} - 1$) as many downloads than

18 We reran the quantile regressions for the upper quantiles of the unrestricted sample as a robustness check. The estimation results are similar to the results for the restricted sample reported here.

Table 3.2. The effect of freemium and ad-supported freemium on app downloads

Variable	Model 1	Model 2	Model 3
Negative binomial			
H1: Freemium		1.768***	2.226***
		(0.041)	(0.044)
Advertising	0.964***	1.206***	2.351***
	(0.058)	(0.060)	(0.081)
H3: Freemium x Advertising			-2.101***
			(0.102)
AppDescription	-0.001	0.001	0.001*
	(0.001)	(0.001)	(0.001)
AppsByDeveloper	-0.001**	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)
AppScreenshots	0.047**	0.030*	0.026*
	(0.018)	(0.014)	(0.012)
AppSize	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Award	1.042	1.032*	0.768
	(0.554)	(0.513)	(0.515)
Bundles	-0.327***	0.008	0.110**
	(0.049)	(0.040)	(0.039)
ConsumerRatings	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Discount	1.059***	1.839***	2.004***
	(0.220)	(0.236)	(0.254)
EditorsChoice	-0.454	0.102	0.174
	(0.324)	(0.284)	(0.289)
Essentials	-0.430	-0.233	-0.288
	(0.486)	(0.428)	(0.434)
Feature	1.153*	1.335***	1.223***
	(0.489)	(0.314)	(0.346)
Review	0.910***	0.873***	0.843***
	(0.234)	(0.182)	(0.167)
TimesCoPurchase	0.348***	0.289***	0.256***
	(0.055)	(0.045)	(0.040)
TopFree	2.578***	2.564***	2.456***
	(0.101)	(0.095)	(0.086)
TopGrossing	1.241***	1.119***	1.062***
	(0.101)	(0.092)	(0.090)
TopPaid	0.638***	1.559***	1.754***
	(0.076)	(0.053)	(0.053)
Update	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Constant	2.879***	2.266***	1.635***
	(0.516)	(0.472)	(0.491)
Inflate			
AppDescription	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)

AppScreenshots	-0.056***	-0.068***	-0.076***
	(0.009)	(0.009)	(0.009)
AppSize	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)
NoRating	5.897***	4.985***	4.720***
	(0.776)	(0.319)	(0.238)
Constant	-3.319***	-2.339***	-2.008***
	(0.783)	(0.329)	(0.246)
Number of apps	76,057	76,057	76,057
Number of observations	463,474	463,474	463,474
Log Likelihood	-1,219,844	-1,209,914	-1,207,329
Wald χ^2	11,737	17,697	19,536

*** p < 0.001, ** p < 0.01, * p < 0.05.
Robust standard errors, clustered by app, are in parentheses. All models include dummy variables to capture time effects and the vectors Category, Compatibility, ContentRating, and ConsumerRating, for which the estimation results are omitted.

apps with a premium business model.

In the third hypothesis, we also predicted that the positive association of the freemium business model and downloads would be attenuated by advertising, so in Model 3 we introduce the interaction effect between *Freemium* and *Advertising*. In support of the third hypothesis, the coefficient of the interaction is negative and significant (β = -2.101, p < .001). We depict this negative interaction effect in Figure 3.1 while keeping all other variables at their means. Visual inspection and slope difference tests (Aiken & West, 1991) show that the positive associations for *Freemium* and *Advertisement* with downloads diminish when they are used in combination, lending support for the third hypothesis.

3.4.2 Implications of Freemium and Ad-Supported Freemium for App Revenue

Tables 3.3 and 3.4 contain the results of our quantile regressions for the associations of freemium and ad-supported freemium business models with app revenue. Hypotheses 2a and 2b suggest that the freemium business model yields more revenue for mass market apps and less revenue for niche apps, when compared to the premium business model. We test these hypotheses in Table 3.3. Recall that the effects of the variables may vary freely across the conditional distribution of app revenue, and that we conceive of mass market and niche apps as observations at the upper and lower tails of the conditional distribution of app revenue, respectively. The coefficient for *Freemium* is negative and significant, though it becomes positive and significant around θ = 0.90. With the premium business model again as the reference category, this evidence suggests that the freemium business model yields less revenue than the premium one for niche

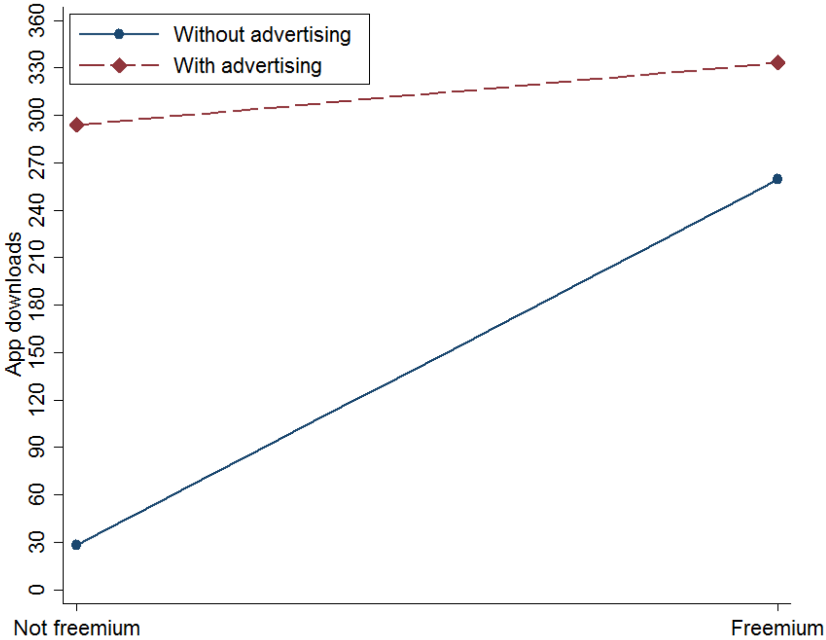

Figure 3.1. The effect of combining freemium with advertising for app downloads

apps (θ = 0.05: β = -0.717, p < 0.001), though more revenue for mass market apps, whose observations lie at the upper tail of the conditional distribution of app revenue (θ = 0.95: β = 0.273, p < 0.001), in support of hypothesis 2a and hypothesis 2b. We depict the changing effect of *Freemium* along percentiles of the conditional distribution of app revenue in the top left panel of Figure 3.22. The shaded area represents the 95% confidence interval.

Regarding the association between the freemium business model and revenue, in hypothesis 4a and hypothesis 4b we predicted it would be attenuated by advertising for mass market apps but benefit the revenues of niche apps, respectively. In Table 3.4 and the top right panel of Figure 3.2, we find support for hypothesis 4a, in that the interaction between *Freemium* and *Advertising* is negative and significant at higher quantiles (θ = 0.95: β = -0.951, p < 0.001), such that mass market apps, on average, do not benefit from the inclusion of advertising as an additional source of revenue. We depict this effect for mass market apps in the bottom left panel of Figure 3.2 at θ = 0.95. Regarding niche apps, the regression results indicate a positive interaction effect between *Freemium* and *Advertising* at lower quantiles (θ = 0.05: β = 0.951, p < 0.001). To interpret the meaning of this effect, in the bottom right panel of Figure 3.2 we depict the interaction effect for niche apps at θ = 0.05. Slope difference tests reveal that the interaction with *Advertising* significantly enhances the effect of *Freemium* at the lower quantiles, in support of hypothesis 4b. Meanwhile, the linear predictions suggest that the total effect of the ad-supported freemium business model remains negative (bottom right panel, Figure 3.2).

3.4.3 Robustness Checks

We test a number of alternative models and different variable specifications to assess the robustness of our findings. First, even though the within-app variance of *Freemium* and *Advertisement* is less than two percent, it might be that the estimated coefficients reflect within-app rather than between-app variation. To this purpose, we repeat our analyses for each month individually. We find that the results of these cross-sectional regressions are similar to the ones reported here.

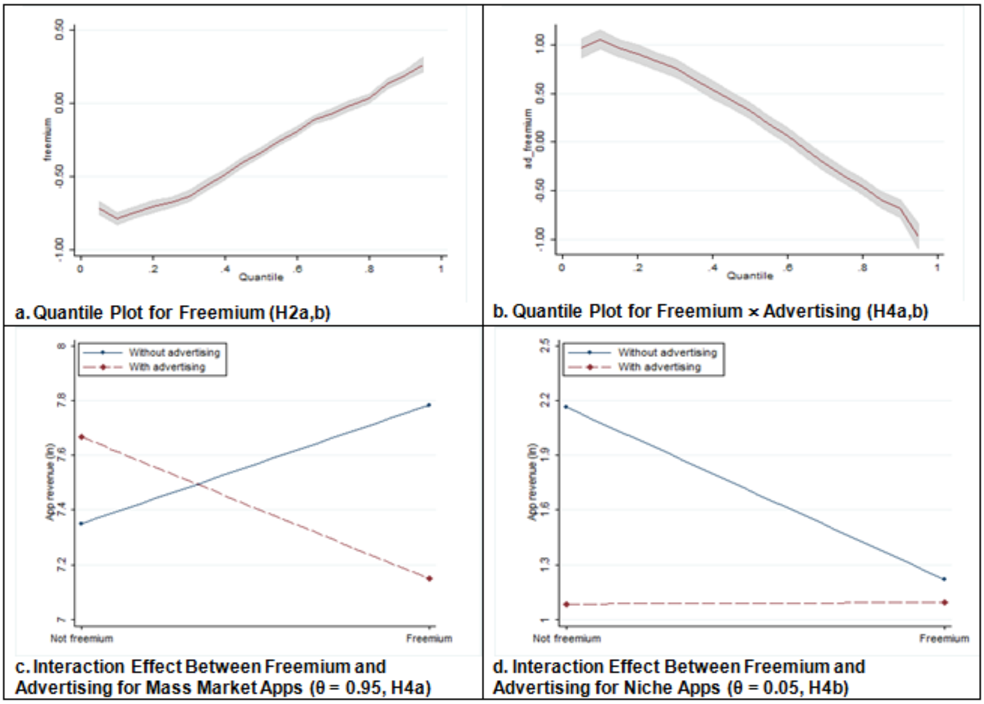

Figure 3.2. Quantile and interaction plots for the app revenue analyses

Second, we did not include apps for which direct economic returns from the App Store were not a goal, but these apps still could influence the download counts of those apps that do seek direct economic returns. As we have argued previously, consumers likely jointly consider apps that do and apps that do not strive for direct economic returns. Therefore, we repeat our zero-inflated negative binomial regressions but include the apps that do not seek direct economic returns from the App Store as a robustness check

Table 3.3. The effect of freemium on app revenue

Variable	Model 4 0.05	Model 5 0.10	Model 6 0.25	Model 7 0.50	Model 8 0.75	Model 9 0.90	Model 10 0.95
H2a,b: Freemium	-0.727***	-0.795***	-0.688***	-0.326***	-0.019	0.196***	0.273***
	(0.031)	(0.035)	(0.037)	(0.044)	(0.041)	(0.043)	(0.061)
Advertising	-0.579***	-0.730***	-0.822***	-0.789***	-0.638***	-0.399***	-0.230**
	(0.030)	(0.033)	(0.041)	(0.050)	(0.053)	(0.055)	(0.081)
AppDescription	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AppsByDeveloper	-0.001	-0.001	-0.001***	-0.001**	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AppScreenshots	0.031***	0.049***	0.061***	0.061***	0.043***	0.034**	0.040*
	(0.009)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)	(0.016)
AppSize	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Award	-0.339	-0.989***	-0.782	0.317	0.539	0.385	0.238
	(0.188)	(0.281)	(1.163)	(1.050)	(0.422)	(0.249)	(0.490)
Bundles	0.246***	0.292***	0.286***	0.289***	0.223***	0.123**	0.058
	(0.043)	(0.043)	(0.039)	(0.036)	(0.031)	(0.038)	(0.036)
ConsumerRatings	0.001	0.001***	0.001***	0.001**	0.001***	0.001**	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discount	0.882*	0.937***	0.343	0.136	-0.083	-0.127	-0.540**
	(0.343)	(0.148)	(0.317)	(0.241)	(0.129)	(0.147)	(0.169)
EditorsChoice	-0.158	1.567	1.355***	0.844	1.020**	0.331*	-0.005
	(1.503)	(0.876)	(0.290)	(0.997)	(0.275)	(0.150)	(0.619)
Essentials	1.205**	0.806*	0.500	0.292	0.273	1.979*	2.013***
	(0.999)	(0.312)	(0.882)	(1.062)	(1.108)	(0.784)	(0.187)
Feature	1.702	1.060*	0.925	0.297	0.124	0.319	0.163
	(0.966)	(0.485)	(0.555)	(0.226)	(0.290)	(0.251)	(0.138)
Review	0.411	0.963**	0.836**	0.985***	0.788***	0.458**	0.420
	(1.225)	(0.330)	(0.261)	(0.234)	(0.152)	(0.118)	(0.291)
TimesCoPurchase	0.025	0.026***	0.024***	0.049***	0.074**	0.143***	0.173***
	(0.063)	(0.006)	(0.005)	(0.008)	(0.025)	(0.035)	(0.025)
TopFree	2.502***	2.583***	2.451***	2.003***	1.618***	1.219***	1.072**
	(0.476)	(0.350)	(0.187)	(0.142)	(0.129)	(0.114)	(0.477)
TopGrossing	3.498***	3.478***	3.569***	3.465***	2.988***	2.553***	2.316***
	(0.350)	(0.253)	(0.175)	(0.156)	(0.131)	(0.143)	(0.231)
TopPaid	3.428***	3.276***	2.815***	2.415***	2.044***	1.982***	1.874***
	(0.088)	(0.068)	(0.058)	(0.059)	(0.060)	(0.093)	(0.119)
Update	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.445	0.952*	1.817***	2.793***	3.792***	4.585***	4.719***
	(0.458)	(0.405)	(0.364)	(0.776)	(0.391)	(0.407)	(0.664)
Number of apps	28,550	28,550	28,550	28,550	28,550	28,550	28,550
Number of observations	112,171	112,171	112,171	112,171	112,171	112,171	112,171
Pseudo R^2	0.239	0.259	0.286	0.301	0.289	0.260	0.239

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

All models consider the conditional distribution of app revenue greater than zero. Robust standard errors, clustered by app, are in parentheses. All models include dummy variables to capture time effects and the vectors Category, Compatibility, ContentRating, and ConsumerRating, for which the estimation results are omitted.

Table 3.4. The effect of ad-supported freemium on app revenue

Variable	Model 11 0.05	Model 12 0.10	Model 3 0.25	Model 14 0.50	Model 15 0.75	Model 16 0.90	Model 17 0.95
H2a,b: Freemium	-0.943*** (0.035)	-1.007*** (0.038)	-0.812*** (0.043)	-0.385*** (0.049)	0.030 (0.043)	0.303*** (0.047)	0.433*** (0.063)
Advertising	-1.078*** (0.035)	-1.300*** (0.045)	-1.282*** (0.056)	-0.981*** (0.065)	-0.443*** (0.074)	-0.023 (0.077)	0.316** (0.105)
H4a,b: Freemium x Advertising	0.951*** (0.054)	1.044*** (0.069)	0.809*** (0.085)	0.326** (0.097)	-0.333** (0.102)	-0.695*** (0.109)	-0.951*** (0.156)
AppDescription	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
AppsByDeveloper	-0.001* (0.000)	-0.001 (0.001)	-0.001** (0.000)	-0.001** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
AppScreenshots	0.032*** (0.009)	0.051*** (0.010)	0.059*** (0.011)	0.061*** (0.011)	0.044*** (0.012)	0.036** (0.012)	0.042** (0.016)
AppSize	0.001* (0.000)	0.001*** (0.000)	0.001** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Award	-0.304 (0.199)	-0.966*** (0.180)	-0.404 (1.848)	0.349 (1.036)	0.480 (0.419)	0.268 (0.264)	0.066 (0.498)
Bundles	0.235*** (0.038)	0.270*** (0.038)	0.270*** (0.040)	0.285*** (0.035)	0.226*** (0.031)	0.139*** (0.037)	0.073 (0.037)
ConsumerRatings	0.001 (0.001)	0.001*** (0.000)	0.001*** (0.000)	0.001** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Discount	0.818** (0.254)	0.779 (0.568)	0.340 (0.472)	0.117 (0.174)	0.138 (0.107)	-0.258 (0.138)	-0.488 (0.452)
EditorsChoice	0.453 (0.924)	1.702 (0.920)	1.281*** (0.224)	0.869 (1.068)	1.020*** (0.279)	0.385* (0.164)	0.213 (0.530)
Essentials	1.178 (0.604)	0.798*** (0.163)	0.462 (0.853)	0.238 (1.081)	0.259 (1.103)	1.914* (0.785)	2.043*** (0.160)
Feature	1.641*** (0.324)	1.106*** (0.208)	1.044*** (0.317)	0.292 (0.229)	0.051 (0.167)	0.316 (0.240)	0.228 (0.126)
Review	0.514*** (0.313)	0.897** (0.398)	0.818** (0.252)	0.949*** (0.250)	0.784*** (0.175)	0.444*** (0.117)	0.343 (0.289)
TimesCoPurchase	0.028** (0.010)	0.027*** (0.004)	0.025*** (0.006)	0.051*** (0.009)	0.073* (0.027)	0.135*** (0.039)	0.174*** (0.044)
TopFree	2.625*** (0.256)	2.708*** (0.224)	2.439*** (0.216)	2.042*** (0.166)	1.624*** (0.143)	1.303*** (0.086)	1.089*** (0.190)
TopGrossing	3.566*** (0.289)	3.482*** (0.185)	3.589*** (0.197)	3.464*** (0.166)	2.974*** (0.131)	2.508*** (0.131)	2.293*** (0.241)
TopPaid	3.380*** (0.111)	3.242*** (0.060)	2.419*** (0.059)	2.411*** (0.059)	2.053*** (0.057)	2.031*** (0.093)	1.870*** (0.109)
Update	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Constant	0.555 (0.464)	0.941** (0.310)	1.668* (0.686)	2.842* (1.276)	3.775*** (0.429)	4.496*** (0.514)	4.333*** (0.697)
Number of apps	28,550	28,550	28,550	28,550	28,550	28,550	28,550
Number of observations	112,171	112,171	112,171	112,171	112,171	112,171	112,171
Pseudo R^2	0.236	0.255	0.285	0.301	0.288	0.258	0.233

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

All models consider the conditional distribution of app revenue greater than zero. Robust standard errors, clustered by app, are in parentheses. All models include dummy variables to capture time effects and the vectors Category, Compatibility, ContentRating, and ConsumerRating, for which the estimation results are omitted.

(n = 185,140); the association between *Freemium* and app downloads remains positive and significant, while the interaction effect between *Freemium* and *Advertising* remains negative and significant.

Third, in our quantile regressions, we considered how the effect of freemium or ad-supported freemium business models changes along the conditional distribution of app revenue. However, recent advances in econometrics suggest that, because conditional quantiles do not always produce averages that are equivalent to their unconditional counterparts, the estimates from our conditional quantile regressions might not necessarily be used to assess the impact of an explanatory variable of interest on the unconditional (i.e., marginal) distribution of app revenue (for a detailed discussion, see Firpo, Fortin, & Lemieux, 2009). Therefore, we test a system of unconditional quantile regressions, following procedures outlined by Firpo et al. (2009) to address these concerns. The results are robust to this procedure: *Freemium* is negatively associated with app revenue at the lower unconditional quantiles, but this association becomes positive at the 90^{th} percentile. The coefficient of the interaction between *Freemium* and *Advertising* is positive at lower quantiles but becomes negative later on.

Fourth, a developer's choice to operate a particular business model might reflect factors that are unobserved in the data. Therefore, we use an instrumental variables approach to address potential endogeneity concerns. In particular, we use two indicator variables that should correlate with a developer's choice for a freemium business model, but not with app downloads or revenue. The first indicator variable, *ForProfit*, denotes whether a developer is profit-seeking. The rationale for using this variable as an instrument is that even if profit-seeking firms and those not necessarily motivated by profits may produce apps that are of sufficient quality to enter consumers' consideration sets, they likely differ in their propensity to operate according to a particular business model (Fitzgerald, 2006; Luthje, Herstatt, & Von Hippel, 2005). We operationalize this measure by training a naïve Bayesian classifier to categorize developer names (Das & Chen, 2007).[19] The second instrumental indicator variable, *MultipleAppsByDeveloper*, describes whether a developer produced multiple apps. The logic for this variable is that it captures cross-developer differences in aspiration levels, which likely influence their business model considerations (Ocasio & Radoynovska, 2016). To instrument the interaction between *Freemium* and *Advertising*, we use the interaction terms between our two instruments and *Advertising* as additional instruments (Wooldridge 2002). For app downloads, we perform the instrumental variables analysis using GMM-style instruments in a count data model (Cameron & Trivedi, 2013), while for app revenue we apply the instrumental variables estimator for conditional quantile regression by Chernozhukov and Hansen

19 We train the naïve Bayesian classifier on a pre-classified set of 1,500 developer names, and further augment it with a list of corporate affixes and suffixes.

(2008) that allows estimations including multiple endogenous indicator variables. We observe that our results are robust to this instrumental variables approach.

