Received: 31 August 2020 | Revised: 10 November 2021 | Accepted: 12 November 2021

DOI: 10.1002/smj.3366

RESEARCH ARTICLE

STRATEGIC MANAGEMENT JOURNAL WILEY

Competing on freemium: Digital competition with network effects

Kevin J. Boudreau[1] | **Lars Bo Jeppesen**[2] | **Milan Miric**[3]

[1]Northeastern University & NBER, Boston, Massachusetts, USA

[2]Copenhagen Business School, Frederiksberg, Denmark

[3]University of Southern California, Los Angeles, California, USA

Correspondence
Milan Miric, University of Southern California, Los Angeles, CA, USA.
Email: mmiric@marshall.usc.edu

Abstract

Research Summary: "Freemium" product strategies—where a free basic version of a product is offered alongside a full "premium" paid version—are often used by companies to attempt to increase the size of their user base and benefit from network effects. However, there is limited empirical evidence of how using freemium strategies impacts firm revenues. We empirically investigate how the strengthening of network effects on the Apple App Store influenced product sales of firms using freemium strategies, contrasting the impacts on both market leaders and followers. We find that stronger network effects did not on their own lead to greater revenues for market leaders with respect to followers. However, in settings where freemium strategies were used, network effects greatly amplified the advantage of leaders over followers.

Managerial Summary: Freemium strategies are increasingly common as a way for firms to increase the number of users and benefit from network effects. However, there has not been much empirical investigation in this regard, particularly in cases where products using freemium strategies face competition. In this article, we investigate how a policy by Apple on the App Store that led to stronger network effects, impacted the performance of market leaders and followers depending on whether they used freemium or not. We find that it led to an increase in revenues of leaders over followers (effectively, market dominance) but only when freemium strategies were used. The analysis demonstrates an interplay the between business model and network effects. In addition, it shows how stronger network effects and freemium strategies only benefitted market leaders in our setting.

KEYWORDS

business models, digital competition, freemium, market dominance, network effects

1 | INTRODUCTION

Network effects, where the value of a product increases with the number of users, are a characteristic of many digital products (Adner, Puranam, & Zhu, 2019; Goldfarb & Tucker, 2019; Greenstein, Lerner, & Stern, 2013). An important consequence of network effects is that they can often lead to a single firm dominating the entire market, which is typically the firm that has the largest user base at the outset (Katz & Shapiro, 1986; Parker & Van Alstyne, 2005; Shankar & Bayus, 2003). To build their user base and to benefit from network effects, many companies offer "freemium" strategies: a free basic version of their products, along with a premium paid version (Rietveld, 2018; Shi, Zhang, & Srinivasan, 2019; Tidhar & Eisenhardt, 2020). Despite the theoretical intuition behind these studies, there is yet little empirical evidence of how the use of freemium strategies in contexts with network effects will influence market outcomes and whether this differs for different market actors. In this article, we investigate how the strengthening of direct (same side) network effects around products influences the revenues being generated by market leaders and followers within the same market niche. We contrast how this may differ when freemium strategies are used in comparison to paid-only strategies.

Prior research studying how network effects shape market outcomes has focused on settings where products are sold for a single price, such as console-based video gaming (Dubé, Hitsch, & Chintagunta, 2010; Shankar & Bayus, 2003). However, many prominent digital companies offer multitiered versions of their products; Google, Microsoft, Spotify, Hulu, Dropbox, and LinkedIn each offer a free version of their products, as well as premium products for a fee. Outside of the research on free digital products, there is a more established general literature on multitiered product offers (Cheng & Liu, 2012; Deneckere & Preston McAfee, 1996; Zhang, Nan, Li, & Tan, 2016). These studies have highlighted the tradeoff when using such a strategy—a free version can increase the number of users, but the availability of a free version may dissuade customers from purchasing the premium version of the product. As a result, this approach is feasible only when the benefits of the free version, for instance, increasing the size of the user base, can outweigh potential lost sales. The majority of studies that have examined the relation between network effects and freemium are theoretical and often focus on a single (monopolist) firm (Cheng & Liu, 2012; Zhang et al., 2016). However, in many cases, firms face competitors which may use similar freemium strategies to try to gain users. The competitive interactions can undermine the potential benefits of freemium strategies, as competition can make it difficult for companies to increase revenues although they may be attracting users (Etzion & Pang, 2014). The benefits of using freemium strategies may also differ, depending on the companies' market position (Shi et al., 2019). For market-leading companies, a freemium strategy may provide a method for exploiting their advantage and expanding their lead over their competitors. For followers, a freemium strategy may provide a way to eat away at the leader's advantage. All of this suggests that where freemium strategies are used, network effects may influence the revenues of market leaders and followers in a more complex way than what the “winner-take-all” logic may imply. However, this has not been studied empirically by earlier research.

We theorize how stronger network effects influence the relative revenues of market leaders and followers, first by considering settings where paid-only (non-freemium) strategies are used. We then expand our theoretical arguments to consider how these effects may differ in the case where freemium strategies are used. Our main theoretical prediction is that stronger network effects will lead to a modest increase in the relative revenue of the market leader over the follower in the case of paid-only products. However, the revenue gap between the leader and the follower will be much greater where freemium strategies are used.

The empirical design is centered on exploiting the introduction of a policy that strengthened network effects around individual products (same-side or demand-side network effects) in the context of the Apple App Store. Before Apple introduced Game Center on the iOs platform, users had a limited ability to interact with one another when playing games on the iOs platform. Following Apple's launch of Game Center, developers could introduce multiplayer and interactive features, increasing the network effects around their products. This policy was established as part of a minor App Store update, without being combined with many other features, and Game Center was widely adopted by the top apps that we investigate in this article.

Our analysis studies the performance of market leaders and followers in the context of the Apple App store following the introduction of game center using a difference-in-differences research design. We compare games categories where network effects were strengthened against the non-games categories that were not affected by the introduction of Game Center. We distinguish between the impact on market leaders and followers and compare the extent to which the impact of stronger network effects led to different outcomes for products that used freemium strategies as opposed to paid-only strategies.

We find that the introduction of network effects had no statistically observable effect on the revenues of either market leaders or followers in cases where paid-only strategies were used. However, where freemium strategies were used, network effects increased the revenues of market leaders relative to those of followers by 55%. This reflects both an increase in revenues of leaders and a reduction in revenues of followers. The results are robust to variety of tests and specifications, including alternative ways of defining treatment and the control groups, alternative units of observation, as well as alternative construction of the performance (revenue) variable.

Our paper makes three contributions. First, it enriches the literature that has considered the role of network effects in shaping market outcomes (Katz & Shapiro, 1986; Kretschmer & Claussen, 2016; Panico & Cennamo, 2020; Schilling, 2002; Shankar & Bayus, 2003; Suarez, 2005). Our paper extends this literature by showing how freemium strategies may shape and potentially amplify the impact of network effects on winner-take-all dynamics. Our results also indicate that network effects have limited impacts on revenues for paid-only products.

Second, our study is among the first to examine empirically how freemium strategies interact with the presence of network effects, and it contributes to the literature on freemium business models by considering the competitive outcomes of freemium pricing strategies (Etzion & Pang, 2014; Pang & Etzion, 2012; Rietveld, 2018; Shi et al., 2019; Tidhar & Eisenhardt, 2020; Zhang et al., 2016). Our study differs from existing research on freemium business models in two important ways. First, it considers freemium strategies with network effects in a competitive setting, as well as the competitive interactions between a market leader and a follower. Our results show that the impact of network effects under freemium strategies can lead to drastically different outcomes for market leaders and followers, distinguishing this article from earlier ones. Second, as our theory suggests and our empirical results confirm, competition and network effects can create a situation where firms find it difficult to gain an advantage over their competitors—even though they may acquire a large user base—limiting their ability to be profitable in such a setting. Our paper shows the asymmetry between a market leader and a follower, as well as how the competitive interactions between the two may directly influence market outcomes in a way that existing studies have not considered.

2 | BACKGROUND AND LITERATURE

2.1 | Network effects

2.1.1 | Direct (same-side) versus indirect (cross-side) network effects

One of the most prominent characteristics of digital industries is the presence of demand-side economies of scale or "direct network effects" (Shapiro, Carl, & Varian, 1998), where the value of a product increases based on the number of users. This feature is important because this effect often leads to "winner-take-all" market dynamics, where firms compete to build up their user base, hoping that they will be able to charge higher fees once they "win" the market (Farrell & Saloner, 1986; Katz & Shapiro, 1985; Schilling, 2002). These winner-take-all dynamics have spurred a wide range of academic inquiry into strategies for "competing in network industries" and how companies may use this feature to their advantage.

One set of studies examines how companies may exploit same-side (or direct) network effects, where the focus is on attracting users to a particular product, system or platform (Cabral, 2011; Farrell & Klemperer, 2007). The emphasis of this literature is often on setting prices to increase the user base, while potentially raising prices later, once the platform has grown in prominence. The empirical papers in this literature have focused on network effects on early network technologies, such as ATMs (Saloner & Shepard, 1992), spreadsheets (Brynjolfsson & Kemerer, 1996; Gandal, 1994), web servers (Gallaugher & Wang, 2002), telecommunications (Suarez, 2005), computer hardware (Greenstein, 1993), and newspaper directories (Rysman, 2004). Many more recent studies have concentrated on how the composition of the network, rather than just its size, may shape the magnitude of the network effect (e.g., Afuah, 2013; Suarez, 2005). These studies have provided evidence regarding how direct (same-side) network effects can shape market outcomes but have not examined the role of pricing strategies.

Other studies have focused on cross-side network effects, where the value of complementary products increases the demand for the platform (Parker & Van Alstyne, 2005; Rochet & Tirole, 2003). Many of these studies have used the empirical context of video game consoles, where the demand for a console increases with the number of video game titles available (Cennamo & Santalo, 2013; Clements & Ohashi, 2005; Corts & Lederman, 2009; Shankar & Bayus, 2003). Although indirect network effects have also been studied in other settings (Dranove & Gandal, 2003; Stremersch, Tellis, Hans Franses, & Binken, 2007). The strategic issue in this literature is often based on devising strategies to ensure that same-side and cross-side network effects are optimized. Although these studies have considered how to price the product and the platform to attract consumers, they have not focused on the specific case of freemium strategies.

In this article, we focus particularly on same-side (direct) network effects and a case with no cross-side network effects. In contrast to the topics of previous studies, our focus is on the interplay between network effects, freemium strategies and competitors' performance.

2.1.2 | Competition in the presence of network effects

Winner-take-all outcomes are often touted as an outcome of direct network-effects. The foundational papers that introduced these concepts also highlighted that this outcome will only occur in certain situations where the market "tips" toward a single firm that captures all users (e.g., Katz & Shapiro, 1986). In cases of market tipping, where a single firm dominates (captures all new customers), there is an intuition that the firm will charge low prices (or give their product away for free) to attract all customers, but once the market tips, that firm can subsequently charge high prices and enjoy windfall profits (Katz & Shapiro, 1985). However, in cases where a market remains competitive and it does not tip, firms (including those with a large user base) face a challenge raising prices because this may drive customers to their competitors (Etzion & Pang, 2014; Pang & Etzion, 2012; Shi et al., 2019). As a result, stronger network effects in competitive markets do not necessarily lead to high revenues, in fact they may often lead to lower revenues.

Beyond these theoretical papers, there are very few empirical papers that study competition under network effects. Markovich and Moenius (2009) show how when there is competition between platforms, the success of the platform may be more important than the success of individual complementors. A complementor that is ranked second on a winning platform may be better off than a complementor that is ranked first on a losing platform. Similarly, Kretschmer and Loh (2021) find that in the case of competition between platforms, the leading platform attracts more effort and contributions than the follower platform.

2.2 | Freemium strategies

Freemium refers to the strategy of companies offering a *basic* version of a product at zero price alongside a full premium *paid* version. In marketing and economics, there has been a long tradition of studying "tiered" product offers (Deneckere & Preston McAfee, 1996; Mussa, 1979). Freemium strategies refer to a specific variant of that approach, where a lower-quality version is offered for zero price. Freemium studies are an increasingly common way of selling digital products (Li, Jain, & Kannan, 2019; Liu, Au, & Choi, 2014; Rietveld, 2018; Tidhar & Eisenhardt, 2020). Freemium strategies have various forms. For example, a company might offer a basic version of its product, which contains limited features, less privacy, more advertising, or limited time usage. Alternatively, a company could offer a basic version priced at zero, while allowing users to purchase "add-ons" in a series of microtransactions or upgraded versions. Freemium strategies inherently represent a tradeoff. By offering a free or basic version, firms are creating a competitor and potentially losing revenues. However, in exchange they may generate greater awareness, increase the overall demand for their product, or have some other benefit. We discuss each of these in turn (Table 1).

Digital products are largely experience goods, where it can be difficult for the consumer to gauge the true value of the products before using them (Caves, 2003; Shapiro et al., 1998). One reason for offering a freemium strategy is that the free version can allow customers to try the product, while expecting that a considerable segment will purchase the premium version for a higher fee, once they truly understand the product's value (Chellappa & Shivendu, 2005; Datta, Foubert, & Van Heerde, 2015; Dey, Lahiri, & Liu, 2013; Greenstein & Markovich, 2012; Lee & Tan, 2013; Nan, Wu, Li, & Tan, 2018). This phenomenon is related to the literature on word-of-mouth diffusion (Dou, Niculescu, & Wu, 2013; Godes & Mayzlin, 2009; Kretschmer & Peukert, 2020; Niculescu & Wu, 2014).

One strategy that relies on this form of growing engagement over time relates to the gradual accumulation of product-specific investments. For instance, Google provides free services (email, storage, etc.), but continual use of these services leads to accumulation of data, creating switching costs (Tucker, 2019). Users may be willing to pay after long exposure, once they run out of free features. There has also been evidence of other behavioral factors, such as growing dependence on the free version of the product, greater loyalty, and perceived value, pushing consumers to eventually pay for premium features (Yang & Peterson, 2004).