3.4.4 App Heterogeneity

We have thus far assumed that apps in the same app category are substitutes, but this assumption might not always be reasonable. A consumer generally lacks the knowledge or time to sift through more than 40,000 apps to find a productivity offering, for example. They likely screen out categories that do not match their needs; for example, the productivity category contains apps for purposes such as cloud storage, managing to-do lists, note taking, password management, reminders, and translating. Any particular app thus likely experiences the most competition from those other apps in the same app category that offer similar functionality, since those are the apps that a consumer will jointly consider.

In turn, we rely on topic modeling as a statistical text mining technique to uncover the latent topics that developers convey through an elaboration of app functionalities in textual descriptions of their app, then cluster apps with a similar topic distribution. Thus we can construct a more fine-grained perspective on which apps jointly appear in a consumers' consideration sets. Topic modeling approaches, such as the unsupervised Bayesian inference-based Latent Dirichlet Allocation (LDA) algorithm implemented here, are generative in the sense that they assume each word in a text document gets drawn probabilistically from the vocabulary of a topic contained in that document (Blei, Ng, & Jordan, 2003). An exhaustive description of LDA is beyond the scope of this article (see Shi, Lee, & Whinston, 2016), but our inclination here is that because app descriptions are a main means for developers to communicate their app's merits to prospective consumers, developers have a strong incentive to provide a thorough overview of the app's functionalities. The app's description then could be thought of as a textual representation of the functionality that the app offers, and therefore we interpret the latent topics that we uncover by means of LDA as different dimensions of this app.

Our topic modeling approach for each app category proceeds according to the following steps. First, we preprocess the app descriptions for all apps in the category. From each description, we remove stop words (e.g., "the," "and," "a"), punctuation, non-English words, and the keywords that we used to operationalize *Advertising*, which have no meaningful role in the description of app functionalities. Second, we use LDA to generate a list of K topics with a vector of words weighted by their importance to the topic and a list of vectors with topic loadings for these K topics per app description, where K is a parameter to be specified by the researcher. We run the LDA model for a different K values (100, 200, and 500), but the results are comparable, so we only report the results for $K = 500$ here. To demonstrate that the topic model results reflect meaningful dimensions of an app, we present ten topics and their five most contributing keywords in Table 3.5. Third, we compute the dissimilarity between each pair of apps as the cosine distance (that is, 1 – cosine similarity) of their corresponding topic distributions. Fourth, we use this dissimilarity measure to group apps with similar topic distributions, using a hierarchical agglomerative clustering algorithm (Manning & Schutze^, 1999). The resulting set of clusters corresponds to different subcategories of apps that a consumer may jointly consider.

Because our data now describe repetitive observations on apps that are grouped in subcategories, we use hierarchical linear models (Raudenbusch & Bryk, 2002) to assess the association of freemium and ad-supported freemium business models with downloads. We model individual observations to be nested within apps and apps to be nested within subcategories and use the natural logarithm of *Downloads* (that is, 1 – ln(*Downloads*) to retain zeros) as the dependent variable. Further, we include random intercepts for both subcategories and individual apps. In Table 3.6, we present the results from this hierarchical linear model. We observe that the results are qualitatively similar to those from the zero-inflated negative binomial regressions. Table 3.7 and 3.8 present the results of the conditional quantile regressions in which we now cluster the standard errors by subcategory. Again, we note that the results are similar to the ones that do not account for app-level heterogeneity.

Table 3.5. Fragment of the LDA output for the productivity app category

Topic	Highest contributing keywords
4	receive, status, alert, push, update
8	tutorial, basic, course, excel, beginner
10	task, manager, list, complete, due
14	measure, object, signal, frequency, angle
28	manage, employee, system, time, use
179	event, member, guest, attend, invite
189	payment, balance, financial, pay, bank
194	note, take, notebook, use, create
196	document, file, format, open, view
198	control, device, connect, remote, computer

Table 3.6. Effect of freemium and ad-supported freemium on app downloads (app-level heterogeneity)

Variable	Model 18	Model 19	Model 20
H1: Freemium		0.624***	0.799***
		(0.013)	(0.015)
Advertising	0.939***	0.801***	1.200***
	(0.016)	(0.016)	(0.022)

H3: Freemium x Advertising			-0.791***
			(0.030)
AppDescription	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
AppsByDeveloper	-0.001*	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)
AppScreenshots	0.039***	0.029***	0.029***
	(0.004)	(0.004)	(0.004)
AppSize	0.001*	0.001*	0.001*
	(0.000)	(0.000)	(0.000)
Award	0.068	0.122	0.078
	(0.244)	(0.243)	(0.243)
Bundles	0.102***	0.136***	0.144***
	(0.013)	(0.013)	(0.013)
ConsumerRatings	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Discount	1.105***	1.153***	1.131***
	(0.111)	(0.111)	(0.111)
EditorsChoice	2.662***	2.791***	2.872***
	(0.554)	(0.547)	(0.547)
Essentials	0.549	0.575	0.563
	(0.415)	(0.411)	(0.410)
Feature	0.508*	0.516**	0.512**
	(0.237)	(0.236)	(0.216)
Review	1.128***	1.113***	1.097***
	(0.107)	(0.107)	(0.106)
TimesCoPurchase	0.037***	0.038***	0.037***
	(0.003)	(0.003)	(0.003)
TopFree	1.708***	1.701***	1.689***
	(0.053)	(0.053)	(0.053)
TopGrossing	0.559***	0.552***	0.554***
	(0.053)	(0.052)	(0.052)
TopPaid	0.688***	0.730***	0.736***
	(0.028)	(0.028)	(0.028)
Update	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Constant	1.692***	1.671***	1.646***
	(0.171)	(0.169)	(0.169)
Number of apps	76,057	76,057	76,057
Number of observations	463,474	463,474	463,474
Log Likelihood	-754,686	-753,559	-753,221
Wald χ^2	133,454	138,234	139,254

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Robust standard errors are in parentheses. All models include dummy variables to capture time effects and the vectors Category, Compatibility, ContentRating, and ConsumerRating, for which the estimation results are omitted.

Table 3.7. Effect of freemium on app-revenue (app-level heterogeneity)

Variable	Model 21 0.05	Model 22 0.10	Model 23 0.25	Model 24 0.50	Model 25 0.75	Model 26 0.90	Model 27 0.95
H2a,b: Freemium	-0.727***	-0.795***	-0.688***	-0.326**	-0.019	0.196*	0.273*
	(0.058)	(0.082)	(0.093)	(0.107)	(0.094)	(0.098)	(0.131)
Advertising	-0.579***	-0.730***	-0.822***	-0.789***	-0.638***	-0.399***	-0.230*
	(0.028)	(0.042)	(0.057)	(0.060)	(0.067)	(0.065)	(0.096)
AppDescription	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AppsByDeveloper	-0.001	-0.001	-0.001**	-0.001*	-0.001*	-0.001***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AppScreenshots	0.031**	0.049***	0.061**	0.061**	0.043*	0.034*	0.040*
	(0.011)	(0.013)	(0.019)	(0.020)	(0.017)	(0.015)	(0.019)
AppSize	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Award	-0.339*	-0.989***	-0.782	0.317	0.539	0.385	0.238
	(0.165)	(0.255)	(1.005)	(1.015)	(0.428)	(0.242)	(0.582)
Bundles	0.246***	0.292***	0.286***	0.289***	0.223***	0.123**	0.058
	(0.044)	(0.045)	(0.041)	(0.042)	(0.050)	(0.044)	(0.052)
ConsumerRatings	0.001*	0.001***	0.001***	0.001**	0.001**	0.001*	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discount	0.882*	0.937***	0.343	0.136	-0.083	-0.127	-0.540**
	(0.375)	(0.168)	(0.403)	(0.241)	(0.139)	(0.171)	(0.179)
EditorsChoice	-0.158	1.567	1.355***	0.844	1.020***	0.331*	-0.005
	(1.323)	(0.811)	(0.260)	(0.810)	(0.207)	(0.153)	(0.716)
Essentials	1.205**	0.806	0.500	0.292	0.273	1.979*	2.013***
	(1.006)	(0.442)	(0.898)	(1.334)	(1.183)	(0.778)	(0.177)
Feature	1.702	1.060	0.925	0.297	0.124	0.319	0.165
	(0.925)	(0.584)	(0.492)	(0.199)	(0.297)	(0.171)	(0.130)
Review	0.411	0.963**	0.836**	0.985**	0.788***	0.458***	0.420
	(1.116)	(0.283)	(0.263)	(0.290)	(0.148)	(0.094)	(0.308)
TimesCoPurchase	0.025	0.026**	0.024***	0.049***	0.074*	0.143***	0.173***
	(0.060)	(0.008)	(0.006)	(0.010)	(0.031)	(0.055)	(0.037)
TopFree	2.502***	2.583***	2.451***	2.003***	1.618***	1.219***	1.072**
	(0.496)	(0.443)	(0.220)	(0.185)	(0.200)	(0.123)	(0.470)
TopGrossing	3.498***	3.480***	3.569***	3.465***	2.988***	2.553***	2.316***
	(0.324)	(0.279)	(0.189)	(0.166)	(0.204)	(0.165)	(0.257)
TopPaid	3.428***	3.276***	2.815***	2.415***	2.044***	1.982***	1.874***
	(0.101)	(0.082)	(0.059)	(0.073)	(0.069)	(0.100)	(0.114)
Update	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.445	0.914*	1.820***	2.793***	3.793***	4.585***	4.719***
	(0.399)	(0.263)	(0.347)	(0.644)	(0.365)	(0.354)	(0.661)
Number of apps	28,550	28,550	28,550	28,550	28,550	28,550	28,550
Number of observations	112,171	112,171	112,171	112,171	112,171	112,171	112,171
Pseudo R^2	0.239	0.259	0.286	0.301	0.289	0.259	0.239

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

All models consider the conditional distribution of app revenue greater than zero. Robust standard errors, clustered by subcategory, are in parentheses. All models include dummy variables to capture time effects and the vectors Category, Compatibility, ContentRating, and ConsumerRating, for which estimation results are omitted.

Table 3.8. Effect of ad-supported freemium on app-revenue (app-level heterogeneity)

Variable	Model 28 0.05	Model 29 0.10	Model 30 0.25	Model 31 0.50	Model 32 0.75	Model 33 0.90	Model 34 0.95
H2a,b: Freemium	-0.943***	-1.007***	-0.812***	-0.385**	0.030	0.303**	0.433**
	(0.065)	(0.087)	(0.101)	(0.117)	(0.100)	(0.109)	(0.133)
Advertising	-1.078***	-1.300***	-1.282***	-0.981***	-0.443***	-0.023	0.316*
	(0.054)	(0.055)	(0.070)	(0.072)	(0.093)	(0.094)	(0.131)
H4a,b: Freemium x Advertising	0.951***	1.045***	0.809***	0.326*	-0.333**	-0.695***	-0.951***
	(0.062)	(0.082)	(0.111)	(0.133)	(0.126)	(0.148)	(0.217)
AppDescription	0.001***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AppsByDeveloper	-0.001	-0.001	-0.001*	-0.001*	-0.001*	-0.001***	-0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AppScreenshots	0.032**	0.051***	0.059**	0.061**	0.044*	0.036**	0.042*
	(0.010)	(0.013)	(0.018)	(0.020)	(0.017)	(0.014)	(0.018)
AppSize	0.001	0.001***	0.001*	0.001***	0.001***	0.002***	0.002**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Award	-0.304	-0.966***	-0.404	0.349	0.480	0.268	0.066
	(0.201)	(0.153)	(1.588)	(0.971)	(0.430)	(0.304)	(0.634)
Bundles	0.235***	0.270***	0.270***	0.285***	0.226***	0.139**	0.073
	(0.037)	(0.039)	(0.041)	(0.039)	(0.050)	(0.044)	(0.048)
ConsumerRatings	0.001*	0.001***	0.001***	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discount	0.818**	0.779	0.340	0.117	0.138	-0.258	-0.488
	(0.295)	(0.603)	(0.584)	(0.176)	(0.107)	(0.157)	(0.488)
EditorsChoice	0.453	1.702*	1.281***	0.869	1.020***	0.387	0.213
	(0.856)	(0.854)	(0.214)	(0.865)	(0.215)	(0.218)	(0.717)
Essentials	1.178	0.798**	0.462	0.238	0.259	1.914*	2.043***
	(0.744)	(0.238)	(0.898)	(1.368)	(1.179)	(0.786)	(0.154)
Feature	1.641***	1.106***	1.044***	0.292	0.051	0.316*	0.228*
	(0.195)	(0.210)	(0.305)	(0.203)	(0.178)	(0.157)	(0.115)
Review	0.514	0.897**	0.818**	0.949**	0.784***	0.444***	0.343
	(0.355)	(0.322)	(0.249)	(0.317)	(0.167)	(0.099)	(0.304)
TimesCoPurchase	0.028*	0.027***	0.025***	0.051***	0.073*	0.135	0.174*
	(0.012)	(0.005)	(0.007)	(0.010)	(0.034)	(0.075)	(0.069)
TopFree	2.625***	2.708***	2.439***	2.042***	1.625***	1.303***	1.089***
	(0.315)	(0.261)	(0.259)	(0.226)	(0.213)	(0.086)	(0.197)
TopGrossing	3.566***	3.482***	3.589***	3.464***	2.974***	2.508***	2.293***
	(0.229)	(0.203)	(0.209)	(0.175)	(0.207)	(0.161)	(0.245)
TopPaid	3.380***	3.242***	2.419***	2.411***	2.053***	2.031***	1.870***
	(0.110)	(0.074)	(0.060)	(0.073)	(0.064)	(0.106)	(0.114)
Update	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.555	0.941**	1.668*	2.842**	3.776***	4.496***	4.334***
	(0.412)	(0.282)	(0.701)	(1.067)	(0.410)	(0.446)	(0.686)
Number of apps	28,550	28,550	28,550	28,550	28,550	28,550	28,550
Number of observations	112,171	112,171	112,171	112,171	112,171	112,171	112,171

Pseudo R^2	0.236	0.255	0.285	0.301	0.288	0.258	0.233

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
All models consider the conditional distribution of app revenue greater than zero. Robust standard errors, clustered by subcategory, are in parentheses. All models include dummy variables to capture time effects and the vectors Category, Compatibility, ContentRating, and ConsumerRating, for which estimation results are omitted.

3.5 Discussion

With this study, we empirically investigated the implications of freemium and ad-supported freemium business models for app downloads and revenue. We tested various theoretical predictions with a unique dataset that contains monthly information on apps in three categories in the U.S. Apple App Store, recorded during May–December 2016. Concerning app downloads, we found that the freemium business model, on average, yields more downloads than the premium business model, but this positive association is attenuated by complementing the freemium business model with advertising. Our zero-inflated negative binomial regression models to produce these results explicitly accommodate the low probability that any app will be downloaded, amid the many competing apps available.

Regarding app revenue, we anticipated that the implications of the freemium business model might differ for mass market apps, which appeal to the majority of consumers, as opposed to specialized, obscure, niche apps. Analyzing our data using quantile regressions reveals that the effect of the freemium business model changes along the conditional distribution of app revenue. It yields more revenues for mass market apps but less revenues for niche apps, compared with the premium business model. Thus, we affirm the previously overlooked importance of acquiring a large consumer base to offset the inhibiting effect of low conversion and retention rates as a means to unlock the potential of the freemium business model. Regarding ad-supported freemium business models, we found that the total effect is negative across the conditional distribution of app revenue, but the effect is especially problematic for mass market apps. Still, there are potential synergistic effects between freemium business models and advertising for niche apps situated in the lower tail of the conditional distribution of app revenue.

3.5.1 Theoretical Implications

There are several theoretical implications of our findings. First, our study informs the literature on business models, which tends to cite freemium as a canonical, successful example of an innovative business model (e.g., Baden-Fuller & Haefliger, 2013; Teece, 2010). However, limited research has been conducted to come to a nuanced understanding of the implications of the freemium business model, despite some helpful analytical contributions (Niculescu & Wu, 2014). We empirically examine the implications of the freemium business model for app downloads and revenue and thereby show that, though a freemium business model yields more downloads than a premium business model, its implications for app revenue are only favorable for mass market apps. Accordingly, we advance both theoretical and empirical understanding of how the freemium business model is associated with performance. Our results suggest a complex relationship between an app's business model and its eventual performance, adding nuance to the stream of research into the performance implications of business model configurations (Clemons, 2009; Zott & Amit, 2007). Further, by proposing and empirically showing the significant interplay between a freemium business model and advertisements, our study highlights the need to understand interactions among different components of a business model—an area that has been underexplored in prior research.

Second, the finding that the optimal business model configuration in terms of app revenue might differ for mass market versus niche apps also is of significant interest to long-tail literature. Recent work in this area notes the relative importance of market-level factors, such as word-of-mouth (Dellarocas et al., 2010; Gu et al., 2013) and recommender systems (Fleder & Hosanagar, 2009; Oestreicher-Singer & Sundararajan, 2012), for mass market versus niche apps. The distinct outcomes of app-level strategies for mass market as opposed to niche apps has been a longstanding question though (Brynjolfsson et al., 2010). Our study fills this research gap by explicitly delineating the implications of operating a freemium business model for a mass market as opposed to a niche app.

Third, our research also adds to literature that considers how the availability of product information influences consumers' download decisions. Driven by the increasing availability and sophistication of products in various industries, scholars have begun to discern the cues that consumers rely on in their value assessments of competing products, including the availability of product information (Ghose & Han, 2014), recommender systems (Oestreicher-Singer & Sundararajan, 2012), word-of-mouth (Chevalier & Mayzlin, 2006), others' download decisions (Duan et al., 2009), and critics' recognition (Wijnberg & Gemser, 2000). While controlling for these factors, we show that consumers' knowledge of an app's business model significantly influences their download decision. By considering the consequences of freemium business models, advertising, and their interaction, we can clarify the influence of some of the most popular business models for apps without any upfront download cost (Baden-Fuller & Haefliger, 2013; Clemons, 2009). In this sense, our study goes beyond a traditional research focus on app pricing (Shampanier et al., 2007) and suggests the possibility of significant heterogeneity in how consumers trade off the different business model configurations of zero-priced apps.

Fourth, more broadly our findings are of interest to the bourgeoning literature on mobile app markets. Research has proliferated in this area, mainly focused on establishing antecedents of app downloads or usage (Han et al., 2016). The lack of actual data on app revenues has hampered understanding of their eventual economic viability. Accordingly, our study complements extant research in the mobile app market by including both app downloads and revenue as dependent variables and revealing how the app's business model, together with various app and market characteristics, shape the distribution of revenue. Pursuing a more fine-grained understanding of the contributions of each variable may offer a fruitful avenue for research too.

3.5.2 Practical Implications

Our research findings have clear implications for developers. Notwithstanding the tremendous growth of the industry, many app developers still grapple with the conundrum of selecting an appropriate business model. Our findings suggest some guidelines and a benchmark regarding the average implications for app downloads and revenue when implementing a freemium business model. In particular, they likely differ for mass market as opposed to niche apps. In terms of app revenue, developers of mass market apps might find that their offerings perform better when operating a freemium business model, but the opposite is true for developers of niche apps. Our results thus provide a cautionary tale regarding the increasing surge of developers adopting freemium business models. Developers of specialized applications (e.g., drawing support for architects, measurement tools for construction workers) might be better off operating a premium business model rather than jumping the freemium bandwagon. Therefore, developers need to assess the market potential of their app carefully and factor this assessment into their selection of an appropriate business model.

Our research also addresses the implications of complementing a freemium business model with advertising, an approach that is increasingly commonplace. The practitioners' premise is that complementing both sources of revenue can help developers recover the costs of supporting an abundance of non-paying consumers. However, our rigorous empirical tests do necessarily not support this intuition; rather, our results suggest that the association between the freemium business model and app revenue is generally attenuated by the inclusion of advertising. This effect is particularly pertinent for mass market apps, which struggle to generate sufficiently large advertising revenues to compensate for the lost revenue, due to reduced upgrades in response to advertising. On the contrary, we find evidence of synergies from combining freemium business models with advertising for niche apps. Developers should thus carefully consider the potential adverse effects of advertising when configuring their freemium business models.

3.5.3 Limitations and Directions for Future Research

We acknowledge some limitations of our study that might be addressed by further research. First, we limited ourselves to considering the distinct implications of freemium and ad-supported freemium business models for app downloads and revenue, in comparison with the premium business model. However, there are other ways to leverage apps to generate direct or indirect returns from app stores. For example, developers might use their apps to affiliate between consumers and partners (e.g., Uber, Airbnb), sell data generated by their consumers (e.g., Waze), or drive consumers to particular retail channels (e.g., Amazon, Walgreens). Albeit difficult to obtain the usually proprietary data related to the economic returns of these business models, it would be interesting to gain insights into their viability. Further research also might provide a more nuanced view of how the interdependence across business models can shape outcomes in the app market (Casadesus-Masanell & Ricart, 2010).