Another potential reason for using freemium strategies is to benefit from network effects, whereby a free version would allow the product to be used by a larger number of users, and through network effects that would increase the overall value of and demand for the product (Dou et al., 2013; Niculescu & Wu, 2014; Shi et al., 2019). Studies that have studied the use of freemium strategies under network effects is mainly based on mathematical models and thus on a clear tradeoff for using freemium strategies—by offering a free version of their products, companies are able to gain a larger user base than they would by offering a single paid version of their products. Freemium strategies can then translate into higher revenues, either by converting the free customers into paid customers or by charging paying customers a higher fee because of the larger user base and network effects. Although these theoretical papers provide mechanisms that explain how these strategies work, which we draw on heavily to develop our theoretical arguments, few empirical studies have examined the use of these strategies in practice. Part of the challenge is that theoretical papers often conclude that there are "regions" or parameter spaces where various strategies may prove optimal. However, in a realistic empirical setting, only one of these regions may often be relevant.

An important issue that has been considered by a small number of existing studies is the impact of a competitor on a freemium paper. The few papers that have done so have used a symmetric modeling setup, where two identical firms choose whether to use freemium strategies (Etzion & Pang, 2014; Nan et al., 2018; Pang & Etzion, 2012; Zhang et al., 2016).[1] These studies illustrate how the seemingly straightforward decision to offer a freemium model can be complicated by the presence of a competitor and provide us with the foundation for our theoretical development. However, they do not consider the case of asymmetric competitors, such as leaders and followers, which is what we would expect in digital markets that often have a clear market leader. One notable exception is one study (Shi et al., 2019) that analytically models how freemium strategies differ in the case of a dominant market leader. However, there have not been many empirical studies testing these competitive dynamics in the case of competition between freemium products.

As mentioned above, several studies have empirically studied the use of freemium strategies (Li et al., 2019; Liu et al., 2014; Rietveld, 2018; Tidhar & Eisenhardt, 2020). While these papers

[1]These studies often model competition with a high–low quality version rather than freemium strategies explicitly. This is a general case, where the lower-quality good can take on any price. However, as the model in the Appendix shows, this often translates into a freemium model as the price of the lower-quality good approaches zero.

TABLE 1 Descriptive statistics for main regression sample

	Variable	Mean	Std.	Min.	Max.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	*ln*($Revenue_F$ + 1)	2.16	2.15	0.00	11.80	1.00								
(2)	*ln*($Revenue_L$ + 1)	1.09	1.36	0.00	8.67	0.78	1.00							
(3)	*ln*(*Rev L/Rev F*)	1.98	1.92	0.00	16.58	0.34	−0.15	1.00						
(4)	*Post GC*	0.50	0.50	0.00	1.00	−0.03	−0.03	−0.00	1.00					
(5)	*Games*	0.25	0.43	0.00	1.00	−0.25	−0.27	0.09	0.00	1.00				
(6)	*Freemium*	0.05	0.21	0.00	1.00	0.07	0.04	0.02	0.04	−0.06	1.00			
(7)	*Post GC × Games*	0.12	0.33	0.00	1.00	−0.18	−0.18	0.04	0.37	0.65	−0.03	1.00		
(8)	*Games × Freemium*	0.008	0.01	0.00	1.00	−0.06	−0.05	−0.02	0.02	0.14	0.36	0.12	1.00	
(9)	*Post GC × Freemium*	0.03	0.27	0.00	1.00	0.06	0.03	0.01	0.17	−0.05	0.76	0.00	0.28	1.00
(10)	*Post GC × Games × Freemium*	0.004	0.17	0.00	1.00	−0.04	−0.04	−0.01	0.06	0.12	0.28	0.16	0.78	0.36

Note: N = 33,543. Descriptive statistics reported for full sample. High degree of correlation between three-way interactions common in difference in difference specifications because of large number of zero values. $Revenue_L$ indicates the daily revenue of the leader. $Revenue_F$ indicates the daily revenue of the follower. The unit of observation is the category-day using the fine-grained category measure.

suggest that products which use freemium strategies benefit from network effects, this is not studied explicitly, particularly in relation to how it shapes market outcomes. One exception is a recent paper by Rietveld and Ploog (2021) who look explicitly at the choice to implement social media features which can strengthen network effects. They discuss explicitly the interplay between freemium strategies and direct network effects, and show how network effects may actually harm freemium products when the network (size of the user base that benefit) is small. The present paper builds on this result, by considering the role of market position of firms in addition to the strength of network effect.

In this article, we are motivated by the idea that network effects will affect market leaders (those with the greatest market shares) and followers (those with smaller market shares) differently, and this will only be amplified by freemium strategies. Our paper adds to the literature by being one of the few to consider asymmetrical competitors under network effects, as well as with freemium strategies, and providing empirical evidence in this regard is one of its contributions.

3 | THEORY AND HYPOTHESES

In this section, we develop predictions on how direct network effects influence the revenues of market leaders and followers and how this differs when freemium strategies are used. We develop verbal theory, drawing on this game-theory literature (as reviewed in Section 2.2), while in the Appendix, based on these previous studies, we present an analytical model that arrives at the same set of predictions.

3.1 | Direct network effects and performance of leaders and followers

As discussed above, direct network effects increase the value of a product as the number of users increases. For instance, if computing software with a single version (not tiered or freemium) has a greater number of consumers than its competitors, then new customers, who were deciding which platform to adopt, would experience a greater benefit from adopting the product with the greatest number of users as that product would allow the greatest level of interoperability (Katz & Shapiro, 1985; Shapiro et al., 1998).

The common intuition is that stronger network effects would increase the market leader's revenue because it would be able to raise prices as a result of its larger user base since consumers might be willing to pay higher prices for products that have a larger use base (Brynjolfsson & Kemerer, 1996; Greenstein, 1993). However, the game-theory literature emphasizes that stronger network effects might also force the market leader to keep prices low because raising prices might push consumers to adopt the product of the follower firms (Katz & Shapiro, 1986; Pang & Etzion, 2012; Zhang et al., 2016). Therefore, while stronger network effects may allow the market leader to attract more consumers, it also makes it more difficult for the market leader to generate more revenues than it would otherwise. The same forces may apply to follower firms in a marketplace. We conceptually focus on *the* follower firm with the second-highest market share, but our arguments could extend to all firms that are not the market leaders.

These arguments suggest that while on average, stronger network effects may benefit the market leader more than the followers, leading to an increase in the revenue gap between the leader and the followers. However, as the above arguments suggest, this gap between leaders and followers may be modest. This provides the basis for our main hypothesis.

Hypothesis (H1). *Stronger network effects increase the difference in the revenues between the market leader and the followers, where paid-only strategies are used.*

3.2 | The amplifying impact of freemium strategies under network effects

Freemium strategies often seem natural ways of exploiting network effects. By offering a free version, companies may be able to increase the size of their user base, as more customers may be willing to adopt a free product. However, as described above, in the case of a market without tipping, where a market leader and followers compete on freemium, the situation may be considerably more complex.

As in the case of paid-only products described above, we can expect stronger network effects to lead to greater revenues for a market leader in comparison to followers. However, the relative revenue advantage of a market leader over followers may be somewhat modest for a paid-only product because network effects require the market leader to keep its price low. For a market leader, freemium strategies provide a way of increasing its user base and potentially raising the price that it may charge (for its premium version). By offering a free version, the market leader can increase the size of its user base and amplify the benefit of network effects subsequently. By offering a premium version, the market leader can also potentially charge a high price for it (Cheng & Liu, 2012; Cheng & Tang, 2010).

For market followers, freemium strategies may not be so beneficial. While a free version may entice consumers, the fact that the market leader also offers a free version makes it unlikely that new consumers would join the follower firms (unlike what would occur in the case of paid-only products, as described in Section 3.1). At the same time, follower firms may offer a premium version, but only a small number of potential consumers may be interested in adopting their products. As a result, stronger network effects may greatly benefit market leaders when freemium strategies are used but may also harm followers. These results are directly predicted by the game-theory models that have been used to jointly study network effects and freemium strategies (Etzion & Pang, 2014; Zhang et al., 2016). In the Appendix, we illustrate how the hypotheses can directly be derived from these canonical models.

Therefore, based on these theoretical arguments, we expect stronger network effects to be associated with a far greater growth in revenues of market leaders with freemium strategies and a decline in revenues of followers with freemium strategies in comparison to paid-only strategies. We therefore expect stronger network effects to lead to a greater advantage (gap) for the market leader than for the followers when freemium strategies are used than when paid-only strategies are used:

Hypothesis (H2). *Stronger network effects lead to a greater difference in the revenues between the market leader and the followers, where freemium product strategies are used (in comparison to paid-only strategies).*

In the Appendix and discussion, we provide more details about why freemium strategies may be used even though they could lead to worse outcomes for followers.

4 | EMPIRICAL CONTEXT AND DATA

Our empirical design exploits a policy event, the introduction of Game Center, which led to stronger network effects around individual products in the Apple App Store. Game Center allowed interactions between users which in turn strengthen network effects. Game Center only was only implemented in games categories. The empirical analysis is based on a difference-in-differences design using non-games as the control group. We also compare the impact on game titles that used freemium with the impact on those that used paid-only strategies. In the following subsections, we provide the background on the empirical context, as well as information regarding the data and sources.

4.1 | Background on the App Store

The Apple App Store is the marketplace for mobile apps for Apple iOS devices (iPhone, iPod, and iPad). The App Store also provides the frameworks and facilities through which apps are made on this platform (Gawer, 2014). This marketplace offers more than 1.5 million unique titles (apps) sold by hundreds of thousands of developers. The total sales of apps in the App Store have exceeded $70 billion in the past decade.

This marketplace is divided into categories (niches, genres, or submarkets) based on the types of products sold, such as action games, utilities, or productivity software. Games comprise approximately 77% of all titles and account for 75% of all sales (revenues). The Game Center event that we study in this article affected only the games categories, and the empirical analysis centers on comparing Games and non-games categories. The market structure in each category is highly concentrated, with the leader in each category capturing roughly 40% of the category's revenues, on average, while the second-ranked followers capture only approximately 17%. See the Appendix for average revenues by rank.

4.1.1 | Introduction of Game Center

In the fall of 2010, Apple released an update for its operating system (iOS 4.1) that enabled Game Center in the operating system. Before Game Center was introduced, the developers' ability to facilitate user interactions within games was actively restricted by Apple to avoid having its customers interact outside the channels that it provided. With the introduction of Game Center, developers could allow users to interact (a) through multiplayer features and (b) by letting users share accomplishments on leaderboards. Thus, Game Center had the effect of increasing the strength of network effects. Although it is difficult to quantify the exact magnitude of these network effects, we can expect that before the introduction of Game Center, given the restrictions imposed by Apple, same-side network effects in the games categories would be minimal, but after, they would be strengthened considerably.

Game Center was introduced with iOS 4.1 in the middle of the OS generation (between iOS 4.0 and 5.0). Importantly, Game Center did not coincide with the introduction of other features that could have influenced firm revenue or the choice of business models. Before the release of iOS 4.1, Apple had shared the Game Center functionality with developers through their standard development kit so that they were able to integrate the functionality into their products, although it was not enabled until the release of iOS 4.1. We verified that the leading firms in the marketplace (in the games categories) adopted the Game Center functionality. This meant that with the exception of the introduction of Game Center, no other policy change occurred that could have affected the network effects. We use the introduction of Game Center to investigate how the strengthening of network effects would influence market outcomes. We manually validated that the top-ranked apps we examined had Game Center enabled.[2]

4.1.2 | Freemium strategies in the App Store

In the App Store, freemium strategies are observed in two forms.[3] The first involves releasing multiple versions of a title (e.g., "lite" and "pro"), where the most basic version is offered for free. The second involves providing a single free version but allowing the user to enable premium features through "in-app" purchases. In our collected data, we observe both forms of freemium. However, the case of a free product with in-app purchases is overwhelmingly the most common of these strategies, especially among the companies examined. Therefore, we define freemium titles as those with a free version and then premium features through "in-app" purchases. There might be some cases of alternative revenue strategies, such as advertising, selling user information, or using apps as a promotion channel. However, these strategies were not particularly diffused in this setting in the studied period (around 2010) or by the examined market leaders and closest followers. For instance, advertising business models became viable revenue models in this marketplace only after 2015.

4.2 | Data sources and variable construction

We assembled the data set by collecting publicly available data from the Apple App Store using machine collection methods. This provided us with a complete list of the more than 1.4 million mobile apps created by over 300,000 app developers that have been launched in the App Store, including the daily top 500 rankings for each category. We combined these data with proprietary data from a market analytics company that provided fine-grained categorization of apps (e.g., instead of action games, we could identify bubble shooter games). This allowed a cleaner comparison of market leaders and followers that had comparable product offerings.

4.2.1 | Defining product market categories

A critical aspect of the analysis is distinguishing the effect between market leaders and followers. We define the market leader as the firm with the highest sales revenue in a particular market category and the follower (second-ranked) as the firm with the second-highest sales revenue in that market category. The data on market categorization were sourced from a mobile app analytics company that classified all apps in the Apple App Store using topic modeling

[2]At this time, tools existed, such as Open Fient, that provided some of this functionality. However, they were used by several hundred titles only, while there were thousands of game titles in the marketplace. Additionally, our empirical analysis focuses on the strengthening of network effects and thus remains valid even if some of the titles had a small degree of network effects because of this technology.

[3]See Apple's website: https://developer.apple.com/app-store/freemium-business-model/.

techniques and human inspection. Similar techniques have been used in other settings to create fine-grained industry classifications (Hannigan et al., 2019; Hoberg & Phillips, 2016). Our final sample was 485 narrowly defined market categories. We analyzed these categories separately for iPhone and iPad devices. Examples of these categories include car racing games, bubble shooter games, and match-three games. We tested the robustness of the results based on the 32 categories provided by Apple and report these results in the Appendix.