Second, consistent with extant research (Ghose & Han, 2014; Liu et al., 2014), we operationalized the freemium business model as a dichotomous variable. But the eventual implications of the freemium business model also might be contingent on an adequate configuration of the in-app purchase menu. For example, an in-app purchase menu with multiple items might help a consumer self-select into an adequate upgrade (Hui et al., 2007). Developers may anticipate this effect by composing an attractive bundle of items available for in-app purchase. Therefore, additional research may consider how the variety and content of the in-app purchase menu moderates the relationship between the freemium business model and app downloads or revenue. Similarly, a richer operationalization can further unpack the multifaceted relationship between freemium business models and advertising. We found a positive interaction between freemium and advertising for some niche apps, yet their combined effect was still negative. Perhaps the synergies between freemium business models and advertising will be more pronounced for certain implementations; developers of video games for instance increasingly incentivize consumers' exposures to advertisements by allowing them to "earn" upgrades by viewing short promotional videos. A richer operationalization of ad-supported business models could investigate this issue.

Third, inherent limitations in our app-level data warrant some caution in the interpretation of our results. Our data cannot reveal whether multiple downloads originate from the same or different consumers. A single consumer could repetitively download and delete an app due to storage limitations or download it onto multiple devices (e.g., iPhone and iPad). Further research might address these limitations by complementing archival data with consumer surveys or clickstream data. Then we could gain a better understanding of how consumers sift through and trade off among a large number of applications.

Fourth, we conducted our study in the Apple App Store, so some caution is necessary when attempting to generalize the findings to other contexts. The freemium business model has since long held favor with developers in the mobile app industry, so consumers may have become accustomed to its benefits and drawbacks. As such, our findings might be representative of other software-based markets. But freemium business models also appear in all sorts of markets, and in some of them, consumers might be less familiar with its concepts. It would be interesting to determine how the implications of the freemium business model differ across such markets.

4

Chapter 4

Differentiation in Platform Marketplaces: An Entrant's Perspective*

* This chapter is co-authored by Joey van Angeren, Govert Vroom, Ksenia Podoynitsyna, and Fred Langerak.

There is a growing recognition that firms face opposing forces in positioning their products. Product market competitions compels firms to differentiate, while strong institutional pressures or widespread knowledge of hit products compel firms to conform. However, we know much less about the performance implications of competitive positioning in contexts where those conformity forces are less prominent. In this study we attempt to enhance our understanding of this issue in one such context; differentiation of complements by firms participating in platform marketplaces. We argue that forces to conform may also stem from demand conditions. More specifically, there is an information asymmetry between firms, who know the true value of their complements, and consumers, who do not. Consumers rely on their knowledge of competing complements to resolve this uncertainty, hence providing firms an incentive to make their complements more similar to their rivals'. Analyzing 6,984 newly introduced paid apps in the U.S. storefront of Apple's iOS App Store we provide support for this prediction, as we find an inverted U-shaped relationship between differentiation and app performance. We also show that peak performance occurs at lower levels of differentiation in markets with a greater share of rated complements, and occurs at higher levels of differentiation in markets with more paid complements.

4.1 Introduction

Competitive positioning remains of critical concern for strategy scholars investigating the origins of persistent performance heterogeneity of firms and products. At the product level of analysis, competitive positioning for firms concerns the issue of carving out unique and defensible positions for their offerings relative to rivals (Adner, Csaszar, & Zemsky, 2014). An emerging stream of literature grappling with this issue contends that firms should aim for intermediate levels of differentiation, or a point of optimal distinctiveness, when positioning their products, as they face opposing forces to differentiate and conform (Durand & Calori, 2006; Porac et al., 1989; Zhao et al., 2017; Zuckermann, 2016). Product market competition compels firms to differentiate. It allows them to stand out among competitors and that way forego the most intense rivalry (Cennamo & Santalo, 2013; Ethiraj & Zhu, 2008; Shamsie, et al., 2004). Meanwhile, at least two forces may prompt firms to more closely conform to the confines of competing products. First, in rigid contexts such as automotive and banking, strong institutional pressures by and large dictate what products should look like and which attributes they should possess. This incentivizes firms to more closely adhere to competing products, because conformity breeds legitimacy for their offering (Deephouse, 1999; DiMaggio & Powell, 1983; Hsu, 2006). Second, in cultural contexts such as popular music and mainstream video games, markets and consumer attention strongly coalesce around widely known and highly successful hit products. Such products serve as exemplars that provide important information to firms concerning consumer demand, and become important yardsticks for consumers in evaluating the value creation potential of newly introduced offerings (Askin & Mauskapf, 2017; Zhao et al., 2018). Hence, firms have a clear motivation to position their products closer to competitors'.

However, there are also contexts where institutional pressures are arguably weaker and clear exemplars not always present, so that the need for conformity is seemingly less salient. One particularly fitting context in this regard is that of digital platforms, such as Google's Android mobile operating system, Facebook's social network, or Salesforce's enterprise cloud software suite. Platform provider firms harness network effects and boundary resources such as application programming interfaces and software development kits to enable a large number of third-party firms to produce complementary products, or simply complements, that add to the value of their platform and that are sold through an associated marketplace (Cennamo & Santalo, 2013; Eaton et al., 2015; Ghazawneh & Henfridsson, 2013; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003). In doing so platforms stimulate generativity and virtually unbridled innovation (Boudreau, 2012), causing platform marketplaces to harbor a large and constantly evolving variety of markets as complements are continuously introduced and retracted (Brynjolfsson et al., 2011; Brynjolfsson et al., 2006; Kapoor & Agarwal, 2017). Because of this, market boundaries are continuously in flux, to the extent that they do not fully institutionalize (Navis & Glynn, 2010). Most markets in platform marketplaces also cater to the preferences of smaller pockets of consumers, so that widely known hit products are unlikely to emerge (Brynjolfsson et al., 2010). This is also true for non-popular music and non-mainstream video games (Anderson, 2006).

Because the optimal distinctiveness hypothesis, and the important role that it ascribes to institutional pressures and hit products, has had a major influence on the recent developments of our understanding of the consequences of product positioning (Zhao et al., 2017; Zuckermann, 2016), we still have limited insight into the consequences of differentiation in contexts such as platforms where these conformity forces are less prominent. Yet, the positioning strategies of complementors and their offerings have also remained largely unexplored by platform scholars, whose main concern has been with discerning the multifaceted consequences of strategies of platform provider firms for complementors' and platform performance (Cennamo & Santalo, 2013; Claussen et al., 2013; Gawer & Henderson, 2007; Li & Agarwal, 2017), but see Eckhardt (2016), Kapoor and Agarwal (2017), and Rietveld and Eggers (2018) for some notable exceptions. As such, despite the increasing economic prevalence and importance of platforms and their associated marketplaces, we still know relatively little about how complement positioning strategies play out in such contexts. In order to attend to this knowledge gap, we ask *what the implications are of differentiation for the performance of newly introduced paid complements in platform marketplaces*.

Our theorizing mainly draws from literature on platforms and information economics. We adopt a demand-based perspective to competition in platform marketplaces in arguing that conformity forces may also stem from demand conditions (Rietveld & Eggers, 2018). Specifically, the information asymmetry that exists between complementors, who know the true value of their offering, and consumers, who do not, can lead to a case of adverse selection (Akerlof, 1970), because consumers are wary of settling for an inferior offering (Simonson, 1992). Since consumers gauge the value creation potential of a new offering drawing from their knowledge of competing incumbent complements (Eckhardt, 2016; Hoeffler, 2003), which we refer to as market information, this pressures complementors to more closely conform to competitors. Yet, platform marketplaces also constitute highly competitive environments thus pressuring complementors to differentiate (Boudreau, 2012; Kapoor & Agarwal, 2017; Yin et al., 2014), so we advance that the level of differentiation of a newly introduced paid complement will exhibit an inverted U-shaped relationship with performance. To probe the theoretical validity of these two forces and further deepen our understanding of positioning in platform marketplaces, we also introduce two contextual, market-level factors that are highly salient in such contexts and that may moderate the relationship between differentiation and complement performance. After all, the point of optimal distinctiveness may differ from one market to another (Zhao et al., 2017). Because consumer rating and review systems are ubiquitous in platform marketplaces, we first focus on the moderating role of the share of rated apps in a market. Apps' ratings constitute a salient and easy-to-access source of market information to consumers and complementors alike (Eckhardt, 2016; Li, Hitt, & Zhang, 2011). In the absence of hit products, those rated apps thus become the most important informational yardsticks around which a market coalesces, so that the informational force strengthens and optimal distinctiveness favors greater conformity in a market with a larger share of rated apps. Also characteristic for platform marketplaces is that paid and free complements coexist (Arora et al., 2017; Mollick, 2016). Given that newly introduced paid complements experience relatively more competition from paid than from free rivals (Eckhardt, 2016; Rietveld, 2018), the competitive force grows with the share of paid apps in a market, causing the point of optimal distinctiveness to shift so that it favors more differentiation in markets with a larger share of paid apps.

Empirical support for these theoretical predictions is provided in the context of Apple´s mobile platform iOS, where we trace the revenue performance of 6,984 newly introduced paid entertainment, productivity, and utilities apps in the U.S. storefront of the platform's associated App Store between May 2016 and June 2017. To this purpose, we constructed a unique proprietary panel dataset with monthly observations on both entrant and incumbent apps, and their monthly revenues. This setting provides a valuable opportunity to study the performance implications of differentiation in markets with varying characteristics. The App Store harbors a palpable variety of distinct markets ranging from task management applications to alarm clocks, and from jigsaw puzzles to calculators. We are able to identify these markets using computational methods (Blei et al., 2003; McLachlan & Basford, 1988), and are therefore capable of studying a newly introduced paid app's differentiation relative to specific set of incumbent competitors. The data also allow us to control for an extensive number of market and app characteristics, address the potential endogeneity of differentiation, and rule out some alternative explanations such as the effect of multi-market competition. Meanwhile, through our focus on paid apps we maintain consistency with prior work, and are able to examine the performance implications of differentiation net of any business model complexity, such as the confluence of multiple revenue streams, that is typical for free apps (Teece, 2010).

With this study, we intend to contribute to our understanding in three main areas.

First, we extend previous scholarship on product positioning by showing that even in platform marketplaces, contexts where institutional pressures are weak and hit products usually absent, the existence of an information asymmetry between complementors and consumers may cause differentiation to exhibit an inverted U-shaped relationship with performance. As such, we relax an important scope condition underlying the current optimal distinctiveness hypothesis by proposing a new theoretical mechanism, the informational disadvantage of consumers, that may pressure firms to more closely conform to their competitors (Askin & Mauskapf, 2017; Deephouse, 1999; Zhao et al. , 2018). Second, we contribute to the small but growing literature that examines the challenges and opportunities faced by complementors in platform marketplaces (Brynjolfsson et al., 2011; Kapoor & Agarwal, 2017; Yin et al., 2014), by advancing and testing a contingency perspective concerning the performance implications of product positioning in such settings. Third, by explicitly incorporating the effect of demand conditions in considering the relationship between differentiation and complement performance in platform marketplaces, we add to the emerging stream of strategy research that takes a demand-based perspective (Priem, 2007; Priem, Li, & Carr, 2012). We go beyond prior research in this area that has characterized demand heterogeneity and its impact on the performance of firms and their products (Adner & Levinthal, 2001; Adner & Snow, 2010; Rietveld & Eggers, 2018), by illuminating one way in which demand conditions determine the viability of positioning strategies.

4.2 Theory and Hypotheses

4.2.1 Differentiation and the Performance of Newly Introduced Paid Complements

Platforms function as interfaces that typically connect two disjoint sets of actors (Gawer, 2009; McIntyre & Srinivasan, 2017). Firms or individuals on the supply-side produce complementary products, which are in turn acquired by consumers on the demand-side. For example, Google's Android mobile operating system connects mobile application developers with consumers that possess Android-supported mobile devices of manufacturers such as Samsung, HTC, Sony, and Huawei. Similarly, Facebook enables the producers of social games to vie for the attention of its users. In doing so, platforms harness network effects, because actors place higher value on platforms adopted by a lot of other actors (Cennamo & Santalo, 2013; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003). This might be because they anticipate to benefit from the presence of more of their peers (i.e., direct network effect), but importantly also because their utility of the platform increases as the number of actors on the other side grows larger (i.e., indirect network effect). So returning to the preceding examples, consumers that use an Android-supported mobile device or Facebook may benefit both from interacting with other consumers that also adopted these platforms, as well as from the ability to download platform-compatible applications or games produced by one of the many platform complementors.

Because the value of a platform so critically depends on the products produced by third-party complementors, platform provider firms make extensive use of boundary resources to facilitate the product development process on the part of complementors. Boundary resources are interfaces that enable third-party–produced complements to interact with the platform (Eaton et al., 2015; Ghazawneh & Henfridsson, 2013). Examples are application programming interfaces that enable complements to utilize and build upon specific sets of functionalities that are offered by the platform, and software development kits that contain the development tools, environment, and language necessary to call upon the platform and all of its interfaces. Boundary resources lower the time necessary, and resources and knowledge required by complementors to produce their products, and are therewith conducive to deepening the pool of would-be complementors around the platform. Moreover, platform provider firms also frequently offer a variety of knowledge resources such as extensive documentation, example source code, support forums, and complementor conferences, further leveling the playing field of third-party product development (Boudreau, 2012).

Platforms' relatively low entry barriers and promise of instantaneous access to a large consumer base generally entice broad entry by complementor firms. Because these complementors are virtually unlimited in the ways in which they may recombine platform functionalities and product attributes into their offerings, this leads to a continuous supply of new complements and a concomitant increase in product variety available to consumers (Boudreau, 2012; Brynjolfsson et al., 2010). This is why platforms are commonly said to serve a long tail of consumer needs (Brynjolfsson et al., 2011; Brynjolfsson et al., 2006). Larger product variety manifests itself in the coexistence of a large number of distinct markets, but also implies that most complements are niche products that will intentionally or unintentionally be targeted at smaller pockets of consumers (Brynjolfsson et al., 2010). Consequently, the vast majority of markets is unlikely to breed widely known hit products. Moreover, consumers are also unlikely to possess institutionalized market knowledge about most such markets that they can readily rely on. This is especially true since complements are introduced and retracted on a continuous basis, which causes market boundaries to frequently shift and change (Kapoor & Agarwal, 2017; Navis & Glynn, 2010).

Despite the fact that platforms generally address a long tail of consumer needs, large numbers of complementors still eventually churn to address the same consumer needs and thus end up in intense competition with one another (Arora et al., 2017; Bain, 1968; Cattani et al., 2017). This increases rivalry and drives down individual complement performance (Chen, 1996; Ketchen, Snow, & Hoover, 2004). Indeed, prior research suggests that platform marketplaces constitute highly competitive environments. For example, some studies have documented the high turnover of complements on the sales leader boards of Apple's iOS and Google's Android mobile platform marketplaces, which prominently display the platform's most successful complements (Kapoor & Agarwal, 2017; Yin et al., 2014). Most complements merely manage to sustain their top performing status for a very limited amount of time, and they are generally unable to regain this status after that. This is especially true around the release of a new generation of the platform (Kapoor & Agarwal, 2017). The introduction of new platform functionalities changes the competitive landscape, as this enables complementors to leverage the platform in new ways, therewith potentially creating superior value for consumers. Competition also escalates further as the platform becomes more mature (Boudreau, 2012). The continued influx of complements gives rise to competitive crowding, either because the supply of new complements outpaces the number of new consumers adopting the platform, or because there are at some point simply too many complements that address the exact same consumer need. Hence, when introducing a new paid complement, complementors have apparent motivations to differentiate (Cennamo & Santalo, 2013; Ethiraj & Zhu, 2008; Shamsie et al., 2004). That is, they may strategically alter or add some attributes, such as the complement's functionality, usability, or target audience relative to what is common in its intended market in order to stand out among a multitude of competitors, and that way escape the most intense competition.

However, as complements differentiate beyond a certain point, the positive effects of differentiation are likely to decline to the extent that it can even hinder their performance. Most complements, such as video games, mobile applications, or software programs, are experience goods, meaning that consumers face ex-ante uncertainty about their quality and whether there will be a fit between a complement's attributes and consumers' preferences (Arora et al., 2017). Experience goods have to be consumed for them to be appropriately evaluated, and as such they stand in stark contrast with search goods such as electronics whose quality and attributes can be objectively determined and understood prior to consumption (Nelson, 1970). In the absence of hit products as strong reference points for consumers (Askin & Mauskapf, 2017; Zhao et al., 2018), this gives rise to a fundamental information asymmetry between complementors, who know the true value of their product, and consumers, who do not.

This information asymmetry is exacerbated for a newly introduced paid complement. Beyond the complement's information page in the platform marketplace, consumers' initial perceptions of it are shaped by external sources of information, such as the ratings submitted by other consumers, reviews of expert critics, or in-store recommendations (Bharadwaj et al., 2017; Fleder & Hosanagar, 2009; Zhu & Zhang, 2010). However, such information is generally unavailable upon, or shortly after, introduction. Consumers can also not rely on complementors' reputation, because most of them are small and usually unknown to even the most informed consumers (Arora et al., 2017; McWilliams & Siegel, 2007). This lack of information on the part of consumers may lead to a case of adverse selection (Akerlof, 1970), as when most consumers are reluctant to acquire complements for which they are uninformed, fearing that they will end up settling for an inferior offering (Simonson, 1992). This becomes especially problematic as the platform becomes more mature, because complementors face a consumer population by and large constituting late adopters that tend to be more risk averse (Rietveld & Eggers, 2018).

The information asymmetry between complementor and consumer provides incentivizes complementors to position their complements closer to the incumbent offerings in their target market. Similar to how careful observation of competing products provides complementors with valuable knowledge regarding the technological and commercial feasibility of a product idea and the potential total consumer demand (Eckhardt, Ciuchta, & Carpenter, 2018; Shamsie et al., 2004), competing products also constitute an important source of information for consumers (Eckhardt, 2016; Hoeffler, 2003). To consumers without market familiarity, the availability of multiple, competing, complements provides opportunities to experiment with different offerings, that way developing a better understanding of how certain product attributes add value and fit with their tastes. To consumers with market familiarity, their prior experiences with competing complements can help them in developing an understanding of how a newly introduced complement adds value beyond what is already there by adding or recombining a number of attributes. For example, to them it might be more readily apparent why there is merit in adding a social sharing functionality to a task management application, enabling users to share their task lists with colleagues, family, or friends. In either case, less differentiation is associated with a reduction of the information asymmetry between complementor and consumer, so that a newly introduced paid complement is less likely to be affected by adverse selection.

The foregoing discussion suggests that complementors in platforms face two opposing forces in positioning their complements. Intense competition compels complementors to differentiate their complements and highlights the positive effect of differentiation on complement performance. By contrast, the information asymmetry between complementor and consumer incentivizes complementors to more closely conform to the confines of their competitors, underscoring the negative effect of differentiation on complement performance. Reconciling those opposing forces, we propose an inverted U-shaped relationship between differentiation and complement performance, so that the performance of a newly introduced paid complement will first increase and then decrease with differentiation. Formally, we postulate the following hypothesis.

Hypothesis 1: *Differentiation will have an inverted U-shaped relationship with a complement's performance.*

4.2.2 The Moderating Role of Market Characteristics: Shares of Rated and Paid Complements

Thus far our theoretical discussion has suggested that there are two opposing forces affecting the relationship between differentiation and paid complement performance: the information asymmetry between complementor and consumer, and platform marketplace competition. However, as platform marketplaces constitute a large number of heterogeneous markets, and the relative strength of each force, and therewith the exact point of optimal distinctiveness, thus differs from one market to another (Zhao et al., 2017). We exploit this variation to develop a contingency perspective of the performance implications of differentiation in platform marketplaces. That way, we further probe the theoretical validity of the underlying forces that shape the relationship between differentiation and paid complement performance and deepen our theoretical understanding of this relationship.

We analyze the moderating role of two market characteristics that are particularly pertinent to platforms and their associated marketplaces, and that theoretically affect either the information asymmetry between complementor and consumer or the level of competition in the paid complement's target market: the share of rated incumbent complements and the share of paid incumbent complements. Consumer rating and review systems are ubiquitous in platform marketplaces. They allow consumers to voice their first-hand experiences with complements. Ratings submitted for competing complements constitute an important source of market information for consumers (Li et al., 2011), and fluctuations in the availability of such information across markets thus influences the relative strength of the information asymmetry between complementor and consumer. Also characteristic for platform marketplaces is that markets typically harbor both paid and free complements (Mollick, 2016). Because a newly introduced paid complement experiences heterogeneous competition from paid and free incumbent complements (Eckhardt, 2016), differences in the share of paid incumbent complements across markets affect the level of competition that it faces. Next, we discuss in detail how these market characteristics affect the relationship between differentiation and the performance of a newly introduced paid complement.

Share of rated complements, differentiation, and paid platform complement performance. Consumer rating and review systems exist in virtually all platform marketplaces. They allow consumers to articulate their first-hand opinions of, and experiences with, complements by rating them on a scale, such as with between one and five stars or from one to ten points, potentially accompanied by a written motivation for their rating. As such, complement ratings constitute a highly valuable source of information. In lieu of experiencing a complement's attributes firsthand, learning about the usage experiences of others essentially is the closest that prospective consumers can get to developing a profound understanding of the offering. Hence, consumers will invest in searching and scrutinizing such information whenever available (Huang, Lurie, & Mitra, 2009; Rietveld & Eggers, 2018).