4.2.2 | Data on product revenues

Apple does not publish information about the revenues that apps generate from sales in the Apple App Store. However, Apple publishes a daily list of the top 500 apps in terms of sales and downloads. Sales ranks reflect in-app purchases and the sales of the app itself (the fee to download and install an app). Using a method developed by Garg and Telang (2013) makes it possible to impute the revenues of these firms based on the revenue rankings and download rankings, as well as the daily pricing data. This method is based on estimating the relationship between the revenue ranking, prices and download ranking. These coefficient estimates can then be transformed into estimates of market share and revenues for the firms that were consistently listed in the top rankings. We only utilize ranking data from the United States.

Thus, for the largest firms, including the majority of the category leaders and followers, we can observe the revenues. Given that the revenue is imputed, it may be subject to bias or other errors arising from the calculation. Therefore, we also use product rankings provided by Apple to confirm the robustness of the results (see the Appendix). However, it is important to note that any biases which occur would be present for both the leaders and followers, and over time. Therefore, these should not impact our hypotheses as they are based on comparing leaders/followers before and after the introduction of game center.

The main outcome variable constitutes the daily product revenues of the market leader and the follower, specifically $ln(Total\ Daily\ Revenues_{c,t,r} + 1)$ for each category (c), day (t), and rank (r) corresponding to 1 or 2 for the market leader and the follower, respectively. We use log-transformation to account for the fact that revenue is highly right-skewed. In the usual fashion, we add 1 to the base of the logarithm (i.e., $\log(x + 1)$) to account for values that may be close to zero.

In parts of the analysis, we compare the revenue of the leader with that of the follower. To do this directly, we take the difference between the logs of the leader and the follower, which equates to $ln(Total\ Daily\ Revenues_{c,t,1}/Total\ Daily\ Revenues_{c,t,2})$. This approach is similar to those used in previous studies (Caves & Ghemawat, 1992; Davies & Geroski, 1997; Ferrier, Smith, & Grimm, 1999).

4.2.3 | Defining freemium business models

In the Apple App Store, the overwhelming majority of firms use paid, free, or freemium business models to generate revenues from their products. With freemium business models, firms release a free version of their products and allow customers to purchase premium features or functionality, most often through in-app purchases.[4] With paid business models, firms charge for the basic version of their application and potentially charge for add-ons (although this was

[4]Offering a free version with in-app purchases was the dominant strategy of the top-ranked companies we examined. The alternative approach was offering two distinct titles, but often, these titles were not highly successful.

not particularly common in the early period of the marketplace examined in this article). With free business models, firms release their products for free and either generate no revenue or small amounts of revenue through advertising. We do not consider free titles as advertising did not constitute a considerable share of the revenues for the companies in this period, particularly for the top-ranked firms we examined.

The empirical analysis is based on comparing products that use freemium and paid-only (or single-tier) strategies. We define freemium products as those that are released for free (i.e., the price of their products is zero) but use in-app purchases to sell premium features. We define paid-only products as those that are sold for a fee (i.e., the price of their products is greater than zero). Some paid developers also use in-app purchases to sell additional features to consumers, but most do not use in-app purchases and sell only the basic version of their products. Alternative freemium strategies, such as selling two distinct products (free and paid), are uncommon, particularly for the top-ranked firms we examined. Generally speaking, when freemium business models are used, they are used by most of the top firms in a particular category. We utilize various robustness checks to ensure that the way we define freemium does not influence the results (see the Appendix where we repeat the analysis, indicating only the categories where freemium strategies are used by market leaders).

5 | ANALYSIS AND RESULTS

5.1 | Research design

The analysis is based on a difference-in-differences design. The introduction of Game Center created stronger network effects on products in the games categories but had no clear impact on products in the non-games categories. The Game Center feature was implemented by the platform owner (Apple) rather than the developers; therefore, the strengthening of network effects as a result of this feature could only occur after it was implemented. We compare the impact of the introduction of Game Center in Games and non-games contrasting products which used freemium strategies in comparison to paid-only strategies.

We include fixed effects at the category level to account for differences across each market category, such as the overall popularity of apps. This also accounts for what may be the baseline level of network effects in a category, as the analysis is focused on comparing the same category before and after the introduction of Game Center. For example, cloud storage or music streaming may have an inherent level of network effects on their products, which may explain the advantage of the leader and the follower. However, as we focus on comparing the difference between before and after the introduction of Game Center and include fixed effects to absorb these inherent differences, we do not expect this to influence the analysis.

We include time trends to account for baseline differences in trends that may exist between the treatment and the control groups.[5] Time trends are particularly important in this setting because we want to ensure that there is a similar pre-trend for the treatment and the control groups, as well as between the categories that use freemium strategies and those that use paid-

[5]The parallel trend assumption between the treatment and the control groups is critical for the difference-in-differences design. To ensure that the treatment and the control groups follow the same pre-trend, we introduce time trends as controls. We also perform matching in the Appendix to ensure a common pre-trend for the treatment and the control groups.

only strategies. As a result, this is not a standard difference in differences framework, as we do not have a parallel trend for the treatment and control groups. We also perform matching on category pre-trends to ensure that our results hold in instances where the parallel trend assumption is not violated and include time-period dummies instead of time trends as an additional check. The basic regression model can be represented as follows:

$$\begin{aligned} Revenues_{i,t} = {} & \alpha + \beta_1 Post\,GC_t + \beta_2 Freemium_{i,t} + \beta_3 Post_t \times Freemium_{i,t} \\ & + \beta_4 Post\,GC_t \times Games_i + \beta_5 Games_i \times Freemium_{i,t} \\ & + \beta_6 Post\,GC_t \times Freemium_i \times Games_i + \mathbf{T}_t \gamma + \mathbf{C}_{i,t} \delta + \epsilon \end{aligned}$$

The unit of observation for the analysis is at the level of revenue for the market leader or the follower in each category (i) and in each period (t). **C** is a vector of category fixed effects, **T** is a vector of time trends or time dummies, and ϵ represents an idiosyncratic error term. We omit time-invariant variables (*Games*) from the above expression because they cannot be included with category fixed effects (**C**). *Post GC* is a dummy variable indicating the periods after the introduction of Game Center. The key parameters of interest in this model are β_4 and β_6. Freemium is an indicator variable that reflect whether the market leader in a particular niche in that particular period uses freemium strategies. Given that category level FE's are included in the analysis, the coefficients β_2 and β_5 indicate how much using a freemium strategy impacts revenues in those categories for both Games and non-games, respectively.

Hypothesis (H1) predicts that the parameter for β_4 will be positive and statistically significant (when we estimate the difference between the two groups). This coefficient provides an estimate of how much the strengthening of network effects affected the revenues of leaders and followers in the games categories overall. The three-way interaction term for the variable *Post GC* $\times$ *Freemium* $\times$ *Games* provides an estimate of how much the introduction of Game Center influenced the revenues of leaders and followers in the games categories where freemium strategies were used. Hypothesis (H2) predicts that the parameter for β_6 will also be positive and statistically significant (when we estimate the difference between the two groups).