As such, ratings of incumbent complements constitute a principal piece of market information for consumers (Li et al., 2011). After all, if the share of rated complements in a market is high, consumers can simply scrutinize those ratings and rely on the usage experiences of others to attain greater market familiarity, rather than going through the more time consuming and tedious process of experimenting with different competing offerings themselves. This causes consumers to be better informed on average, but also implies that, in the absence of hit products, rated incumbent complements become the most prominent yardsticks against which the value creation potential of a newly introduced paid complement is judged (Navis & Glynn, 2010), because consumers will be more reliant on this information. In turn, this exacerbates the negative effects of differentiation on complement performance. While the increased availability of market information aids consumers in better understanding how newly introduced but limitedly differentiated paid complements add value beyond what is already there, their informedness simultaneously makes more differentiated paid complements, shrouded by uncertainty, seem like progressively more risky bets. This effect is further reinforced by the fact that rated incumbent complements also simply constitute relatively safe alternatives for consumers in and of themselves, especially if their ratings are positive (Rietveld & Eggers, 2018; Zhu & Zhang, 2010). Meanwhile, the attention of complementors will also more strongly coalesce around rated incumbent complements, because ratings provide them important information about consumers' wants and needs (Eckhardt, 2016). Taken together, in markets with a relatively high share of rated complements, complementors are more incentivized to conform than to differentiate their newly introduced paid complements. Accordingly, we predict that peak complement performance will manifest itself at lower levels of differentiation in markets with a larger share of rated complements, and formalize this in the following hypothesis.

Hypothesis 2: *The share of rated complements in a market moderates the inverted U-shaped relationship between differentiation and a paid complement's performance in such a way that peak complement performance will occur at lower levels of differentiation in markets with a greater share of rated complements.*

Share of paid complements, differentiation, and paid platform complement performance.

Another important characteristic of most platform marketplaces is that paid and free complements coexist (Arora et al., 2017; Eckhardt, 2016; Mollick, 2016). That is, other than producing complements and distributing them to consumers who pay for them, complementors can also choose to make their products available for free. For example, in early 2018 roughly 90 percent of the more than 2.8 million applications in Android's Google Play marketplace could be acquired without paying a fee (Statistia, 2018). Complementors may make their products available for free for a variety of reasons. Those seeking profits may offer free complements with the hopes that they can subsequently monetize the consumers that they attracted, for instance by exposing them to advertisements (Casadesus-Masanell & Zhu, 2010), asking them to pay for a more advanced version of their offering (Arora et al., 2017; Rietveld, 2018), or reselling some of their information (Casadesus-Masanell & Hervas-Drane, 2014). Others, may produce free complements out of an intrinsic motivation to solve the problems of others, or as a means to showcase their technical skills with the purpose of building their reputation in search for lucrative opportunities, such as jobs, projects, or rewards (Lerner & Tirole, 2002; Roberts, Hann, & Slaughter, 2006).

While the prevalence of paid relative to free complements in a market does not diminish the information asymmetry problem between complementor and consumer in and of itself, the incentive for a to-be introduced paid complement to more closely conform to incumbent complements likely becomes weaker in markets with a larger share of paid apps. In the absence of fee that is to be paid by consumers, free complements simply constitute a more easy-to-access source of market information compared to paid complements (Eckhardt, 2016). Consumers can simply acquire the complement, experience its attributes firsthand, and that way get more knowledge of the market and how the attributes of the complements contained herein fit their preferences.

Perhaps more importantly though, as the share of paid complements in markets increases, the incentive to differentiate becomes somewhat more pronounced so that the strength of the positive effect of differentiation on complement performance becomes stronger. Once consumers spend money on an offering, it affects their perceptions of gains and losses and as a result also their subsequent decisions (Thaler, 1985). This implies that, once consumers acquire a paid complement, they are more likely to keep using it because they have to somehow justify their expenses with the benefits that they reap from using the offering, even if they had initially merely acquired it with the purpose of reducing their uncertainty by getting familiarized with the market (Prelec & Loewenstein, 1998). Consumers are therefore less likely to adopt a newly introduced paid complement when they have previously acquired a rival paid complement compared to when they have previously acquired a rival free complement (Rietveld, 2018). As such, relative to free complements, paid complements constitute a relatively stronger competitive threat to a newly introduced paid complement (Eckhardt, 2016). Thus, paid complements face stronger competition when introduced into a market with a greater share of paid apps, strengthening the positive effect of differentiation of complement performance. This causes us to postulate that peak complement performance will manifest itself at higher levels of differentiation in markets with a larger share of paid complements, articulated in the hypothesis.

Hypothesis 3: *The share of paid complements in a market moderates the inverted U-shaped relationship between differentiation and a paid complement's performance in such a way that peak complement performance will occur at higher levels of differentiation in markets with a greater share of paid complements.*

4.3 Methods and Data

4.3.1 Study Context and Data Collection

The empirical context for our study is the U.S. market of Apple's iOS App Store between May 2016 and June 2017. It constitutes the storefront wherefrom U.S.-based consumers owning an iPhone, iPad, iPod, or Apple Watch acquire Apple-approved complements—more commonly referred to as mobile applications or simply apps—that enable them to perform ancillary activities with their iOS-supported devices, such as playing games, listening to music, reading the news, or editing pictures. The smartphone industry, and Apple's iOS in particular, has grown to become one of the hallmarks of the platform business model. After introducing the first iPhone in 2007, Apple opened up its platform for third-party complementors in 2008 by making available a wide array of boundary resources (Ghazawneh & Henfridsson, 2013). Leveraging those boundary resources and harnessing network effects, iOS then witnessed unprecedented growth. The App Store grew from containing merely 500 apps in 2008 to more than 1.9 million apps by the start of our sampling period (Statista, 2017c). Thus, by studying the App Store we are able to observe a highly competitive platform marketplace that harbors a large number of distinct app markets that wildly vary in their characteristics. The App Store also bears great economic significance. Apps earned more than $28 billion in gross revenues from the App Store in 2016 (Apple, 2017). A substantial proportion of those revenues are incurred by the roughly 20% of paid apps in the App Store. This in contrast to Android's Google Play marketplace where an even larger share of apps is available for free.

Using machine collection methods, we gathered data on the entire population of apps in the entertainment, productivity, and utilities app categories with an English app description based on information that was publicly available from the U.S. storefront of the App Store. We chose to focus on those app categories because they are among the largest in the App Store, though comparably less likely to harbor apps merely serving as channel extensions for firms whose core business lies outside of the app market (e.g., Amazon, Delta Airlines, *The New York Times*) or events and conferences (e.g., Academy of Management Meetings, Apple's Annual Worldwide Developer Conferences, Strategic Management Society Conferences). Apps in the entertainment, productivity, and utilities app categories make up roughly fifteen percent of the entire App Store. Our data consists of all information that consumers can scrutinize when they browse the App Store, among others including details about apps' developers, categorizations, textual descriptions, screenshots, file sizes, release dates, in-store-recommendations, and consumer ratings and reviews. The data were collected on a monthly basis, and contain observations on 227,844 unique apps. Among those observations, we identified 6,984 newly introduced paid apps, excluding product line extensions and sequels of incumbent apps. We chose to focus on paid apps for two main reasons. First, it allows us to maintain consistency with prior work, which has by and large focused on the performance implications of positioning of paid products (Adner et al., 2014; Askin & Mauskapf, 2017; Shamsie et al., 2004; Zhaoet al., 2018). Second, our focus on paid apps allows us to examine the performance implications of differentiation net of any observed or unobserved business model complexity. That is, whereas paid apps' revenues by and large stem from app purchases, free apps' revenues tend to originate from a complex arrangement of various in-app purchase menu items and in-app advertising among others (Teece, 2010).

Because information on app performance is not readily available from the App Store, we complemented this data with a proprietary dataset from Apptopia (http://www.apptopia.com), a leading app market analytics firm. The dataset contains daily-granular app performance estimates for the U.S. market of the App Store, which we then aggregated to the monthly level. Apptopia calibrates apps' ranks on store-wide and category-specific sales leader boards to approximate app downloads and revenues, an approach that is also widely documented and applied in academic literature (Carare, 2012; Garg & Telang, 2013; Kapoor & Agarwal, 2017; Wang et al., 2018). However, rather than simply relying on those raw predictions, Apptopia combines them with proprietary data, including true performance figures for a subset of apps, to arrive at its final estimations. Therefore, acquiring this proprietary dataset had preference over inferring app performance estimations ourselves. To avoid issues of simultaneity, we collected all publicly available app information at the start of each month, while Apptopia's performance estimations reflect apps' performance throughout the entire month.

4.3.2 Uncovering Attributes of Apps

Complementors position their offerings relative to others by optimizing a mix of attributes such as functionalities, usability, target audience, and interoperability across different Apple devices (Adner et al., 2014). In kind, consumers map apps onto a multidimensional attribute space, deeming them more (or less) differentiated based on the attributes they do and do not share with one another (Askin & Mauskapf, 2017; Lancaster, 1966). In order to do so, they rely on apps' textual descriptions, which are prominently displayed on their information pages in the App Store. Similar to how patent abstracts embody innovative ideas (Arts, Cassiman, & Gomez, 2018; Kaplan & Vakili, 2015), or how firms' summaries in industry databases capture different dimensions of their business activities (Shi et al., 2016), app descriptions outline apps' attributes and articulate how those create value for consumers (Barroso, Giarratana, Reis, & Sorenson, 2016; Dimoka, Hong, & Pavlou, 2012). App descriptions constitute the main communication channel between complementor and consumer, and complementors are therefore incentivized to provide a thorough, clear, and accurate overview of their app and its main merits (Lee, Raghu, & Park, 2015).

Apps' attributes could be thought of as latent in their textual descriptions. That is, while consumers and competitors are able to directly observe the app description and the words it embodies, they infer the attributes that this vocabulary corresponds to by mapping words to themes. For example, the co-occurrence of words such as "accident," "road," and "closure" may indicate that an app provides real-time traffic information to consumers. When the researchers' concern is to systematically identify themes in this way over a large volume of text documents, topic modeling may be used to replicate and automate this process (Blei, 2012).

Topic models, such as the Bayesian statistical learning technique of latent Dirichlet allocation (LDA) that we used (Blei et al., 2003), rely on the co-occurrence of words across the textual description of apps in our sample to uncover the themes that are latent in them, and we take those themes to represent the attributes that apps might possess (Shi et al., 2016; Wang et al., 2018). Given a preprocessed corpus of app descriptions,[20] the LDA topic model provides two outputs: (1) a list of themes with a vector of words weighted by their importance to the theme; and (2) a list of app descriptions per app-month with a vector of the themes it contains weighted by their prominence in the document.[21] We refer to the latter as apps' attribute vectors, because they represent apps' time-varying positioning in the attribute space. This representation is consistent with much of recent empirical research on positioning in product markets, which has typically characterized offerings as multidimensional vectors (Askin & Mauskapf, 2017; Sweeting, 2010; Wang & Shaver, 2014; Zhao et al., 2018).

LDA topic models are parametric in that they require the researcher to specify the maximum number of distinct themes, or app attributes, that may exist in the collection of text documents under study. For us, this involved a fundamental trade-off: pre-specifying a large number of themes would allow us to capture more peripheral attributes of apps at the cost of straightforward semantic interpretation, while choosing for a few themes would enable us to focus on apps' core attributes though at the same time blurring some of the more peripheral differences between them (Chang, Gerrish, Wang, Boyd-Graber, & Blei, 2009). After experimenting with various values for the number of themes between 50 and 500, we chose to run our LDA topic models using 150 themes per app category, subsequently eliminating between ten and fifteen themes per app category based on manual inspection.[22] This is the maximum value that provided both statistically and semantically meaningful themes. It also allowed us to capture some less prevalent, or peripheral, attributes of apps, which tend to play an important role

20 Theoretically, LDA can also be applied without preprocessing the collection of app descriptions first, but this increases computational complexity and the results tend to have higher error margins. Accordingly, we eliminated words that typically do not carry any information about apps' attributes; we neglected punctuation, removed non-English and stop words (e.g., "and," "is," "or," "with"), and limited ourselves to analyzing nouns and verbs that likely carry most information about apps' attributes. We also standardized the remaining words in the app descriptions to their root form (e.g., "connected, " "connecting," and "connection" become "connect") using Porter's (1980) stemming algorithm to reduce lexical complexity. To prevent overrepresentation of the attributes of product families, we trained our LDA topic models only including the most recently released app per product family (Kaplan & Vakili, 2015).

21 Refer to Blei (2012) for a primer on topic modeling, and to Kaplan and Vakili (2015) for a recent application in the area of strategic management.

22 Apps' textual descriptions sometimes conclude with a paragraph outlining some of the liabilities associated with using the app. We eliminated themes capturing aspects of such disclaimers, because they do not carry any information about apps' attributes. For example, we excluded a theme with keywords such as "location," "gps," "background," "reduce," and "battery", because it simply reflects that apps' continued location tracking may decrease the device's battery life.

in differentiation (Hargadon & Douglas, 2001; Porac et al., 1989; Zhao et al., 2018). Table 4.1 illustrates the mapping between the app descriptions of apps and the attributes that they embody as inferred by our LDA topic models. The attributes are represented by their five most characteristic keywords.

4.3.3 App Market Identification

Apps' categorizations are the most granular level of app market demarcations readily observable in our data. However, app categories do not adequately circumscribe the boundaries within which product substitution takes place and where as a consequence the most intensive product market competition ensues (Bain, 1968; Barroso et al., 2016; Cattani et al., 2017). The smallest app category in our sample, productivity, harbors roughly 40,000 distinct apps, ranging from scientific calculators to task management applications and from alarm clocks to mobile contact backup services. Moreover, industry reports persistently indicate that the majority of consumers navigates the App Store and discovers apps by searching for offerings using a specific set of keywords (Forrester, 2013; Nielsen, 2011; TUNE, 2015). Merely those apps with similar core attributes will show up in the same search.

An emerging stream of empirical work has sought to deal with this issue by grouping products into markets or niches based on the consumer audience to which they attempt to appeal (Barroso et al., 2016; Hoberg & Philips, 2016; Kovacs & Johnson, 2014). We followed this tradition, clustering apps according to the similarity of their inferred attribute vectors to subdivide app categories into markets—apps targeted at a pocket of consumers with similar preferences. To this end, we relied on the Gaussian mixture model (GMM) clustering algorithm (McLachlan & Basford, 1988) because of its ability to detect clusters (i.e., markets) that differ in density, shape, and size, a feature that is particularly pertinent in our empirical context. This is feasible since the GMM clustering algorithm allows each cluster, represented by a normal distribution, to have its own covariance matrix. GMM's cluster assignments are based on a probabilistic model that represents the data as a mixture of a number of normal distributions, usually predefined by the researcher, their dimensions fitted so as to maximize the likelihood of the data.
We chose to not impose any assumptions in our GMM clustering algorithm regarding the number of distinct app markets that might exist, instead leaving the market structure to be naturally borne out of our data. To this purpose, we repetitively ran the algorithm at the interval $[1..N_c]$, where N_c is the total number of apps in a certain app category, optimizing a Bayesian Information Criterion (BIC) (Fraley & Raftery, 1998; Zuniga-Vincente, De La Fuente-Sabate, & Rodriguez-Puerta, 2004). Put differently, we systematically varied the number of markets that may exist in an app category and relied on likelihood analysis to compare and evaluate which model best fits our data, rather

Table 4.1. Illustration of mapping between apps' textual descriptions and their attributes using LDA topic models, and market identification using GMM-based clustering

Tile	Description fragment	Attributes	Market
ContactsBook - AddressBook	Group management There are functions to; -create, edit and delete a group. -select group icon. -create group icon from photo or text. -order group tabs. Contacts management There are functions to; -create, edit and delete a contact. -call a contact. -send eMail or SMS/MMS to a contact. -classify a contact using drag and drop to group. -classify multiple contacts using drag and drop in edit mode. -order contacts using drag and drop. -sort contacts by name, organization name, color, creation date and birthday. Messaging There are functions to; -send eMail to group members. -send text message to group members.	[group, create, people, contact, manage]; [message, send, text, email, receive]	Contacts management
Groupy	Groupy provides a simple interface to create and manage groups of your contacts from your iPad, iPhone or iPod Touch. It allows you to create, delete, rename groups as well as to add and remove contacts from your groups.	[group, create, people, contact, manage];	Contacts management
GContact Lite 2	Features 1.Drag & drop for the group editing 2. Contact could be gathered in the groups automatically by company names. 3. Groups could be created, edited, or deleted freely. 4. You could also create, delete, and edit a single contact. 5. It support to search for contacts 6. And send email to all group members 7. Fantastic respond speed 8. Support to send sms/mms to all group members *The group mms just support the emoji only,picture and camera it can not be support in this version. 8.You could change the group's sort 9.You could change the group's color 10.Backup your contacts and shared your archive file by iTunes connect or Mail	[group, create, people, contact, manage]; [contact, backup, phone, restore,sync]; [message, send, text, email, receive]	Contacts management

Countdown, Auto-Monthly Payments (Timer, Reminders)	1. The Latest List * Show the list of countdown the d-day and monthly expenses in nearest dates 2. Timer * Multiple Timers (Cooking, Meditation, Break, etc. number of timers can be managed in one screen) * Timer that is being used frequently can be arranged at the top of the list 3. Countdown D-days * Anniversary, Birthday, Children's birthday, party, meeting, social event and concert, etc. All of your events are managed in one screen * Listed from the nearest date 4. Monthly Expenses (Notification for monthly fees) * Letting you know the list of monthly expenses on time * You can pre-set the details of expenses to let you know on time * Monthly expenses are automatically repeating every month	[money, expense, bill, pay, balance]; [remind, set, forget, date, repeat]; [time, count, set, break, start];	Expenditure tracking
Expense Scout: Shopping List, Bill Reminders & Expense Tracker	BUDGET: -Customize the budget to match your expense groups & goals. -Set expense limits & tracking periods. -View unspent expenses and remaining balances for each budget group. -Tracking and Alerts -Analyze monthly expenses and find out ways to save more. BILL REMINDERS & TRACKING: -iCalendar reminders two days prior to due date. -Amber alerts one week prior and red warnings on and after the due date. -Check off as you make payments & keep track easily. GROCERY LIST: -A shopping list with prices simply by scanning & tagging. -All previous purchases in one place. Re-use with just a tap. -A list organized by aisles in your store & save time in store. -Keep track of your shopping expenses while shopping. -Sync & share your shopping list with family & friends.	[money, expense, bill, pay, balance]; [time, count, set, break, start]; [remind, set, forget, date, repeat]; [list, shop, add, item, grocery]; [share, family, group, create, people]	Expenditure tracking

Expenses N+W	Expenses N+W is an app that helps you calculate how much is Spent & Left of a given amount of cash. By creating lists as you go along adding expense items & the ability to archive them for later viewing. Using colorful Expense Stripes to tell them apart. In two words, Its Instantaneous & Colorful! How To: - Tap the Plus to add an Expense Stripe. - Tap on the numbers to add an Amount. - Tap the Checkmark when Done. - Tap the Circle to change a Stripe color. - Tap the List Circle to ReOrder & Delete Stripes. - Tap on Spent & Left Stripes, then tap on Cash, to change its Amount. - Tap Archive Expenses, to Clear the Expenses List, & have it archived. - Tap the Circle, then tap (i) to access customization options. Customizations: - Background : Choose from the 25 colors, or from your own Photos. - Plus: Choose from the 25 colors, & the Thickness or Thinness of the Plus. - Stripe: Choose from different Stripe styles. Spaced, Full, No (Text takes color of Stripe instead), Sidelined & Underlined stripe styles. - Font: Choose color of font from Black, Grey & White. & six font options. - Lists: Choose to Show or Hide Lists, which are 5 when shown.	[money, expense, bill, pay, balance]; [color, choose, scheme, background, change]; [size, font, text, style, change]	Expenditure tracking

than simply enforcing this parameter ourselves in advance. Subsequent to determining the number of markets, we ran the GMM clustering algorithm once at the earliest month of our sample (May 2016), then holding the identified markets fixed throughout (Hoberg & Philips, 2016). Because GMMs are fuzzy clustering algorithms, meaning that they return the probability that apps fit into certain markets rather than hard market assignments, we associated new app introductions with the market for which they had the highest probability upon introduction.

We identified a total of 2,688 app markets, distributed as follows: 650 markets for productivity apps; 1,151 markets for entertainment apps; and 887 markets for utilities apps. The 6,984 paid app entries in our sample were introduced into 1,600 distinct markets. The most right column of Table 1 outlines fragments of two markets for productivity and utilities apps as identified from our data. As Table 4.1 illustrates, the market structure uncovered by our clustering algorithm has high face validity; apps in the same market share similar core attributes, but differ in their peripheral attributes. For example, from our data we identified a market for contacts management applications in the utilities app category. All identified apps enable users to create, manage, and edit groups for their iOS contacts, but merely some offer contacts backup and in-app messaging or emailing functionalities.

4.3.4 Dependent Variable

The key dependent variable of interest as theorized in our hypotheses is the performance of a newly introduced paid app. We measured app performance as the app's aggregate monthly gross revenue in U.S. dollars from paid downloads and in-app purchases, prior to the deduction of Apple's royalty fee.[23] As such, our dependent variable reflects an app's earnings from direct consumer spending, the main source of income in the App Store. Because earnings in our context are highly skewed, we used the natural logarithm of monthly gross revenue in our analyses, adding a small constant of one to prevent division by zero.

4.3.5 Independent and Moderating Variables

The independent variable is the level of differentiation of newly introduced apps vis-à-vis their incumbent competitors. To operationalize this variable, we first dichotomized all app attribute vectors, and then measured differentiation as the average Hamming distance between a newly introduced paid app and all other apps in the same market—the mean number of attributes that differs among their app attribute vectors.[24] We normalized this measure by dividing it by the number of distinct app attributes that exist in the app category to arrive at a measure of differentiation that ranges between zero and one, where zero corresponds to total conformity and one to complete differentiation. Subsequently, we created a squared term of this variable to test the hypothesized inverted U-shaped relationship between differentiation and app performance.

The first moderator that we proposed is share of rated apps in an app market. Subsequent

23 Because consumers' payments for app downloads and in-app items proceed directly in the App Store, Apple collects those payments on behalf of complementors. Subsequently, it aggregates those payments, deducts a royalty fee of between 15% and 30%, and pays the remaining earnings out to complementors.

24 Whereas apps' attribute loadings aid in distinguishing core from peripheral attributes (e.g., a to-do list application versus a project management application that also includes the ability to create a to-do list) and are therefore instrumental to the adequate identification of app markets, complementors position their apps relative to rivals by choosing whether to incorporate certain attributes. In dichotomizing the app attribute vectors, we set a loading threshold of five percent to determine if an attribute is present or absent, to avoid erroneously taking very small attribute loadings as evidence of it being incorporated in the app. In supplementary analysis, we assessed the sensitivity of our results with respect to the specification of this threshold. We find that our results are insensitive to lowering or omitting the attribute loading threshold.

to downloading an app, consumers can rate it on a scale between one and five stars and potentially leave a textual review in which they motivate their rating. Hence, we measured the share of rated apps in an app market by dividing the number of rated incumbent apps by the total number of apps in the market. Our second moderator is the share of paid apps in a market, which we computed as the number of paid incumbent apps divided by the total number of incumbent apps in the market. We preferred a ratio over an absolute count for both moderators because it is less prone to also capture other aspects of a market, such as its level of competition or maturity.

4.3.6 Control Variables

We coded several market-level and app-level control variables to account for alternative factors that may affect the performance of newly introduced paid apps. At the market level, we included multiple variables to account for varying levels of app market competition. Apps in market is a count of the total number of incumbent competitors that a newly introduced paid app faces (Boudreau, 2012). Given that competition may intensify as the app market becomes more mature (Zhao et al., 2018), market maturity captures the number of months that have passed since the oldest app in the app market was released. We also included the Herfindahl-Hirschman Index (HHI) as a measure of market concentration, which we computed as the sum of squared download market shares of the individual apps in a market. We chose to utilize download instead of revenue market share to more explicitly account for competition from free apps beyond those seeking for immediate profits. Because prior research ascribes an important role to hit apps as salient anchoring points for both complementors and consumers (Askin & Mauskapf, 2017; Zhao et al., 2018), we controlled for the presence of exemplars in markets using an indicator variable that takes a value of one if they were present and zero when they were absent. We defined hit apps as those apps that were persistently ranked among the top 150 most downloaded or best earning apps for at least one day in the last three months on one of the App Store's designated store-wide leader boards.[25] We also accounted for the log-transformed number of other apps by the same complementor in the same market. Prior research suggests that complementors may introduce new apps in response to competition, rather than repositioning their existing apps (Wang & Shaver, 2016).

At the app level, we focused on controlling for important app characteristics that have been shown to affect their performance. First, we accounted for the information that consumers can find about the app on its information page in the App Store (Ghose &

25 While the app leader boards published by app market analytics firms typically stretch well beyond 150 unique apps, the view of the leader boards in the App Store is limited to the 150 best performing apps. Hence, we chose to code our variables accordingly as it reflects the information available to most consumers. Taking the top 500, 1000, or 1500 apps into consideration does not change our results.

Han, 2014). App description length captures the number of words in the app's textual description, and number of screenshots is a count of the number of app images that are displayed on the information page. As noted in our theorizing, app ratings constitute an important source of information for consumers. So if ratings become available shortly after the paid app is introduced, it is likely to affect its subsequent performance. Hence, we also included a measure of the app's rating valence—its star rating between one and five stars, or zero when no ratings have been submitted.

Second, we also controlled for other external sources of app information that may have become available after apps' introductions into the market, reducing the information asymmetry between complementor and consumer. Complementors sometimes offer their apps at a temporal discount through a third-party app to entice consumers to try the app. Hence, we included an indicator variable that takes a value of one if an app was discounted at any day during a month in four of the most popular discounting apps, App of the Day, App of the Week, AppAdvice, or AppGratis, and zero otherwise. Analogously, we also controlled for whether apps received media coverage or reviews in some influential media, such as CNET, MacWorld, Mashable, and *The New York Times*. The information pages on the App Store also contain app recommendations, suggestions of related apps that consumers may also like (Fleder & Hosanagar, 2009). Our models contained a log-transformed count of the number of distinct app information pages on which a focal app appeared. Consumers also observe the app downloading decisions of others through the store-wide leader boards in the App Store (Duan et al., 2009), and thus we controlled for whether an app appeared among the 150 highest ranked apps.
Finally, we controlled for a number of other app characteristics. Our models included the app's price and the average price of its in-app purchase items. The latter was coded zero if the app did not offer any possibilities for additional purchases. We accounted for app lifecycle effects by controlling for the number of months that passed since the app was introduced into the App Store, and whether a new version of the app was released during the most recent month. We also included apps' log-transformed file size measured in megabytes.

In addition, we included some fixed effects to partial out unobserved confounding effects in app performance that do not stem from differentiation. App category fixed effects capture systematic differences in the performance of apps in markets across disparate categories. Time fixed effects account for temporaneous shocks in app performance and competition, such as those caused by the hike in demand for apps around the holidays or the increased app market competition around the release of a new generation of the iOS mobile operating system. Moreover, we included fixed effects to control for apps' age ratings and their compatibility with different stand-alone iOS devices to account for other layers of market segmentation.[26]

4.3.7 Analytical Strategy

Once complementors have introduced their new paid app into the App Store, they rarely reposition their offering in response to market-level factors such as the increasing availability of market information or mounting competition. Consequently, apps' level of differentiation rarely changes over time, and fixed-effects regressions would therefore struggle in estimating the effect of differentiation on app performance (Plumper & Troeger, 2007). For this reason, we chose to analyze the relationship between differentiation and app performance using random-effects regressions, which also account for unobserved heterogeneity between apps (Wooldridge, 2002).

A critical assumption underlying the random-effects regression model is that all variables have to be uncorrelated with apps' unobserved heterogeneity for it to produce consistent estimates (Mundlak, 1978). Our differentiation variable likely violates this assumption. An app's positioning is a strategic choice by a complementor that likely reflects factors unobserved in our data, such as managers' judgements about market potential or how well a newly introduced paid app fits within the existing app portfolio of a complementor. We accounted for this potential endogeneity problem using a control function approach (Wooldridge, 2002).

In a first-stage regression model, we regressed differentiation on a set of exogenous instruments and control variables. More specifically, of our control variables we included all market characteristics and fixed effects, and a number of app characteristics such as file size and the length of the app description that become known directly upon apps' introduction into the App Store. In addition, we identified a complementor's propensity to differentiate, computed as the average differentiation of its other apps in our sample, as an instrument for a newly introduced paid app's level of differentiation. The rationale for this instrument is that complementors with a tendency to differentiate will simply be more likely to position their new paid app at higher levels of differentiation as well. Meanwhile, this tendency of complementors to differentiate solely manifests itself through the apps it introduces and therefore does not independently affect app performance. Recall, complementors are by and large unknown to even the most informed consumers

26 We included fixed effects to capture apps' compatibility with iPhone, iPad, and iPod, but not the Apple Watch because it has to be used in conjunction with an iPhone in order to download and use apps. Hence, the app attribute vectors capture apps' compatibility with the Apple Watch as a peripheral attribute.

(Arora et al., 2017).[27] Because some complementors are new to the App Store, we also included an indicator variable that denotes whether the complementor that introduced the paid app was de novo or de alio.

We then used the residual from this first-stage regression as an additional independent variable in our random-effects regressions to correct for the potential endogeneity of differentiation. It represents the component of differentiation that is correlated with apps' unobserved heterogeneity. Because using an estimated residual in the second-stage can induce measurement error, we panel-bootstrapped the standard errors. Addressing endogeneity in this way allowed us to consistently estimate higher order and interaction effects of differentiation without needing additional instruments (Wooldridge, 2015, p. 428), which are difficult to find in our context (Arora et al., 2017; Wang et al., 2018).

Table 4.2. Descriptive statistics

Variable	Mean	S.D.	Min	Max
App performance	1.22	2.12	0.00	11.70
Differentiation	0.05	0.02	0.00	0.14
Share of rated apps	0.30	0.15	0.00	0.90
Share of paid apps	0.45	0.22	0.00	1.00
Hit apps	0.00	0.03	0.00	1.00
HHI	0.46	0.29	0.00	1.00
Maturity	81.17	20.81	1.00	109.00
Number of apps	76.91	49.49	6.00	288.00
Number of apps by complementor in market	0.50	0.89	0.00	3.85
Appearance in App Store recommendations	0.00	0.03	0.00	3.43
Average in-app purchase price	0.08	0.33	0.00	6.91
Description length	143.57	106.06	20.00	706.00
Discounted	0.00	0.01	0.00	1.00
File size	3.09	1.24	0.18	7.92
Media coverage	0.00	0.02	0.00	1.00
New version	0.22	0.41	0.00	1.00
Number of months since introduction	4.92	3.58	0.00	15.00
Number of screenshots	3.94	1.20	1.00	5.00
Number of ratings	0.36	1.13	0.00	10.15
Price	1.15	0.57	0.69	6.91
Ranked	0.03	0.16	0.00	1.00
Complementor's propensity to differentiate	0.03	0.02	0.00	0.14
De novo	0.25	0.44	0.00	1.00

27 To verify this, we included the instruments, a complementor's propensity to differentiate and de novo introductions, in a fully specified random effects model that tests the relationship between differentiation and app performance. We found that neither of the instruments did significantly relate to app performance.

Table 4.3. Pairwise correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. App performance	1.00													
2. Differentiation	0.02	1.00												
3. Share of apps with ratings	0.15	0.08	1.00											
4. Share of paid apps	0.00	-0.51	-0.08	1.00										
5. Hit apps	0.10	0.03	0.02	-0.01	1.00									
6. HHI	-0.11	0.03	-0.06	-0.23	0.00	1.00								
7. Maturity	-0.02	0.55	0.26	-0.47	0.01	0.11	1.00							
8. Number of apps	0.08	0.22	-0.08	0.00	0.00	-0.23	0.15	1.00						
9. Number of apps by complementor in market	-0.02	-0.37	0.25	0.52	0.00	-0.17	-0.42	0.19	1.00					
10. Appearance in App Store recommendations	0.05	0.01	0.01	-0.02	0.03	0.00	0.02	0.02	0.00	1.00				
11. Average in-app purchase price	0.03	-0.07	0.12	0.01	0.01	-0.01	-0.07	0.01	0.09	0.04	1.00			
12. Description length	0.12	0.13	0.10	-0.10	0.01	0.01	0.10	0.02	-0.05	0.03	0.04	1.00		
13. Discounted	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.01	1.00	
14. File size	0.01	-0.10	-0.19	0.17	0.04	-0.02	-0.07	0.03	0.28	0.01	0.05	0.02	0.01	1.00
15. Media coverage	0.07	-0.01	0.03	-0.01	0.00	0.02	0.00	-0.01	-0.01	0.02	0.00	0.06	0.08	0.01
16. New version	0.08	0.01	0.03	0.01	0.01	0.01	0.00	0.00	-0.05	0.01	0.03	0.07	0.00	-0.05
17. Number of months since introduction	-0.02	0.05	-0.01	-0.10	0.00	-0.01	0.07	0.02	-0.01	0.00	0.02	-0.01	0.00	0.05
18. Number of screenshots	0.42	-0.03	0.21	0.01	0.14	-0.07	-0.05	0.03	0.00	0.15	0.24	0.10	0.03	0.06
19. Number of ratings	0.01	-0.04	-0.10	0.07	0.01	-0.01	-0.05	-0.03	0.10	0.01	0.04	0.15	0.01	0.20
20. Price	0.02	0.07	-0.12	-0.01	0.01	0.04	0.03	-0.05	0.02	0.00	0.04	0.10	0.00	0.12
21. Ranked	0.40	0.01	0.09	0.01	0.18	-0.04	-0.03	0.03	-0.02	0.07	0.03	0.07	0.01	0.07
22. Complementor's propensity to differentiate	0.01	0.13	0.06	-0.11	0.02	0.03	0.12	0.00	0.00	0.00	0.04	0.02	0.00	-0.07
23. De novo	0.00	0.24	0.04	-0.20	-0.01	0.02	0.17	0.01	-0.33	0.00	-0.09	0.09	-0.01	-0.08

Variable	15	16	17	18	19	20	21	22
15. Media coverage	1.00							
16. New version	0.03	1.00						
17. Number of months since introduction	-0.01	-0.43	1.00					
18. Number of screenshots	0.08	0.02	0.08	1.00				
19. Number of ratings	0.01	0.00	0.06	0.05	1.00			
20. Price	0.03	0.03	0.03	0.01	0.11	1.00		
21. Ranked	0.05	0.07	-0.01	0.46	0.04	0.04	1.00	
22. Complementor's propensity to differentiate	-0.02	-0.05	0.06	0.02	-0.06	0.00	0.02	1.00
23. De novo	0.02	0.05	-0.01	-0.02	0.01	0.02	-0.01	-0.76

Table 4.4. First-stage regressions predicting a newly introduced paid app's level of differentiation

Variable	Model 1	Model 2
Complementor's propensity to differentiate		0.197***
		(0.015)
De novo introduction		0.010***
		(0.001)
Share of apps with ratings	-0.002+	-0.002*
	(0.001)	(0.001)
Share of paid apps	-0.013***	0.012***
	(0.001)	(0.001)
Market characteristics		
hit apps	0.002+	0.002
	(0.001)	(0.001)
HHI	-0.001***	-0.000***
	(0.000)	(0.000)
Maturity	0.000***	0.000***
	(0.000)	(0.000)
Number of apps	0.000***	0.000***
	(0.000)	(0.000)
Number of apps by complementor in market	-0.003***	-0.002***
	(0.000)	(0.000)
App characteristics		
Average in-app purchase price	0.000	0.000
	(0.000)	(0.000)
Description length	0.000**	0.000**
	(0.000)	(0.000)
File size	-0.001***	-0.001***
	(0.000)	(0.000)
Number of screenshots	-0.000	-0.000
	(0.001)	(0.000)
Price	0.000	0.000
	(0.000)	(0.000)
Constant	0.036***	0.028***
	(0.003)	(0.003)
Fixed effects		
Age rating	Included	Included
App category	Included	Included
Device compatibility	Included	Included
Time	Included	Included
Number of apps	6,984	6,984
Number of app-months	45,204	45,204
R^2 overall	0.376	0.430

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.
Coefficients are reported; robust standard errors are in parentheses.

4.4 Results

Descriptive statistics are listed in Table 4.2. The average level of differentiation in our sample equals 0.05, a value that is comparable to the figures reported in much of prior work (Askin & Mauskapf, 2017; Zhao et al., 2018). The correlation matrix is presented in Table 4.3. Multicollinearity is unlikely to be a problem; the mean variance inflation factor (VIF) equals 3.01, well below the commonly accepted thresholds. Table 4.4 outlines the results of our first-stage regressions. As expected and can be seen in Model 2, a complementor's propensity to differentiate is a positive and significant predictor of its newly introduced paid app's level of differentiation ($\beta = 0.197$, $p < 0.001$). Similarly, de novo introductions also exhibit higher levels of differentiation ($\beta = 0.010$, $p < 0.001$). The substantial increase in model fit from the baseline model, reported in Model 1, to Model 2 including the two instruments also suggests that our instruments are strong.

4.4.1 Hypotheses

We test our hypotheses in Table 4.5. Model 3 constitutes our baseline model including all control and moderating variables. In Model 4 differentiation and its squared term are added to test our first hypothesis. Models 5 and 6 test our second and third hypotheses, by introducing the interactions between differentiation, its squared term, and the share of rated and paid apps in a market, respectively. For the sake of consistency and comparability with prior work (Askin & Mauskapf, 2017; Deephouse, 1999; Zhao et al., 2018), Models 7 to 9 report the results of our hypotheses tests without endogeneity correction.

Hypothesis 1 predicted that differentiation of a newly introduced paid app would exhibit an inverted U-shaped relationship with app performance. This hypothesis is supported by the estimations reported in Model 4. The coefficient of differentiation is positive and significant ($\beta = 7.889$, $p < 0.01$), while the coefficient of differentiation squared is negative and significant ($\beta = -89.307$, $p < 0.001$). Figure 4.1 illustrates the effect of differentiation on app performance. It illustrates that the turning point of the curve is well within the range of observed values. The point of optimal distinctiveness occurs when the level of differentiation equals 0.044. In considering the magnitude of this effect, we find that a newly introduced paid app that is optimally distinct will have a 15.6% increase in revenues compared to an app that is undifferentiated and it will earn 7.5% more than a highly differentiated app at the 90th percentile of the differentiation distribution in our sample. To assess the robustness of the observed inverted U-shaped relationship, we split the data into two parts around the point of optimal distinctiveness and estimate the model for each side individually (Haans, Pieters, & He, 2016). In support of our hypothesis, we find that the effect of differentiation is positive and significant at low levels of differentiation ($\beta = 5.434$, $p < 0.05$) and negative and significant at high levels of differentiation ($\beta = -3.670$, $p < 0.05$).

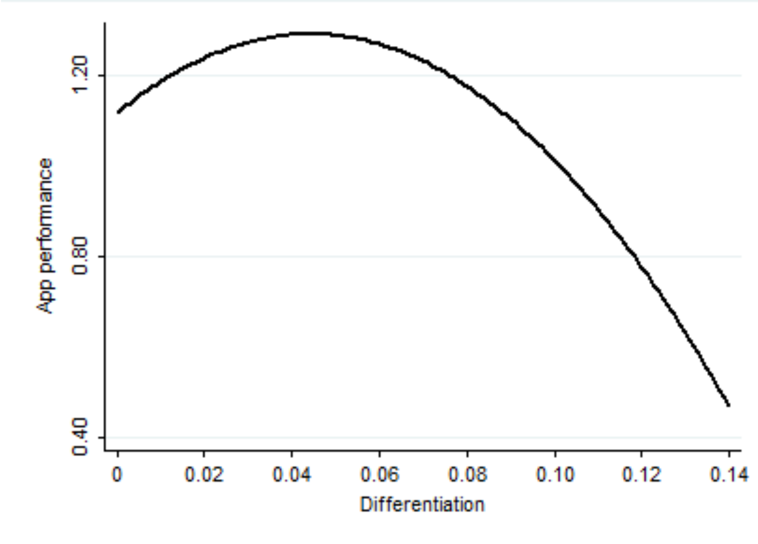

Figure 4.1. The effect of differentiation on app performance

Hypothesis 2 postulated that the share of rated apps in a market would moderate the inverted U-shaped relationship between differentiation and app performance, so that peak app performance would occur at lower levels of differentiation in markets with a greater share of rated apps. Model 5 provides support for this assertion; the interaction between differentiation and the share of rated apps is negative and significant ($\beta = -33.040$, $p < 0.05$), and $\beta^{\text{differentiation squared}} \times \beta^{\text{differentiation x share of rated apps}} > \beta^{\text{differentiation}} \times \beta^{\text{differentiation squared x share of rated apps}}$ (Haans et al., 2016). Figure 4.2 shows how low and high shares of rated apps in a market, defined as one standard deviation below and above the mean, moderate the relationship between differentiation and app performance. As Figure 4.2 illustrates, the point of optimal distinctiveness lies further to the left in markets that harbor a high share of rated apps. The point of optimal distinctiveness shifts from 0.050 in markets that harbor a low share of rated apps to 0.026 in markets that harbor a high share of rated apps.