5.1.1 | Time window for analysis

One empirical concern may be that products will shift from paid-only to freemium strategies as a consequence of the introduction of Game Center and stronger network effects. We exploit the fact that it took some time for developers to shift their business models in response to freemium strategies. Shifting to freemium strategies is part of a broader business model that involves designing products around in-app purchases, rather than simply changing the price. This strategy includes creating support functions and designing the application to be continuously updated as new features are introduced. This process is time-consuming, and developers did not launch new products with freemium business models until the next major product update was released.[6] We exploit a short time window of 70 days after the introduction of Game Center (iOS 4.1) and before the subsequent update (iOS 4.2) to investigate how the strength of network effects influenced these outcomes, without our results being conflated with the product development decisions of these companies. We use an equivalent period of 70 days before the shock

[6]iOS 4.1 was released on September 8, 2010; the following update was released on November 22, 2010.

so that we have a balanced sample before and after the shock. Although a sample of 140 days may not seem a long time in conventional industries, app markets are particularly dynamic. On average, a market category would undergo dozens of leadership changes within this short time window. We illustrate how the use of freemium strategies by developers did not change until after the 70-day window (see the Appendix [Figure B8.1]).

5.2 | Descriptive results

In Figure 1, we plot the average difference in revenues between the market leader and the follower for Games with paid-only and freemium strategies, as well as non-games, which serves as the control group for the analysis.[7] For both the control group (non-games) and the paid-only games, we observe no large divergence (increase in the difference) before and after the introduction of Game Center, suggesting no clear support for Hypothesis (H1). However, following the introduction of Game Center, we do observe considerable divergence (increase in the difference) between the revenues of the leader and the follower (represented by the upward sloping blue line) in the case where Freemium strategies are used, indicating support for Hypothesis (H2). One concern from Figure 1 is that we cannot confirm that the treatment and the control groups follow a parallel trend prior to the introduction of Game Center.

To ensure a parallel trend between the treatment and the control groups, we perform matching on the pre-Game Center period for both leaders and followers and plot the results in Figure 2. Matching is performed separately because the pre-trend for leaders and followers may differ. This is the same matching method used in later sections of this article, and we observe that the treatment and the control groups follow a similar trend for the matched data prior to the introduction of Game Center for the matched data. In the case of paid-only games (the left side of Figure 2), we observe an increase in the revenues generated by paid-only games relative to non-game titles. However, this is true for both the leader and the follower, which does not support Hypothesis (H1), although it is consistent with the idea that stronger network effects may increase overall demand. In the case of freemium games (the right side of Figure 2), we observe an increase in the revenues of market leaders after the introduction of Game Center (in comparison to the control group) but none in those of followers, supporting Hypothesis (H2).

5.3 | Regression results for leader and follower revenues

In this subsection, we report the main regression results. We report ordinary least squares (OLS) regression results with heteroscedasticity and autocorrelation consistent (HAC) *SE*s to account for the fact that difference-in-difference regressions, particularly with daily data, may be influenced by serial correlation (Bertrand et al., 2004).

In Table 2, we present the difference-in-differences regressions with the outcome variable, the log-transformed daily revenues at the product level.[8] We perform the regressions for the leader (products with the highest daily revenue, first ranked) and the first follower (second-

[7]The figure is based on a Kernel-weighted local polynomial smoothed line graph (lpoly in Stata), which conveys the average trend for each of the groups alongside 95% confidence intervals. Epanechnikov kernel with 20-day bw is used.
[8]The results are similar at the firm level because the top- and lower-ranked titles are seldom sold by the same firm.

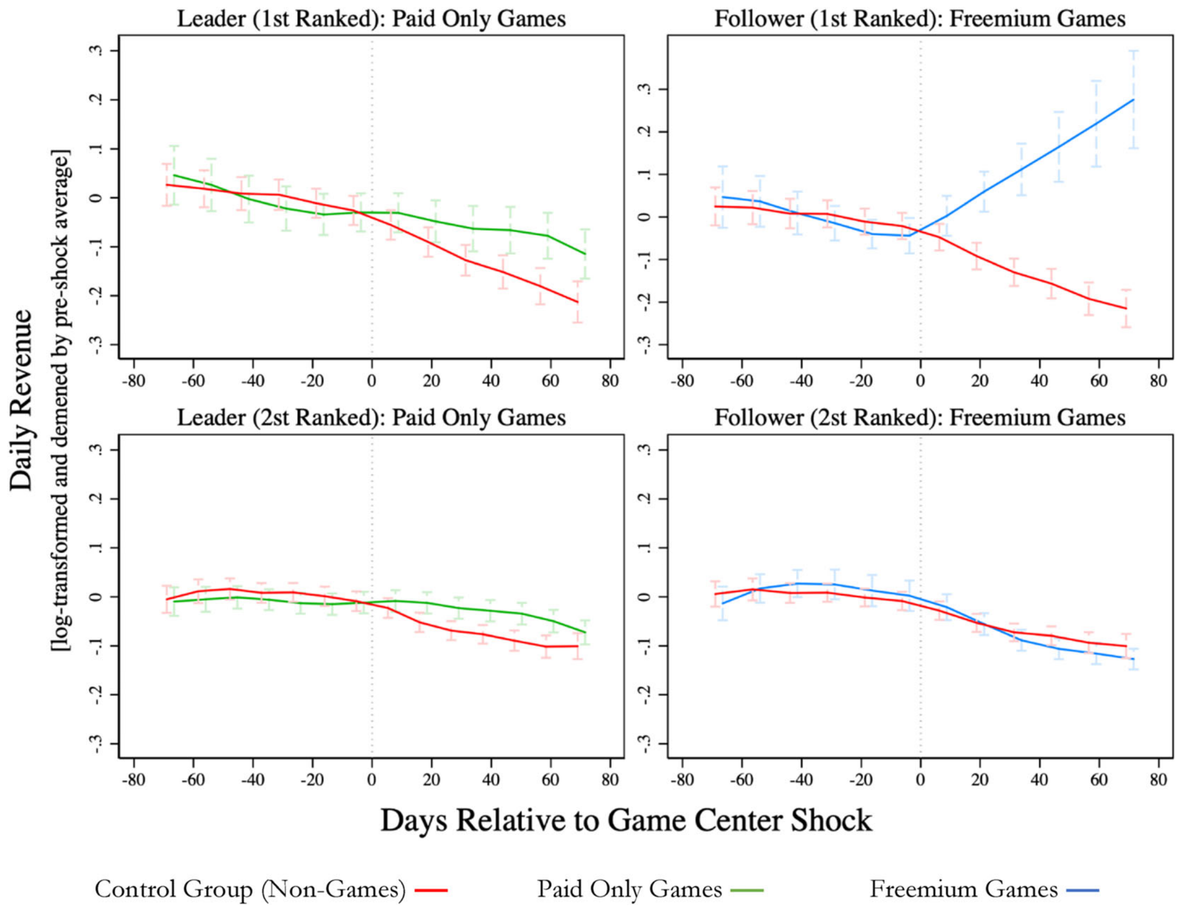

FIGURE 1 Average revenues of market leader and follower across games (with and without freemium) and non-games. Lines plotted represent the average revenues of the market leaders and followers for both the treatment and control groups for the matched sample. We performed matching based on the pre-sample trend (average change in daily revenues between three evenly divided pre-sample periods). Matching performed based on the coarsened exact matching (CEM) algorithm. Matching performed separately for leaders and followers. Values demeaned by the pre-shock average to ensure that figures are comparable for the different groups (*Pre-sample average is therefore zero*). Lines based on smoothed polynomial (unit of observation is day-category) using Epanechnikov kernel and 20-day time window. Vertical bars indicate 90% confidence intervals at 10-day increments. As shown, the treatment and control groups generally follow one another (parallel trend assumption supported) for the matched sample. In the upper row, we report the results for the market leaders (first ranked firms) for paid only (left) and freemium (right) titles. In the lower row, we report the results for followers (second ranked firms) for paid only (left) and freemium (right) titles. For paid only titles, there is a slight increase in revenues for both market leaders and followers after the introduction of Game Center

ranked product). In the Appendix, we show that the results are consistent for lower-ranked products.