Our third hypothesis stated that the inverted U-shaped relationship between differentiation and app performance would be moderated by the share of paid apps in a market in such a way that peak app performance would occur at higher levels of differentiation in markets with a greater share of paid apps. We examine this prediction in Model 6. Interestingly, the estimation results provide evidence of a shape flip (Haans et al., 2016). When the share of paid apps in a market is low, differentiation exhibits

Table 4.5. The effect of differentiation on app performance

	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Variable	**RE**	**RE-CF**	**RE-CF**	**RE-CF**	**RE**	**RE**	**RE**
Differentiation		7.889**	17.132***	-10.655*	8.319**	17.607***	-10.513*
		(2.700)	(4.325)	(5.249)	(2.652)	(4.197)	(5.291)
Differentiation^2		-89.307***	-159.606**	109.024***	-91.458***	-162.578**	108.803**
		(23.699)	(48.291)	(49.057)	(24.009)	(47.471)	(49.459)
Share of apps with ratings	0.902***	0.885***	1.627***	0.830***	0.878***	1.631***	0.823***
	(0.126)	(0.128)	(0.287)	(0.131)	(0.126)	(0.288)	(0.130)
Share of apps with ratings x differentiation			-33.040*			-33.523*	
			(13.293)			(13.159)	
Share of apps with ratings x differentiation^2			258.177+			262.635+	
			(145.725)			(144.526)	
Share of paid apps	-0.126	-0.067	-0.030	0.721**	-0.127	-0.079	-0.774***
	(0.094)	(0.128)	(0.130)	(0.225)	(0.078)	(0.100)	(0.204)
Share of paid apps x differentiation				39.558***			39.880***
				(8.682)			(8.487)
Share of paid apps x differentiation^2				-456.312***			-459.202***
				(97.311)			(95.449)
Residual first-stage regression		4.462	3.501	3.374			
		(6.250)	(6.245)	(6.235)			
Market characteristics							
Hit apps	0.582***	0.596***	0.593***	0.618***	0.606***	0.601***	0.626***
	(0.106)	(0.111)	(0.112)	(0.113)	(0.104)	(0.106)	(0.107)
HHI	-0.156***	-0.153***	-0.153***	-0.149***	-0.156***	-0.155***	-0.151***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Maturity	-0.004***	-0.005***	-0.005***	-0.005***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of apps	0.001***	0.001**	0.001**	0.001**	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of apps by complementor in market	-0.058*	-0.044	-0.045	-0.044	-0.056*	-0.055+	-0.053+
	(0.027)	(0.033)	(0.033)	(0.033)	(0.028)	(0.028)	(0.028)

App characteristics							
Appearance in App Store recommendations	-0.073	-0.074	-0.071	-0.083	-0.073	-0.069	-0.082
	(0.332)	(0.341)	(0.342)	(0.340)	(0.334)	(0.334)	(0.333)
Average in-app purchase price	-0.136*	-0.133*	-0.135*	-0.132*	-0.133*	-0.135*	-0.132*
	(0.064)	(0.065)	(0.065)	(0.065)	(0.064)	(0.065)	(0.064)
Description length	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discounted	0.065	0.074	0.078	0.080	0.075	0.079	0.081
	(0.213)	(0.260)	(0.261)	(0.260)	(0.207)	(0.208)	(0.207)
File size	0.010	0.019	0.022	0.019	0.013	0.017	0.015
	(0.017)	(0.020)	(0.020)	(0.020)	(0.017)	(0.017)	(0.017)
Media coverage	2.045***	2.061***	2.059***	2.055***	2.059***	2.058***	2.054***
	(0.528)	(0.575)	(0.575)	(0.571)	(0.529)	(0.529)	(0.526)
New version	0.110***	0.110***	0.110***	0.110***	0.110***	0.110***	0.110***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Number of months since introduction	-0.019**	-0.019***	-0.019***	-0.018***	-0.019***	-0.019***	-0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Number of ratings	0.363***	0.364***	0.363***	0.365***	0.364***	0.363***	0.365***
	(0.022)	(0.024)	(0.024)	(0.024)	(0.022)	(0.022)	(0.022)
Number of screenshots	-0.011	-0.012	-0.013	-0.013	-0.012	-0.013	-0.013
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)
Price	0.083+	0.084+	0.085*	0.086*	0.085*	0.086*	0.086*
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Ranked	1.455***	1.445***	1.454***	1.457***	1.456***	1.454***	1.458***
	(0.075)	(0.078)	(0.078)	(0.078)	(0.075)	(0.075)	(0.075)
Constant	-0.513***	-0.769***	-0.950***	-0.343	-0.620***	-0.835***	-0.225
	(0.190)	(0.273)	(0.274)	(0.302)	(0.194)	(0.199)	(0.213)
Fixed effects							
Age rating	Included	Included	Included	Included	Included	Included	Included
App category	Included	Included	Included	Included	Included	Included	Included
Device compatibility	Included	Included	Included	Included	Included	Included	Included

Time	Included	Included	Included	Included	Included	Included	Included
Number of apps	6,984	6,984	6,984	6,984	6,984	6,984	6,984
Number of app-months	45,204	45,204	45,204	45,204	45,204	45,204	45,204
R^2 overall	0.260	0.261	0.262	0.264	0.261	0.262	0.264

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.

Coefficients are reported. Models 4–6: random effects control function regressions (RE-CF) bootstrapped standard errors based on 1,000 replications are in parentheses. Models 3, and 7–9: random effects regressions; robust standard errors are in parentheses.

an overall U-shaped relationship with app performance (strategic differentiation: β = -10.655, $p < 0.05$; strategic differentiation squared: β = 109.024, $p < 0.05$). By contrast, when the share of paid apps in a market is high, differentiation has an inverted U-shaped relationship with app performance (interaction between strategic differentiation and share of paid apps: β = 39.558,

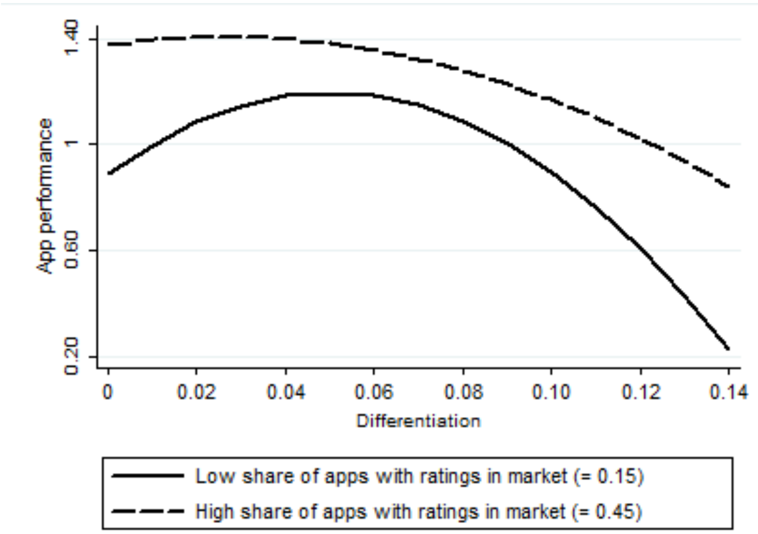

Figure 4.2. The moderating effect of the share of rated apps in a market on the relationship between differentiation and app performance

$p < 0.001$; interaction between strategic differentiation squared and share of paid apps: β = -456.879, $p < 0.001$). Figure 4.3 aids in the interpretation of these results; it plots the moderating effect of how low, average, and high shares of paid apps in a market, defined as the 10th, 50th, and 90th percentile of the differentiation distribution, moderate the relationship between differentiation and app performance. Figure 4.3 shows that when the share of paid apps in a market is low, the point of optimal distinctiveness favors total conformity or total differentiation. Note that the level of differentiation needs to be at least 0.13, which is well above the 99th percentile of the differentiation distribution in our sample. When the share of paid apps lies at the 50th percentile of its distribution, the point of optimal distinctiveness has shifted to the right so that the relationship between differentiation and app performance becomes inverted U-shaped. It then moves further to the right in markets that harbor a high share of paid apps. Taken together, these results provide support for our third hypothesis; peak app performance occurs at higher levels of strategic differentiation in markets with a greater share of paid rival apps.

4.4.2 Robustness Checks

We performed multiple tests to establish the robustness of our findings, the results of which are presented in Table 4.6, 4.7, and 4.8. In a first set of robustness checks, we experimented with alternative specifications of some of our key variables. Following Zhao et al. (2018), we created a weighted differentiation measure that accounts for the fact that apps constituting of

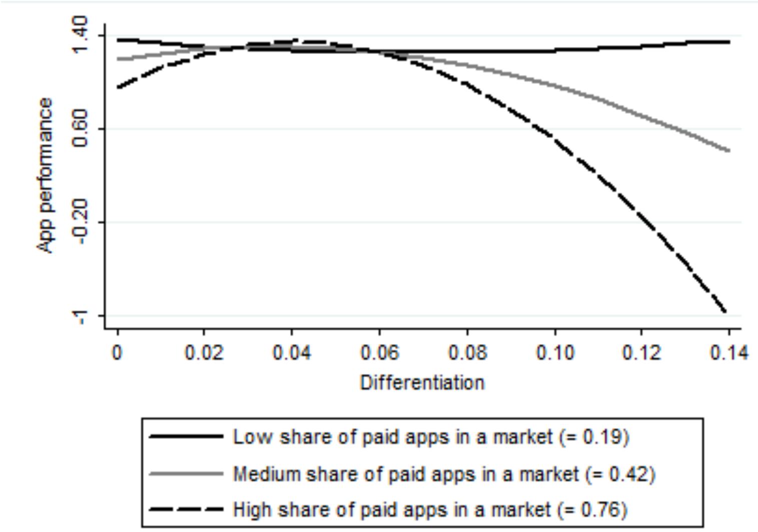

Figure 4.3. The moderating effect of the share of paid apps in a market on the relationship between differentiation and app performance

attributes that are rare in a market are conceived of as more differentiated by consumers compared to others that do not. To this purpose, we constructed app attribute vectors with each value denoting the fraction of competing apps for which the attribute is also present or absent. Subsequently, we computed the average distance between newly introduced paid apps' and their competitors in Euclidean space. Because written textual reviews are likely more informative to consumers and complementors than star ratings and not every consumer leaves a review, we also estimated our models using the share of reviewed apps in a market as a more conservative test of our second hypothesis. Moreover, given that most apps remain in the App Store despite having fallen out of favor with consumers, we also reran our models using measures that reflect a newly introduced paid app's level of strategic differentiation and the share of rated and paid apps in a market only considering active competitors. We defined active competitors as those apps that were updated or released after the major update of iOS in September 2014, the most recent iOS release ending compatibility with older iOS-devices. In all three cases, our findings remained consistent.

As a second set of robustness checks, we assessed the sensitivity of our findings to alternative model specifications. Because autocorrelation and unobserved app heterogeneity are of concern we ran estimations using generalized estimation equations (GEEs), specifying a Gaussian distribution, identity link function, and autoregressive error structures (Liang & Zeger, 1986). Next, mindful of the fact that complementors rarely reposition their apps after they are introduced, we ran ordinary least squares regressions to examine the effect of differentiation on first month app performance. We reasoned that confounding effects, such as fluctuations in app positioning due to market dynamics and a reduction in the information asymmetry between complementor and consumer due to the increasing availability of app ratings, media coverage, and other forms of word-of-mouth communication should be weaker right after the app's introduction. In either of those alternative model specifications, our findings hold.

A third set of robustness checks constituted some split sample analyses. While we controlled for the market presence of hit apps, they may still influence the dynamics in those markets (Zhao et al., 2018). The same goes in case a newly introduced paid app is produced by a complementor that already had other active apps in the same market; its level of differentiation may also reflect other considerations, most notably its relationship with the complementor's other apps (Wang & Shaver, 2016). To rule out that this influenced our results, we estimated our models excluding either those apps introduced into markets with hit apps or by complementors with more apps in the same market. We observe that merely seventeen apps were introduced into a market with a hit app, in support of our assertion that the prevalence of such exemplars is low in our context. Overall, the split sample analyses are consistent with our main results.

In a final set of robustness checks we addressed the role of multi-market competition. That is, even though we paired each app to its closest incumbent competitors, it might be that some apps in reality compete in multiple markets at the same time (Zhao et al., 2018). We dealt with this concern using the original output of our GMM clustering algorithm. Recall that GMM is a fuzzy clustering algorithm that for each app returns a vector with probabilities denoting the likelihood that it fits into a certain market. Hence, we computed newly introduced paid apps' distance vis-à-vis competitors for all markets that they may realistically belong to, then weighing these distances by the market-fit likelihood, which we interpret as indicative of the amount of competition that the app experiences from this market. Analogously, our moderating variables now reflect the weighted cumulative sum of shares of rated and paid apps in all those markets. Our findings remain consistent.

Table 4.6. Alternative variable specifications

	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
Variable	**Weighted differentiation measure**	**Weighted differentiation measure**	**Weighted differentiation measure**	**Only active competitors**	**Only active competitors**	**Only active competitors**	**Share of textual reviews**
Differentiation	0.497***	0.659***	-0.454*	14.944***	23.895***	-11.616*	17.198***
	(0.099)	(0.132)	(0.215)	(3.061)	(4.941)	(5.773)	(4.440
Differentiation^2	-0.134***	-0.148**	0.148**	-132.612***	-218.532***	152.977**	-148.419**
	(0.026)	(0.045)	(0.056)	(27.700)	(53.874)	(51.657)	(49.042)
Share of apps with ratings	0.816***	1.851***	0.821***	0.951***	1.623***	0.884***	1.998***
	(0.130)	(0.452)	(0.132)	(0.116)	(0.333)	(0.117)	(0.325)
Share of apps with ratings x differentiation		-0.911+			-33.216*		-37.701*
		(0.493)			(15.811)		(14.591)
Share of apps with ratings x differentiation^2		0.146			307.479+		260.060+
		(0.154)			(173.502)		(155.732)
Share of paid apps	-0.077	-0.027	-1.107***	-0.018	-0.026	0.941***	-0.001
	(0.128)	(0.129)	(0.269)	(0.115)	(0.116)	(0.232)	(0.129)
Share of paid apps x differentiation			1.697***			60.932***	
			(0.285)			(9.779)	
Share of paid apps x differentiation^2			-0.558***			-727.350***	
			(0.092)			(113.226)	
Residual first-stage regression	2.054	1.550	2.244	-0.367	-0.106	-1.222	3.436
	(6.203)	(6.189)	(6.183)	(5.600)	(5.599)	(5.598)	(6.229)
Market characteristics							
Hit apps	0.595***	0.599***	0.606***	0.612***	0.596***	0.631***	0.594***
	(0.113)	(0.112)	(0.113)	(0.113)	(0.118)	(0.112)	(0.112)
HHI	-0.154***	-0.155***	-0.150***	-0.147***	-0.147***	-0.142***	-0.152***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Maturity	-0.005***	-0.005***	-0.005***	-0.004**	-0.005***	-0.004**	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of apps	0.001**	0.001**	0.001**	0.002***	0.002***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Number of apps by complementor in market	-0.043	-0.043	-0.045	-0.063+	-0.060+	-0.060+	-0.040
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
App characteristics							
Appearance in App Store recommendations	-0.076	-0.069	-0.082	-0.064	-0.066	-0.077	-0.067
	(0.340)	(0.340)	(0.340)	(0.342)	(0.343)	(0.341)	(0.344)
Average in-app purchase price	-0.132*	-0.135*	-0.132*	-0.142*	-0.143*	-0.139*	-0.134*
	(0.065)	(0.065)	(0.065)	(0.062)	(0.062)	(0.062)	(0.065)
Description length	0.002***	0.002***	0.002***	0.002***	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discounted	0.070	0.077	0.074	0.071	0.072	0.076	0.068
	(0.264)	(0.262)	(0.264)	(0.261)	(0.260)	(0.265)	(0.260)
File size	0.018	0.021	0.017	0.018	0.020	0.018	0.023
	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
Media coverage	2.093***	2.082***	2.073***	2.025***	2.055***	2.030***	2.056***
	(0.580)	(0.577)	(0.575)	(0.548)	(0.550)	(0.547)	(0.571)
New version	0.110***	0.110***	0.111***	0.111***	0.111***	0.111***	0.110***
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.018)
Number of months since introduction	-0.018***	-0.019***	-0.018***	-0.018***	-0.017**	-0.017**	-0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Number of ratings	0.365***	0.364***	0.365***	0.357***	0.359***	0.359***	0.364***
	(0.024)	(0.024)	(0.024)	(0.022)	(0.022)	(0.022)	(0.024)
Number of screenshots	-0.013	-0.014	-0.014	-0.012	-0.012	-0.013	-0.012
	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)
Price	0.084+	0.084+	0.083+	0.085*	0.087*	0.088*	0.086*
	(0.043)	(0.043)	(0.043)	(0.042)	(0.043)	(0.042)	(0.043)
Ranked	1.454***	1.453***	1.452***	1.456***	1.459***	1.456***	1.454***
	(0.078)	(0.078)	(0.079)	(0.078)	(0.078)	(0.078)	(0.078)
Constant	-0.856**	-1.068***	-0.173	-0.863**	-1.023***	-0.304	-1.014***
	(0.272)	(0.273)	(0.328)	(0.262)	(0.267)	(0.299)	(0.271)
Fixed effects							
Age rating	Included	Included	Included	Included	Included	Included	Included

App category	Included	Included	Included	Included	Included	Included	Included
Device compatibility	Included	Included	Included	Included	Included	Included	Included
Time	Included	Included	Included	Included	Included	Included	Included
Number of apps	6,984	6,984	6,984	6,969	6,969	6,969	6,984
Number of app-months	45,204	45,204	45,204	45,091	45,091	45,091	45,204
R^2 overall	0.263	0.263	0.264	0.264	0.264	0.267	0.264

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.
Coefficients are reported; bootstrapped standard errors based on 1,000 replications are in parentheses.

Table 4.7. Alternative model specifications

	Model 17	Model 18	Model A19	Model A20	Model A21	Model A22
Variable	**Generalized estimation equations**	**Generalized estimation equations**	**Generalized estimation equations**	**First month performance**	**First month performance**	**First month performance**
Differentiation	13.638*** (3.113)	21.271*** (4.981)	-19.125** (6.075)	12.202** (4.160)	34.293*** (7.057)	-31.138*** (8.450)
Differentiation²	-130.641*** (28.253)	-201.566*** (57.550)	217.125*** (59.567)	-135.546*** (39.023)	-325.323*** (83.848)	312.658*** (88.111)
Share of apps with ratings	1.243*** (0.149)	1.757*** (0.331)	1.107*** (0.155)	1.620*** (0.188)	3.066*** (0.383)	1.336*** (0.199)
Share of apps with ratings x differentiation		-26.577+ (15.410)			-75.746*** (20.690)	
Share of apps with ratings x differentiation²		246.653 (174.223)			663.430** (251.940)	
Share of paid apps	0.122 (0.140)	0.154 (0.143)	-1.032*** (0.236)	-0.392* (0.199)	-0.248 (0.204)	-1.858*** (0.310)
Share of paid apps x differentiation			69.801*** (10.047)			90.434*** (14.370)
Share of paid apps x differentiation²			-798.542*** (120.549)			-987.407*** (180.525)
Residual first-stage regression	8.000 (6.658)	7.387 (6.648)	6.363 (6.660)	0.381 (9.391)	-1.731 (9.381)	-0.724 (9.406)
Market characteristics						
Hit apps	0.525*** (0.085)	0.521*** (0.085)	0.542*** (0.087)			
HHI	-0.207*** (0.039)	-0.206*** (0.009)	-0.204*** (0.039)	-0.410*** (0.082)	-0.398*** (0.082)	-0.407*** (0.082)
Maturity	-0.007*** (0.001)	-0.007*** (0.001)	-0.007*** (0.001)	-0.009*** (0.002)	-0.009*** (0.002)	-0.010*** (0.002)
Number of apps	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)

Number of apps by complementor in market	-0.003	-0.006	-0.006	-0.083+	-0.089+	-0.078+
	(0.038)	(0.038)	(0.038)	(0.046)	(0.046)	(0.045)
App characteristics						
Appearance in App Store recommendations	-0.368	-0.367	-0.389	0.173	0.221	0.166
	(0.318)	(0.318)	(0.321)	(0.767)	(0.761)	(0.767)
Average in-app purchase price	-0.404***	-0.407***	-0.398***	-0.287**	-0.295**	-0.271**
	(0.073)	(0.073)	(0.073)	(0.088)	(0.089)	(0.089)
Descriptionlength	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discounted	1.277	1.274	1.280			
	(1.655)	(1.660)	(1.655)			
Filesize	0.019	0.021	0.018	0.008	0.010	0.008
	(0.020)	(0.020)	(0.020)	(0.024)	(0.025)	(0.025)
Mediacoverage	1.594**	1.589**	1.581**	2.261***	2.329***	2.328***
	(0.576)	(0.574)	(0.567)	(0.615)	(0.596)	(0.581)
Newversion	0.097***	0.097***	0.095***	0.410	0.515	0.525
	(0.021)	(0.021)	(0.021)	(0.333)	(0.337)	(0.335)
Numberofmonthssinceintroduction	-0.029***	-0.030***	-0.030**			
	(0.005)	(0.006)	(0.006)			
Numberofratings	0.613***	0.612***	0.613***	0.444***	0.441***	0.448***
	(0.027)	(0.027)	(0.027)	(0.037)	(0.037)	(0.037)
Numberofscreenshots	-0.048**	-0.049**	-0.048**	-0.044*	-0.046*	-0.044*
	(0.018)	(0.018)	(0.017)	(0.020)	(0.020)	(0.020)
Price	0.145**	0.146**	0.149**	0.126**	0.128**	0.133**
	(0.043)	(0.043)	(0.043)	(0.047)	(0.046)	(0.046)
Ranked	1.404***	1.402***	1.400***	3.888***	3.877***	3.860***
	(0.093)	(0.093)	(0.093)	(0.122)	(0.123)	(0.123)
Constant	-1.042**	-1.173***	-0.294	-0.906+	-1.223*	0.126
	(0.297)	(0.303)	(0.334)	(0.491)	(0.496)	(0.529)
Fixedeffects						
Agerating	Included	Included	Included	Included	Included	Included

Appcategory	Included	Included	Included	Included	Included	Included
Devicecompatibility	Included	Included	Included	Included	Included	Included
Time	Included	Included	Included	Included	Included	Included
Numberofapps	5,704	5,704	5,704	6,969	6,969	6,969
Numberofapp-months	40,226	40,226	40,226			
R^2				0.304	0.305	0.307
Waldχ^2	3,134	3,156	3,327			

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.
Coefficients are reported; bootstrapped standard errors based on 1,000 replications are in parentheses.