In Columns 1–5, we report the results for the market leaders, and in Columns 6–10, we report the results for the followers. In Columns 1 and 2, we introduce the main covariates, including the interaction between *Post GC* × *Games*. In Column 3, we introduce the three-way interaction term. In Column 4, we repeat the analysis without time trends and instead, include time dummies as controls. The results in Columns 1–4 are based on the full sample of observations, where the parallel trend assumption does not hold; therefore, we require time trends as

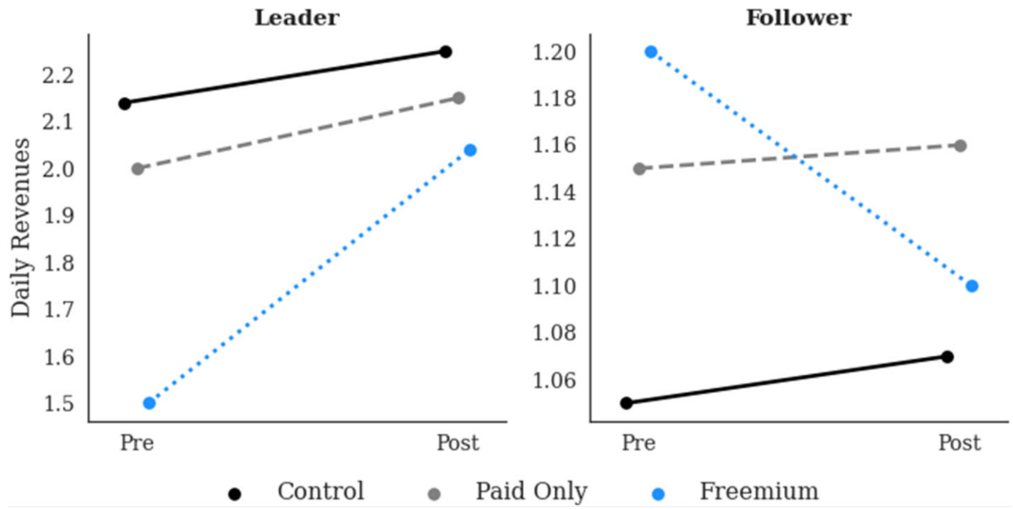

FIGURE 2 Marginal effects for regression results for leader and follower revenues. Marginal effects based on regression results in Table 2, Column 3 and Table 2, Column 8. Outcome in both regressions is log transformed daily revenues for market leader and follower

controls. In Column 5, we repeat the analysis for the pre-trend matched sample, for which the parallel trend assumption holds. We repeat the same sequence of analysis for follower (second-ranked) firms in Columns 6–10. We find that the introduction of Game Center is associated with an increase in revenue for the leading firms where freemium strategies are used (C3: $\beta = .44$, $SE = 0.15$; C5: $\beta = .63$, $SE = 0.16$), but we find no effect for the firms that use paid-only products (C3: $\beta = .04$, $SE = 0.06$; C5: $\beta = -.01$, $SE = 0.03$). Additionally, we do not find any positive relation (estimates with a negative sign) for the followers using paid-only strategies (C8: $\beta = -.01$, $SE = 0.04$; C10: $\beta = .05$, $SE = 0.02$) and freemium (C8: $\beta = -.08$, $SE = 0.06$; C10: $\beta = -.09$, $SE = 0.09$) strategies.

For a better interpretation of these effects, we plot the marginal effects for Columns 4 and 8 in Figure 2. These figures illustrate an increase in revenues for market leaders in the games categories that used freemium from approximately 1.5 to 2.0 ($\Delta = 0.50$, an increase of approximately 83% in daily sales USD[9]), while followers' revenues decreased from 1.20 to 1.10 ($\Delta = 0.10$, a reduction of 16% in daily revenues). In contrast, for market leaders that used paid-only strategies in the games categories, their revenues increased from approximately 2.0 to 2.1 on average ($\Delta = 0.1$, an increase of approximately 12%), while followers' revenues increased from approximately 1.15 to 1.16 ($\Delta = 0.01$, an increase of approximately 2%). In comparison, the revenues for both market leaders and followers changed very little in the non-games categories. Note that these are marginal effects, so they represent the average values for the outcome variable, accounting for all control variables. These results support Hypothesis (H2) but not Hypothesis (H1).[10]

In Table 3, we report a variety of additional robustness checks. In Columns 1–3 and 6–8, we report a variety of alternative specifications that can account for serial correlation, which may

[9]Since the outcome variable is log transformed (difference between leader and follower), we compute this by comparing the exponentiated values.

[10]We repeat the analysis for fifth-ranked firms and find comparable results. These results are shown in the Appendix. The fifth rank is selected as an example since we are still able to observe the revenues for a large number of products.

TABLE 2 Results for difference-in-differences regressions for leader and follower revenues