Table 4.8. Alternative explanations

	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31
	Excluding markets with hit apps	**Excluding markets with hit apps**	**Excluding markets with hit apps**	**Without introductions associated with active incumbent apps**	**Without introductions associated with active incumbent apps**	**Without introductions associated with active incumbent apps**	**Multi-market competition**	**Multi-market competition**	**Multi-market competition**
Differentiation	8.151** (2.696)	17.573*** (4.376)	-10.096+ (5.201)	5.934* (2.794)	12.964** (4.709)	-10.786+ (5.508)	5.301* (2.189)	16.001*** (3.711)	-8.396+ (4.713)
Differentiation^2	-93.291*** (24.718)	-165.492** (49.318)	103.945* (49.565)	-73.856** (24.466)	-100.568* (50.877)	99.640 (51.191)	-60.067*** (15.430)	-147.665*** (33.984)	67.222 (40.938)
Share of apps with ratings	0.885*** (0.127)	1.635*** (0.307)	0.826*** (0.129)	1.023*** (0.135)	1.778*** (0.344)	0.973*** (0.139)	0.889*** (0.128)	1.674*** (0.268)	0.817*** (0.131)
Share of apps with ratings x differentiation		-33.932* (13.942)			-25.755+ (14.546)			-36.071** (11.017)	
Share of apps with ratings x differentiation^2		268.151+ (152.023)			122.755 (152.628)			290.515** (177.644)	
Share of paid apps	-0.058 (0.124)	0.024 (0.126)	-0.702** (0.219)	-0.068 (0.130)	-0.015 (0.129)	-0.706* (0.237)	-0.081 (0.127)	-0.046 (0.128)	-0.650** (0.215)
Share of paid apps x differentiation			39.221*** (8.512)			36.393*** (8.892)			29.153*** (7.808)
Share of paid apps x differentiation^2			-457.859*** (96.691)			-404.430*** (98.099)			-288.727*** (80.938)
Residual first-stage regression	4.924 (6.168)	3.142 (6.168)	3.014 (6.157)	7.248 (5.317)	6.407 (5.328)	6.293 (5.398)	3.861 (6.121)	2.796 (6.118)	2.957 (6.129)
Market characteristics									
Hit apps				0.550*** (0.141)	0.555*** (0.140)	0.573*** (0.114)	0.584*** (0.112)	0.582*** (0.114)	0.597*** (0.112)

HHI	-0.157***	-0.155***	-0.151***	-0.149***	-0.149***	-0.145***	-0.154***	-0.153***	-0.151***
	(0.037)	(0.037)	(0.037)	(0.040)	(0.041)	(0.040)	(0.037)	(0.037)	(0.037)
Maturity	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.004***	-0.004***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of apps	0.001**	0.001**	0.001**	0.002***	0.002***	0.002***	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of apps by complementor in market	-0.042	-0.047	-0.046				-0.046	-0.047	-0.044
	(0.034)	(0.034)	(0.033)				(0.033)	(0.032)	(0.032)
App characteristics									
Appearance in App Store recommendations	-0.054	-0.050	-0.063	-0.164	-0.157	-0.172	-0.074	-0.070	-0.077
	(0.353)	(0.353)	(0.351)	(0.386)	(0.386)	(0.385)	(0.341)	(0.674)	(0.339)
Average in-app purchase price	-0.130*	-0.130*	-0.127*	-0.114+	-0.117+	-0.116+	-0.134*	-0.136*	-0.133*
	(0.064)	(0.064)	(0.064)	(0.066)	(0.066)	(0.066)	(0.065)	(0.065)	(0.065)
Description length	0.002***	0.002***	0.002***	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Discounted	0.081	0.084	0.086	-0.085	0.074	0.079	0.065	0.071	0.070
	(0.259)	(0.262)	(0.262)	(0.300)	(0.298)	(0.301)	(0.265)	(0.265)	(0.265)
File size	0.015	0.017	0.015	0.019	0.022	0.019	0.018	0.020	0.019
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)
Media coverage	2.043**	2.058**	2.047**	1.982**	1.983**	1.979**	2.055***	2.053***	2.043***
	(0.746)	(0.744)	(0.738)	(0.592)	(0.591)	(0.589)	(0.574)	(0.574)	(0.570)
New version	0.110***	0.109***	0.109***	0.117***	0.117***	0.117***	0.110***	0.110***	0.110***
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
Number of months since introduction	-0.019***	-0.019***	-0.018***	-0.015**	-0.015**	-0.014**	-0.019***	-0.019***	-0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Number of ratings	0.351***	0.354***	0.356***	0.401***	0.402***	0.402***	0.364***	0.363***	0.365***
	(0.023)	(0.023)	(0.023)	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.025)
Number of screenshots	-0.012	-0.013	-0.013	-0.000	-0.001	-0.001	-0.012	-0.013	-0.013
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)

Price	0.079+	0.082+	0.083+	0.107*	0.106*	0.108*	0.083+	0.084+	0.083+
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)
Ranked	1.418***	1.411***	1.415***	1.530***	1.528***	1.532***	1.454***	1.453***	1.456***
	(0.079)	(0.078)	(0.078)	(0.084)	(0.084)	(0.085)	(0.078)	(0.078)	(0.078)
Constant	-0.783**	-0.911***	-0.312	-1.011***	-1.216***	-0.618*	-0.720**	-0.914**	-0.340
	(0.279)	(0.283)	(0.314)	(0.265)	(0.269)	(0.300)	(0.272)	(0.272)	(0.295)
Fixed effects									
Age rating	Included	Included	Included	Included	Included	Included	Included	Included	Included
App category	Included	Included	Included	Included	Included	Included	Included	Included	Included
Device compatibility	Included	Included	Included	Included	Included	Included	Included	Included	Included
Time	Included	Included	Included	Included	Included	Included	Included	Included	Included
Number of apps	6,967	6,967	6,967	6,572	6,572	6,572	6,572	6,984	6,984
Number of app-months	45,052	45,052	45,052	41,524	41,524	41,524	41,524	45,204	45,204
R^2 overall	0.239	0.240	0.244	0.262	0.262	0.264	0.261	0.261	0.263

+ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; two-tailed tests.
Coefficients are reported; bootstrapped standard errors based on 1,000 replications are in parentheses.

4.5 Discussion

This study examined the implications of differentiation for the performance of newly introduced paid complements in platform marketplaces. We theorized that complementors face two opposing forces in positioning their offerings. First, platform market competition compels them to differentiate, underscoring the positive effect of differentiation on complement performance. Second, the information asymmetry that exists between complementors, who know the value of their products, and consumers, who do not, draws complements closer to one another, highlighting the negative effect of differentiation for complement performance. This is the case because consumers rely on their experiences with, and knowledge of, competing products in gauging the value creation potential of new offerings, so that newly introduced and highly differentiated paid complements are more likely to suffer from adverse selection. We reconciled these two opposing pressures by suggesting that differentiation exhibits an inverted U-shaped relationship with the performance of a paid complement. Furthermore, we argued that the share of rated and paid apps in a market moderate this relationship. Specifically, peak complement performance occurs at lower levels of differentiation in markets with a high share of rated apps, while it manifests itself at higher levels of differentiation in markets with a high share of paid apps. Analyzing the performance of 6,984 newly introduced paid apps in the U.S. market of Apple's iOS App Store between May 2016 and June 2017 and drawing from computational methods to quantify a complement's level of differentiation relative to a specific set of incumbent competitors, we presented empirical results that were consistent with our theory.

There are some limitations to this study. Our empirical analysis is limited to a single empirical context, and it thus follows that their validity has to be established across other contexts. More specifically, our findings appear most readily generalizable to other contexts that are software-based, such as computer programs, mobile applications, video games, and others. However, at least parts of our theory may also carry over to certain classes of products on online marketplaces, such as Amazon or eBay. Moreover, in our market identification and operationalization of the differentiation measure, we relied on the product descriptions available in the platform marketplace that provide a rich overview of complements and their attributes (Barroso et al., 2016; Hoberg & Philips, 2016; Shi et al., 2016; Wang et al., 2018). However, product descriptions are composed by complementors, and it might be that complementors deliberately exaggerate or underplay the prominence of certain attributes of their complements. Future research may therefore seek to investigate the performance implications of differentiation in contexts in which even richer product information, such as source code or extensive product documentation, is available. For example, even if similar functionalities might be implemented in myriad ways, carefully scrutinizing complements' source code may yield a list of the functionalities that they actually include. That way, it becomes possible to construct a more objective measure of differentiation, free from the potential biases that could emanate from our reliance on the language use of complementors. On a related note, our market identification was constrained by the platform marketplace's predefined categorical boundaries. However, our data suggest that similar markets may coexist across disparate product categories. The extent to which complements experience competition from rivals across categorical boundaries provides another interesting opportunity for future research.

Notwithstanding these limitations, our study contributes in a number of ways. First, this study contributes to the literature on competitive positioning, and its emerging stream of work on optimal distinctiveness in particular. Research in this area has established that firms should strive to position their products at intermediate levels of differentiation, because of facing opposing forces to differentiate and conform (Zhao et al., 2017; Zuckermann, 2016). However, in theoretically and empirically developing firms' and products' need for conformity, prior work has by and large drawn from two specific contexts. It has either focused on rigid contexts such as banking where institutional pressures are invariably potent and dictate what products should look like and which attributes they should contain (Deephouse, 1999), or cultural contexts such as popular music and mainstream video games where markets and consumer attention strongly coalesce around widely known hit products (Askin & Mauskapf, 2017; Zhao et al., 2018). We thus contribute by focusing on competitive positioning of paid complements in platform marketplaces, contexts where institutional pressures are weaker and exemplars usually not present. We observed that even here, differentiation exhibits an inverted U-shaped relationship with complement performance. This is the case because the information asymmetry between complementors and consumers incentivizes firms to position their offerings closer to rivals in order to reduce consumers' uncertainty, As such, we contribute a novel theoretical mechanism driving conformity, and therewith we relax the scope condition of strong institutional pressures and exemplars that underlies the current optimal distinctiveness hypothesis. Moreover, by examining how the share of rated and paid complements in a market moderate the relationship between differentiation and complement performance, we showed that market characteristics help determine if optimal distinctiveness favors greater differentiation or conformity, or whether optimal distinctiveness occurs at all (Zhao et al., 2017). That way, our study makes a first step towards establishing the boundary conditions to optimal distinctiveness.

Second, we add to the small but growing body of work that grapples with the challenges and opportunities that complementors face in the marketplaces set around platforms. Research in this area has particularly focused on establishing the antecedents of heterogeneity in the performance of complements. In so doing, it has successfully linked factors such as complements' characteristics and business models (Arora et al., 2017; Ghose & Han, 2014; Rietveld, 2018; Yin et al., 2014), and platforms' evolutionary features (Boudreau, 2012; Eckhardt, 2016; Kapoor & Agarwal, 2017; Rietveld & Eggers, 2018) to complement performance. We complement these studies by focusing on the role of complements' positioning in attribute space. While controlling for other antecedents of complement performance, we showed that the positioning of a complement relative to its rivals upon its introduction into the platform marketplace is a significant predictor of its performance. We also found that the optimal position wildly varies across distinct markets in platform marketplaces, and that way offer one explanation for the heterogeneity in complement positioning that can be observed in practice. Markets characterized by a high share of rated apps favor more conformity; markets harboring a high share of paid apps require greater differentiation. As such, our findings also have important implications for complementors. Most prominently, our study makes a pledge for divergent complement positioning strategies informed by market characteristics.

Finally, we contribute to the strategy literature that takes a demand-based perspective (Priem, 2007; Priem et al., 2012), which has mostly focused on characterizing demand heterogeneity and establishing the implications hereof for the performance of firms and their products (Adner & Levinthal, 2001; Adner & Snow, 2010; Rietveld & Eggers, 2018). We go beyond extant work in this area in two ways. First, compared to prior work, we take a next step by explicitly considering at least one role that demand conditions play in shaping the effectiveness of complements' positioning strategies. We illuminate that the severity and salience of consumers' informational disadvantage relative to complementors has an important bearing on the range of fruitful positions in a market. Second, by theorizing the role of consumers' informational disadvantage, we consider the implications of a demand condition that is different from consumer preference heterogeneity, which has been the focus of most of studies in the demand-based literature stream in strategy (Priem et al., 2012).

5

Chapter 5

Conclusion

This chapter summarizes the findings of the three empirical studies that constitute this dissertation. Collectively, the three studies advance competitive positioning and business model choice as two critical antecedents of complement performance in platform marketplaces. It also discusses the theoretical and practical implications of those findings. Theoretically, this dissertation makes various contributions to disparate literature streams in organization theory, information systems, and strategy. Practically, this dissertation produces guidelines for complementors and platform provider firms alike. This chapter concludes with a reflection upon some of this dissertation's limitations and the opportunities for future research that they might bring, followed by closing remarks.

5.1 Summary of Findings

What are the implications of competitive positioning and business model choice for the performance of complements in platform marketplaces? Motivated by the increasing prevalence of platforms and their marketplaces as new areas of business activity and the surprising lack of research that specifically considers how complementors survive and thrive in these highly competitive contexts, this dissertation set out to explore the performance implications of two fundamental choices that every complementor has to make concerning the creation and capture of value from their complements. It did so through three independent studies that each addressed their own research question, in turn corresponding to part of this dissertation's overarching question. Theoretically, each study adopted a dinstinct lens, originating from the management disciplines of organization theory, information systems, and strategy, respectively. That way, this dissertation resembles the multidisciplinary nature of extant research on platforms and their marketplaces (Jacobides, Cennamo, & Gawer, 2018). Empirically, the three studies examined the performance implications of competitive positioning, business model choice, or both in the context of the U.S. market of Apple's iOS App Store, a canonical example of a platform marketplace.

The first study (Chapter 2) started out from the observation that, by virtue of generativity and network effects (Boudreau 2012; Cennamo & Santalo, 2013; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003), in most platform marketplaces the volume of available complements has grown so substantial that product classification systems, such as product categories or labels, alone are insufficient to adquately constrain consumers' initial consideration sets (Bowers, 2015). Therefore, it explored whether the value-capturing portion of complements' business models, referred to as logics for value capture, may serve as a secondary criterion by which consumers filter out some viable alternatives from further consideration. To this purpose, this study focused on how combining multiple value-capturing mechanisms in the logics of value capture of free complements influenced their downloads. After all, in the absence of an up-front download price barriers to acquire one free complement relative to another should not differ, ceteris paribus. Conditional fixed-effects negative binomial regressions of complements' logics for value capture on downloads for 24,194 free apps in the iOS App Store show that adopting code-violating logics for value capture—combinations of value-capturing mechanisms with distinct approaches to the extraction of economic value—lead to a reduction in downloads of around three precent. By contrast, adding additional value-capturing mechanisms while retaining a consistent approach to the extraction of economic value increases downloads. Taken together, these findings suggest that the value-capturing portions of complements' business models may indeed serve as salient markers for consumers in screening out offerings worthy of consideration from irrelevant ones.

The second study (Chapter 3) examined the download and revenue implications of freemium and ad-supported freemium business models relative to simply distributing complements for-a-fee. Freemium and ad-supported freemium business models have become increasingly prevalent in platform marketplaces (Kumar, 2014; Niculescu & Wu, 2014), even if their performance implications have thus far remained poorly understood. Analyses were based on an assessment of how 76,051 freemium and paid apps fared in the iOS App Store between May and December 2016. Regarding downloads, the results show that freemium complements garner more downloads than paid complements, but that this effect is weaker for those complements combining freemium with advertising. The zero-inflated negative binomial regression models producing those results explicitly accounted for the relatively low probablility that any complement is downloaded amid a multitude of competitors. Regarding revenues, the findings suggest that the optimal business model depends on whether complements are positioned to target mass or niche markets. Conceiving of mass market and niche complements as those observations that, due to their disparity in consumers' appeal, lie at the opposite ends of the conditional distribution of complement revenue (Brynjolfsson et al., 2010), quantile regression estimations show that, when compared to distributing complements at-a-fee, the freemium approach yields inferior revenues for complements positioned to target niche markets and superior revenues for complements positioned to target mass markets. The implications of combining freemium with advertising work in the opposite direction: combining freemium with advertising is particularly problematic for complements positioned to target mass markets, while sometimes synergies exist for ad-supported freemium complements positioned to target niche markets.

The third study (Chapter 4) focused on the consquences of competitive positioning by investigating the implications of differentiation for the revenues of newly introduduced paid complements. It advanced the idea that complementors have to reconcile two opposing forces in positioning their complements. Intense competition in the platform marketplace compels complementors to differentiate, while consumers' reliance on extant market knowledge in gauging the true value of newly introduced complements prompts complementors to conform. Analyzing the performance of 6,984 newly introduced paid apps in the iOS App Store from May 2016 until June 2017 by means of random effects regressions yielded support for this idea: theere is an inverted U-shaped relationship between differentiation and paid complement performance. A complement that is positioned at the optimal point of differentiation enjoys a 15.6% increase in revenues compared to a complement that is undifferentiated, while it earns 7.5% more than a highly differentiated complement. Additional analyses also suggested that this point of optimal distinctiveness is contingent on the characteristics of the market in which the paid complement is introduced. Newly introduced paid complements' peak performance occurs at lower levels of differentiation in markets with a high share of rated complements, while manifesting itself at higher levels of differentiation in markets that harbor a high share of paid complements.

5.2 Theoretical Implications

Owing to this dissertation's multidisciplinary perspective on platforms and their marketplaces, it contributes to a number of disparate literature streams. The remainder of this section outlines those theoretical contributions, as they relate to the development of our knowledge in the management disciplines of organization theory, information systems, and strategy.

5.2.1 Contributions to Literature in Organization Theory

This dissertation contributes to two streams of literature within the discipline of organization theory. First, the first and second study hold implications for the business model literature that is firmly centered on developing an understanding of how firms and their products create and capture value (Massa, Tucci, & Afuah, 2017; Zott et al., 2011). This dissertation enhances the theoretical and empirical understanding of the performance implications of various business models for free complements, a particularly prevalent class of business models that is worthy of greater scholarly attention (Baden-Fuller & Haefliger, 2013; Teece, 2010). In so doing, the findings suggest that there is a complex relationship between complements' choice of business model and their performance. The second study shows that there are distinct optimality regions where paid, freemium, or ad-supported freemium complements yield superior performance. Meanwhile, the first study provided a comprehensive account of different value-capturing mechanisms that can or cannot be combined. As such, this dissertation adds further nuance to the empirical literature that grapples with business model configurations (Aversa et al., 2015; 2017; Clemons, 2009; Zott & Amit, 2007), and calls for greater research attention for the interaction between different components of business models. Moreover, the performance heterogeneity of business models as empirically observed throughout the first two studies of this dissertation is theorized to result, for an important part, from consumers' perceptions. The basic argument holds that the business model configuration influences consumers' perceptions of a complement, and that these perceptions affect its eventual performance in the platform marketplace. This is counter to the conventional explanation in the literature concerning the business model components or value-capturing mechanisms that can or cannot be combined, which is based on the manifestation of operational difficulties or inefficiencies (Aversa et al., 2017; Casadesus-Masanell & Zhu, 2010; Markides, 2013), essentially leaving the consumers that ultimately evaluate these decisions in the product market out of consideration. Looking both inward into the firm and outward onto the product market therefore seems critical to developing a complete understanding of the performance implications of business model choice.

Second, the first study complements extant work on the implications of market categories. Research in this area has thoroughly established the important role that product classification systems reflecting consumer value propositions, or product-level value creation, play for consumers in screening out those offerings worthy of further consideration from irrelevant ones. Most notably, it has done so by showing that violation of categorical boundaries is negatively associated with indicators of product performance, because it adversely affects the identity of the firm or its product (e.g., Hsu, 2006; Pontikes, 2012; Zuckerman, 1999). However, the first study in this dissertation shows that the downloads of free complements in platform marketplaces are equally contingent on the combination of value-capturing mechanisms that they enact and how those are perceived by consumers, suggesting that consumers also screen out complements based on the logic for value capture of their business model. Consumers tend to hold strong preferences towards particular ways of paying for products, and viable alternatives abound, they can afford to act upon those preferences by selecting some offerings with certain logics for value capture for further consideration, while neglecting others. As such, this dissertation suggests that the identities of complements in platform marketplaces are established or muddied along multiple dimensions of their business model, at least including their consumer value proposition and logic for value capture.

5.2.2 Contributions to Literature in Information Systems

This dissertation holds additional implications for research on information systems. First, the findings from the second study are of interest to the literature on long-tail markets. Motivated by the empirical observation that products targeted at mass and niche markets often coexist (Brynjolfsson et al., 2010; Brynjolfsson et al., 2011), a number of studies has documented the differential impact of factors such as in-store recommendations from recommender systems and consumer ratings for both types of products (Dellarocas et al., 2010; Fleder & Hosanagar, 2008; Gu et al., 2013; Oestreicher-Singer & Sundararajan, 2012). However, despite these efforts it has remained a longstanding question whether the consequences of product strategies may equally differ for products positioned to target mass versus niche markets (Brynjolfsson et al., 2010). This dissertation responds to this call, by explicitly delineating the revenue implications of freemium and ad-supported freemium business models for both types of complements. Since the results reveal apparent differences, this dissertation challenges the prescriptive value of prior research on platform marketplaces for niche complements, whose findings by and large derive from only the most popular complements (e.g., Ghose & Han, 2014; Kapoor & Agarwal, 2017; Liu et al., 2014; Yin et al., 2014). As such, this dissertation calls for more research that explicitly focuses on the product strategies of niche complements.

Second, developing an increased understanding of the workings of freemium business models also speaks to the literature on versioning and sampling of information goods. Despite the popularity of offering free versions for digital products such as software and video games, this literature has hitherto remained devoid of large-scale empirical investigations. Instead, it has focused on establishing the effectiveness of offering free versions in theoretical models with none or a limited number of competing products, therewith naturally focusing on the contingent role of product and consumer characteristics (e.g., Bhargava & Choudhary, 2008; Dey & Lahiri, 2016; Niculescu & Wu, 2014). Hence, the contribution of the second study to this literature is twofold. On the one hand, it adds value by empirically examining the performance implications of offering free versions across a large number of complements in a platform marketplace. On the other hand, the finding that the effectiveness of the free offering embedded in a complement's freemium business model is contingent on the size of the consumer audience that its market appeals to, shifts the focus of the literature from consumer and product characteristics towards market characteristics.

Third, the first and second study contribute to the literature that considers how the availability of product information influences consumers' download decisions. Because complements are typically experience goods (Arora et al, 2017), consumers strongly rely on the information available in or surrounding a platform marketplace to make a value assessment for a particular complement. Indeed, sources of product information such as product descriptions and screenshots (Ghose & Han, 2014), recommendations from in-store recommender systems (Fleder & Hosanagar, 2008), the download decisions of other consumers (Duan et al., 2009), consumer reviews (Zhu & Zhang, 2010), and reviews by expert critics (Wijnberg & Gemser, 2000) have all been found to affect complements' downloads. Most closely related to this dissertation, Shampanier et al. (2007) also document pricing as critical in consumers' decision-making processes. However, the results of the first and second study suggest that the impact of the business model on consumers' download decisions is not limited to product pricing alone, as these studies document that free complements' downloads vary dependent on the configuration of value-capturing mechanisms they enact. As such, these findings suggest that there is a certain heterogeneity in the way in which consumers trade-off between different business model configurations of competing zero-priced complements.

5.2.3 Contributions to Literature in Strategy

The findings presented in this dissertation also hold theoretical implications for various strands of literature within the strategy discipline. First, the third study contributes to our understanding of the implications of competitive positioning of products, which is a central tenet in the strategy literature (Adner et al., 2014; Barroso et al., 2016). More specifically, the third study adds to the bourgeoning literature on optimal distinctiveness, which contends that firms should position their products at intermediate levels of differentiation because they face opposing forces to differentiate and conform (Zhao et al., 2017; Zuckerman, 2016). While product market competition is the invariable force that compels firms to differentiate, prior research has advanced at least two forces that may prompt firms to conform. In rigid contexts, such as automotive or banking, strong institutional pressures dictate what is to be expected of products, that way setting the confines within which profitable differentiation may take place (Deephouse, 1999). In cultural contexts, such as popular music or mainstream video games, consumers' and firms' attention strongly coalesces around widely known hit products, causing products to become more similar to one another (Askin & Mauskapf, 2017; Zhao et al., 2018). Thus, the presence of strong institutional pressures or widespread knowledge of hit products constitute critical boundary conditions underpinning the optimal distinctiveness hypothesis. The third study relaxes this boundary condition by examining the performance implications of differentiation in platform marketplaces, a context where institutional pressures are weaker because market boundaries are continuously in flux (Navis & Glynn, 2010), and where by virtue of their long-tailed market structure widely known hit products are usually absent (Brynjolfsson et al., 2010). The study's results show that the differentiation of newly introduced paid complements exhibit an inverted U-shaped relationship with complement performance, because consumers' rely on their knowledge of, and experience with, competing offerings in gauging the value creation potential of a new offering. That way, the third study advances a novel theoretical mechanism that may drive complements' need for conformity.

Second, all three studies add to the small, but growing body of research that investigates the challenges and opportunities that complementors face in doing business in platform marketplaces. Prior work in this area has primarily focused on linking complements' characteristics to performance (Ghose & Han, 2014; Lee & Raghu, 2014; Yin et al., 2014), and developing an understanding of how platforms' evolutionary features, such as intergenerational transitions or maturity, affect complement success (Boudreau, 2012; Eckhardt, 2016; Kapoor & Agarwal, 2017; Rietveld & Eggers, 2018). This dissertation supplements those works by investigating the performance implications of two crucial decisions concerning the creation and capture of value from complements in platform marketplaces, that way firmly focusing on what complementors themselves can do to be successful in such contexts. Collectively, the three studies in this dissertation advance a complement's differentiation and business model as two fundamental antecedents of its performance. Moreover, the findings of the second and third study also suggest that the implications of competitive positioning and business model choice wildly vary across distinct markets within a platform marketplace. To illustrate, the third study shows that the optimal level of complement differentiation depends on the share of rival rated and paid complements in a market, and the second study indicates that the best performing business model is contingent on the consumer appeal of the market within which the complement is set. This heterogeneity goes beyond the platform marketplace's predefined product categories, which in prior research have typically been treated as synonymous with markets (Arora et al., 2017; Boudreau, 2012; Eckhardt, 2016; Liu et al., 2014; Yin et al., 2014). As such, this dissertation calls for a renewed appreciation of, and fine-grained attention for, the palpable variety of distinct markets that exists in platform marketplaces and the implications that result for complements' strategies and performance.

Third, all three studies also contribute to the literature that takes a demand-based perspective to strategy. In its essence, this literature regards product markets as key sources of value creation and capture for firms, rather than looking upstream towards factor markets (Priem 2007; Priem et al., 2012). In so doing, scholars in this area have mostly focused on characterizing demand heterogeneity in product markets and establishing the implications hereof for the performance of firms and their products (Adner & Livinthal, 2001; Adner & Snow, 2010; Rietveld & Eggers, 2018; Ye, Priem, & Alshwer, 2012). This dissertation takes a next step by explicitly theorizing and testing the role that demand conditions play in shaping the performance outcomes of complements' strategies, a key premise of the demand-based perspective (Priem et al., 2012). For example, the first study illuminates how consumers' product-payment preferences influence the value-capturing mechanisms that can or cannot be combined in the business model of free complements, while the third study shows that the severity of the information asymmetry between a complementor and consumer has an important bearing on the range of profitable product positions that a market may support.

5.3 Practical Implications

This dissertation also offers valuable insights to practitioners. Foremost, it provides guidance to complementors that compete in densely populated platform marketplaces in general, and software-based platform marketplaces in particular. Notwithstanding the tremendous growth and increasing importance of platform marketplaces as legitimate business contexts, not all complements are created equal. In fact, many complementors grapple to make a profit, as is aptly illustrated in the mobile app industry (e.g., App Promo, 2014; SurveyMonkey Intelligence, 2016; Vision Mobile, 2015), and there is hardly any guidance or best practice advice for complementors to improve the performance of their complements. To their benefit, this dissertation suggests some guidelines and a benchmark concerning the average performance implications of various business model configuration for free complements, freemium and ad-supported freemium business models, imitation, and differentiation.

In recent years, especially software-based platform marketplaces have turned into contexts where the prevailing market prices are zero. For example, by the end of the first quarter of 2018, more than 94 percent of the complements in Google's Play Store of its Android mobile platform were free (Statista, 2018). Complementors seem to routinely jump the free products bandwagon (Arora et al., 2017), possibly wary of falling out of favor with consumers as soon as they decide to charge for their complement up front. However, this dissertation provides a cautionary tale concerning this trend. The results of the second study show that freemium is the optimal business model only for those complements situated above the 90th percentile of the conditional distribution of complement revenue. In other words, those complements that appeal to a large consumer audience. Hence, producers of most specialized complements, such as scientific calculators, measurement tools for construction workers, and vintage games, are arguably better off simply charging for their complement, underscoring the importance of weighing in a complement's market potential when determining its business model. To those complementors nevertheless determined to stick to a freemium business model, the results of the first study provide guidance on the value-capturing mechanisms that they may or may not enact in tandem.

Similarly, this dissertation provides insights regarding other commonly made decisions concerning the creation and capture of value from complements. The second study provides insights into the consequences of complementing a freemium business model with advertising, as a way to recover some of the costs that result from supporting an abundance of non-paying consumers. It shows that this approach, albeit attractive, is generally counterproductive. Consumers disliking of advertising erodes their trial experience. This effect is particularly pertinent for complements positioned to target mass markets. Moreover, the findings of the third study vouch against blunt imitation of other complements. Instead, a moderate level of differentiation is required to achieve optimal complement performance.

More generally, this dissertation suggests that the performance of complements is largely contingent on the specific market conditions of the narrowly defined market niche within which the complement is positioned. What may work in one market, leads to adverse effects in another. For example, the third study suggests that the optimal positioning of a paid complement highly depends on the share of rated and paid complements in its market. Less differentiation should be preferred in markets with many rated complements, because consumers strongly rely on ratings and reviews of rival offerings in reducing their uncertainty about the true value of the focal complement in question. By contrast, more differentiation is warranted in markets with a larger share of paid apps. Complementors should thus carefully assess and review the characteristics of the market within which its complement is, or will be, set. This suggestion seems to be in line with the increasing proliferation of market analytics firms that are dedicated to offering such competitor intelligence, as can for instance be observed in the mobile app industry.

As such, this dissertation also holds implications for platform provider firms. The empirical observation concerning the tremendous heterogeneity of complements in platform marketplaces suggests that, by virtue of indirect network effects, the differential contribution to the overall value of the platform may differ from one complement to another. Complements that are plentiful add relatively little value to the platform when compared to those that are scarce, and this effect goes beyond the predefined set of product categories in platform marketplaces. This suggests that platform provider firms may benefit from running detailed analytics on their platform marketplace to identify those markets or niches that represent the most promising avenues for consumer traction and growth, allowing them to nudge complementors' efforts at the level of the market niche, rather than the level of the product category as is commonly done. Analogously, the same logic applies to the promotion of selected complements by platform provider firms. Because consumers navigate the platform marketplace based on searches reflecting a particular need or want, the selective promotion of complements should reflect this behavior.

5.4 Limitations and Directions for Future Research

While this dissertation constitutes three large-scale empirical studies into the performance implications of competitive positioning and business model choice in platform marketplaces, some limitations remain that open up new avenues for future research.

First, all three studies were conducted in a single empirical context, the U.S. storefront of Apple's iOS App Store, which limits the generalizability of this dissertation's findings. After all, iOS constitutes as much of a canonical example as it does an extreme case of the platform-based business model. For one, the number of competing complements in the iOS App Store far exceeds that of most other platforms, such as the Xbox One, Salesforce, or Facebook. Hence, viewed as a whole, the findings in this dissertation seem most readily generalizable to complements on other mobile platforms, or complements for laptop and desktop computers that satisfy by and large the characteristics. However, this does not necessarily imply that the findings of individual studies may not carry over to other contexts. For example, the findings concerning the performance implications of business model choice from the first two studies may be applicable in contexts such as software or video gaming where the marginal costs of production and distribution tend to be lower, whereas the consequences of differentiation as illustrated in the third study may more readily apply to densely populated platform marketplaces, including Amazon and eBay.

Second, all the studies in this dissertation are quantitative in nature; the analyses based on sophisticated econometric models. As such, the studies provide a thorough test of the performance implications of competitive positioning and business model choice, robust to idiosyncratic differences in complements and markets. However, they provide less insight into the rationale behind those choices. It might for instance be that some hobbyist complementors explicitly prefer a freemium over a paid complement despite its inferior revenue performance, simply because the freemium complement has the additional benefit of increased exposure due to attracting more consumers, which may yield non-monetary gains (Lerner & Tirole, 2002; Roberts et al., 2006). Complementing the large-scale empirical enquiries presented in this dissertation with fine-grained qualitative studies of complementors may therefore lead to a more complete understanding of the multifaceted consequences of competitive positioning and business model choice in platform marketplaces.

Third, while much of the theorizing concerning the performance implications of competitive positioning and business model choice in this dissertation adopts a demand-based lens that is largely consumer-centric, the secondary aggregate-level nature of the empirical data collected for this dissertation impeded observing consumers' download and purchase decisions directly. Rather, the empirical data reflect downloading and spending behavior at the level of the entire consumer audience. Albeit that there likely is a correlation between the download behavior of individual consumers and that of the entire consumer audience, it is not possible to determine whether certain spikes in downloads are the consequence of repetitive installing and uninstalling by a single, or a small group of, consumer. Future research may address this issue through individual-level data or field experiments, as for instance occasionally happens in the information systems discipline (e.g., Han et al., 2016).

Fourth, the operationalization of measures for aspects of competitive positioning and business model choice across all three studies in this dissertation have to fewer or greater extent relied on various pieces of textual product information that are available from the platform marketplace. Because such product information constitutes the main communication channel between complementor and consumer (Lee, Raghu, & Park, 2015), it generally provides a rich and encompassing overview of complements, business models, and their attributes. However, this information is usually supplied by complementors, which leaves open the possibility that they deliberately exaggerate or underplay particular aspects of their complement or its business model, potentially having some bearing on the employed measures of competitive positioning and business model choice. Future research may therefore seek to investigate the performance implications of competitive positioning and business model choice in contexts where even richer, or diverse, source of product information are available. For example, researchers may investigate the consequences of differentiation in a context where access to the source code is available, or the implications of business model choice by surveying complementors on the different value-capturing mechanisms that they enact.

Finally, to adequately study competitive positioning in the second and third study, it was necessary to segregate the iOS App Store into narrowly defined markets or niches, because it is merely those complements targeted at the same pocket of consumers that end up in intense competition with one another (Cattani et al., 2017). As this is a computationally complex task, especially when the dataset consists of tens of thousands of complements, the market identification procedures were constrained by the platform marketplace's predefined set of product categories. In other words, the platform marketplace was surmised to exhibit a nested structure, so that complements are nested in markets, while markets are nested in product categories. However, empirical observations across the second and third study suggest that similar markets may coexist across different product categories. For example, QR code scanners and readers can be found in both the productivity and utilities category in the iOS App Store. This opens up an interesting avenue for future research, as complementors are deliberately choosing to enlist their complements in different or less fitting product categories in a bid to position themselves away from rivals and that way forego competition. Scholars may, for instance, investigate when complementors resort to enlisting their complements in seemingly less fitting product categories as well as the conditions under which such a strategy is beneficial.

5.5 Concluding Remarks

This dissertation set out to explore the performance implications of competitive positioning and business model choice for complements in platform marketplaces. Complementors constitute the vast majority of actors in platform-dominated industries, yet prior research has by and large directed itself at the unitary actor that orchestrates the platform. Three independent empirical studies were conducted, focusing on the consequences of competitive positioning, business model choice, or both. Theoretically, each study adopted a distinct theoretical lens, emanating from the management disciplines of organization theory, information systems, and strategy. Empirically, all studies examined the performance of complements in the U.S. market of Apple's iOS App Store.

Collectively, the three studies in this dissertation underline the value of adopting a multidisciplinary perspective to develop complementary insights. The results advance competitive positioning and business model choice as two critical antecedents of complement performance. This suggests that, even in highly crowded and competitive contexts such as platform marketplaces, complementors have strong agency concerning their own failure or success, In turn, this echoes the importance of shifting part of the research attention from the platform provider firm and its platform to the complementors that populate its platform marketplace.

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Summary

Creating and Capturing Value from Digital Products: Implications of Business Model Choice and Competitive Positioning in the Mobile App Market

Fueled by digitization, a growing number of industries has become dominated by platforms, concomitantly contributing to the emergence of their associated marketplaces as increasingly prominent areas of business activity. Near-zero marginal costs of production and distribution around platforms tremendously deepen the pool of would-be producers of complementary products. Indeed, by now thousands and thousands of firms have built their businesses by producing and selling complements for one or more platforms. However, such low entry barriers also imply that platform marketplaces tend to be highly competitive. Complementor firms have to position their complements relative to a multitude of rival complementors addressing the same consumer needs. Moreover, comparable complements abound, complementor firms are compelled to choose for business models somehow based on free product distribution, of which the performance implications are not yet well understood.

This dissertation addresses these issues by asking what are the consequences of competitive positioning and business model choice for the performance of complements in platform marketplaces? It does so through three independent empirical studies. Theoretically, in the tradition of the literature on platforms, each study adopts a distinct theoretical perspective, hailing from the management disciplines of organization theory, information systems, and strategy. Empirically, all three studies investigate the performance implications of competitive positioning or business model choice in the context of the U.S. storefront of Apple's iOS App Store.

The first study starts from the observation that the number of complements in any single category in a platform marketplace such as the iOS App Store is simply beyond what consumers can assess, and that they are therefore prone to apply secondary selection criteria to screen out some complements from further consideration. This study then postulates that the value-capturing portion of complements' business models, referred to as logics for value capture, is one such criterion. Logics for value capture are highly diverse because complementors frequently combine multiple value-capturing mechanisms, are generally apparent to consumers, and represent a marker to which consumers hold strong preferences. This idea is tested by examining how code-preserving and code-violating changes in the logics for value capture of a large number of free complements in the App Store affect their number of downloads using conditional fixed-effects negative binomial regressions. Results show that code-preserving changes in logics for value capture—the addition or subtraction of value-capturing mechanisms that preserve a coherent

approach to the extraction of value—favorably affect downloads, while code-violating changes—resulting in logics for value capture constituting value-capturing mechanisms that each represent a different value extraction approach—are negatively associated with downloads.

The second study is motivated by the fact that freemium and ad-supported freemium business models have become increasingly viable alternatives to simply distributing complements for-a-fee following a premium business model. That is, complementors distribute their complement for free and then charge a fee for upgrades, sometimes complemented with advertising as an additional value-capturing mechanism. Drawing from the notion that mass market complements, positioned to appeal to the majority of the platform's consumers, and niche complements that are positioned to attract smaller specialized audiences coexist in platform marketplaces, it is theorized that the performance implications of freemium should differ across these types of complements. More specifically, the argument is that because conversion and retention rates for freemium complements are low, accumulating a large consumer base is a critical precursor to operating a freemium business model. Therefore, freemium should yield more revenue for mass market complements and less revenue for niche complements, relative to the premium business model. Using a panel data set with observations on complements from the iOS App Store and their monthly revenues, quantile regressions confirm this prediction. Moreover, including advertising as an additional value-capturing mechanism is found to attenuate revenues of mass market complements, while it helps revenues of niche complements.

The third study investigates the performance implications of differentiation of paid complements in platform marketplaces. It suggests that complementors face two opposing forces in positioning their complements. First, intense competition in the platform marketplace compels them to differentiate. It allows their complements to stand out among their rivals' and that way forego the most intense competition. Second, the information asymmetry that exists between complementors, who know the true value of their complements, and consumers, who do not, prompt complementors to conform. Consumers rely on their experiences with, and knowledge of, rival complements in gauging the value creating potential of new complements, hence providing complementors an incentive to make their complements more similar to their rivals'. Analyzing the revenue performance of newly introduced paid iOS complements provides support for this assertion. The proposed opposing forces pan out in an inverted U-shaped relationship between differentiation and complement performance. Moreover, the results show that the effect of differentiation on complement performance is contingent on market characteristics. Peak complement performance occurs at lower levels of differentiation in markets with a greater share of rated complements, while it occurs at higher levels of differentiation in markets with more rated complements.

Taken together, these three studies advance competitive positioning and business model choice as two critical antecedents of complementor performance. As such, this dissertation makes theoretical contributions to disparate literature streams in organization theory, information systems, and strategy. This also provides valuable insights for complementors and platform provider firms alike. To the interest of complementors, it provides guidelines concerning the creation and capture of value from complements in platform marketplaces. To the merit of platform provider firms, it captures some of the intricate competitive dynamics that characterize platform marketplaces.

Curriculum Vitae

Joey was Angeren was born on February 9, 1989, in Utrecht, The Netherlands. After completing his B.Sc. in Information Science at Utrecht University in 2011, he received his M.Sc. (cum laude) in 2013 from the same university. During his Master's, Joey was awarded a fellowship in the Google Europe Scholarships for Students with Disabilities program. In 2014, he started his Ph.D. project at the Innovation, Technology Entrepreneurship, and Marketing (ITEM) research group of the School of Industrial Engineering at Eindhoven University of Technology, the result of which is presented in this dissertation. His research has been published in the Journal of Systems and Software, and presented at numerous prestigious conferences in the broad research domains of software engineering and management. One of his papers was a finalist for the Best Student Paper Award of the Technology and Innovation Management Division during the 2016 Annual Meeting of the Academy of Management. After working as a researcher and lecturer at the Jheronimus Academy of Data Science, Joey currently is an Assistant Professor at the Knowledge, Information, and Innovation (KIN) research group of the School of Business and Economics at VU Amsterdam.