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sample: *Leader firms* (*Rank 1*)					**Sample: *Follower firms* (*Rank 2*)**				
	Full sample of categories				**Pre-trend matched**	**Full sample of categories**				**Pre-trend matched**
Post GC	0.12 (0.03)	0.10 (0.04)	0.11 (0.04)	−0.29 (0.11)	−0.17 (0.11)	0.02 (0.02)	0.02 (0.03)	0.02 (0.03)	−0.10 (0.07)	−0.05 (0.07)
Freemium	0.32 (0.09)	0.47 (0.10)	0.50 (0.10)	0.57 (0.08)	0.79 (0.11)	0.11 (0.05)	0.13 (0.06)	0.12 (0.06)	0.15 (0.04)	0.21 (0.05)
Post GC × Fames		0.06 (0.06)	0.04 (0.06)	−0.06 (0.03)	−0.01 (0.03)		−0.01 (0.04)	−0.01 (0.04)	0.09 (0.02)	0.05 (0.02)
Post GC × Freemium		−0.82 (0.11)	−1.10 (0.13)	−1.15 (0.13)	−1.33 (0.15)		−0.15 (0.05)	−0.10 (0.06)	−0.12 (0.06)	−0.18 (0.07)
Freemium × Games		0.03 (0.15)	−0.05 (0.16)	0.08 (0.08)	−0.19 (0.10)		−0.05 (0.11)	−0.03 (0.12)	0.00 (0.06)	0.01 (0.07)
Post GC × Games × Freemium			0.44 (0.15)	0.48 (0.15)	0.63 (0.16)			−0.08 (0.08)	−0.09 (0.08)	−0.09 (0.09)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trends	Yes	Yes	Yes			Yes	Yes	Yes		
Time dummies				Yes	Yes				Yes	Yes
F	47.92	36.38	34.47	10.59	7.59	28.39	19.17	17.78	10.26	5.60
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: DV: *log*(*Daily App Revenue + 1*), unit of observation: *Category-Day*. HAC *SE*s reported in parentheses (calculated with a bandwidth of two periods, robust to alternative specifications). *HAC SE's do not allow for clustering*. Results with clustered *SE*'s reported in Table 4. Results reported for sample of market leaders (product Ranked #1 in Revenues) within a market niche, and followers (products Ranked #2 in Daily Revenues). In Columns 1–4 and 6–9, the results for the full sample of categories (n = 33,543). In Columns 5 and 10, we report the results for treatment and control variables matched based on the trend (logarithm of daily app revenues) prior to the outcome (n = 29,537; n = 24,856, respectively). In Columns 1 and 6, we include the *Game Center* and *Freemium* variables. In Columns 2 and 7, we introduce the two-way interactions. In Columns 3 and 8 we introduce the full three-way interactions. Note that time invariant variables are omitted (i.e., *Games* category indicator). Results indicate that there was no increase the revenues of paid-only market leaders within games categories (C3 *Post* × *Games*: β = .04; z = 0.7; p = .489), but that there was a considerable increase in the revenues of freemium market leaders within games categories (C3 *Post* × *Games* × *Freemium*: β = .44; z = 3.0; p = .003) and no significant increase for followers (C8: β = −.08; z = −1.07; p = .287). We report the results with Time-Trends included as a control variable results because we cannot guarantee that the parallel trend assumption is not violated. In Columns 4 and 9, we repeat the analysis with time dummies (day dummies) instead of time trends. Results remain consistent (C4: β = .48; z = 3.2; p = .001; C9: β = −.09; z = −1.2; p = .252). Finally, to correct for the parallel trend assumption, we match the treated (games) with control (non-games) categories based on the pre-trend (change in outcome variable by weeks), using CEM. We illustrate the treatment and control trends in Figures 1 and 2. In Columns 5 and 10, we report the results with the matched samples, where we again include time (day) dummies. Results remain consistent for three-way interaction (C5: β = .63; z = 3.9; p = .000; C10: β = −.09; z = −1.1; p = .266).
Abbreviations: CEM, coarsened exact matching; HAC, heteroscedasticity and autocorrelation robust.

influence the results. In Columns 1 and 6, we report the results based on bootstrapped *SE*s. In Columns 2 and 7, we report the results with *SE*s clustered at the level of the category and the week, similar to the state-year clusters used by Bertrand et al. (2004). The results are robust to alternative clustering strategies. In Columns 3 and 8, we follow the suggested approach by Bertrand et al. (2004) and collapse our data to a single pre–post period, which effectively removes the issue of serial correlation. The results remain consistent with the earlier analysis, supporting Hypothesis (H2) (C3: $\beta = 3.09$, $SE = 0.98$; C8: $\beta = -.36$, $SE = 0.63$) but not Hypothesis (H1) (C3: $\beta = -.45$, $SE = 0.26$; C8: $\beta = .11$, $SE = 0.17$).

In Columns 4 and 9, we include an additional set of fixed effects at the level of the individual leader firms. This is only possible with the daily revenue data, as this requires multiple observations for each date and observations of the same market leaders before and after the introduction of Game Center. The results remain consistent, supporting Hypothesis (H2) (C4: $\beta = .69$, $SE = 0.11$; C9: $\beta = -.15$, $SE = .11$) but not Hypothesis (H1) (C4: $\beta = -.25$, $SE = 0.03$; C9: $\beta = .03$, $SE = 0.02$). In Columns 5 and 9, we repeat the analysis but include fixed effects at the level of the individual market leader–follower pair, and the results remain consistent, supporting Hypothesis (H2) but not Hypothesis (H1).

5.4 | Regression results for the revenue gap between leader and follower

In the preceding analysis, we do not directly estimate the difference between leaders and followers, which is the hypothesized relation. To do so, we calculate the difference in revenues between the market leader and the follower. We do this with the difference between the log-transformed revenues of the market leader and the follower. This relative performance measure has been used in previous studies (Caves & Ghemawat, 1992; Davies & Geroski, 1997; Ferrier et al., 1999).

In Table 4, we present the results for the revenue difference between the market leader and the follower (second-ranked). In Columns 1–4, we provide the baseline results for the full sample and find support for Hypothesis (H2) (C3: $\beta = 1.16$; $SE = 0.19$), but we find no evidence to support Hypothesis (H1) (C3: $\beta = -.16$; $SE = 0.07$). Note that these results are reported using HAC robust *SE*s. In Column 5, we report the results for the regression based on the matched sample, where we can ensure that the treatment and the control groups follow a comparable pre-shock trend. The results remain consistent, supporting Hypothesis (H2) (C5: $\beta = .91$; $SE = 0.23$) but not Hypothesis (H1) (C5: $\beta = -.10$; $SE = 0.05$). In Columns 6–8, we report the same robustness checks as in Table 3, including reporting bootstrapped *SE*s (C6), clustered *SE*s (C7), results for a single period before and after the introduction of Game Center (C7), fixed effects at the level of the market leader firm (C8), and fixed effects at the level of the market leader–follower pair (C8). These results are consistent with the earlier analysis, supporting Hypothesis (H2) but not Hypothesis (H1).

5.5 | Robustness tests and additional evidence

5.5.1 | Supplementary checks

We perform several additional checks to confirm the robustness of the results. First, we want to ensure that the treatment and the control groups do not violate the parallel trend assumption

TABLE 3 Robustness checks for difference-in-differences regressions for leader and follower revenuesDV: *log*(*Daily App Revenue + 1*), unit of observation: *Category-Day or Category—Pre/Post* (*Only Col 3 & 8*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sample: *Leader firms* (*Rank 1*)					**Sample: *Follower firms* (*Rank 2*)**				
	Robustness checks for serial correlation			**Robustness checks with product fixed effects**		**Robustness checks for serial correlation**			**Robustness checks with product fixed effects**	
	Bootstrap SE	***Clustered SE***	***Collapsed pre/post***	***Only leader FE***	***Leader + follower FE***	***Bootstrap SE***	***Clustered SE***	***Collapsed pre/post***	***Only leader FE***	***Leader + follower FE***
Post GC	0.11 (0.03)	−0.15 (0.03)	−0.11 (0.13)	−0.25 (0.02)	−0.28 (0.02)	0.02 (0.02)	−0.13 (0.02)	−0.12 (0.09)	−0.19 (0.01)	−0.21 (0.01)
Post GC × Games	0.50 (0.08)	−0.06 (0.06)	−0.45 (0.26)	−0.25 (0.03)	−0.16 (0.03)	0.12 (0.06)	0.08 (0.03)	0.11 (0.17)	0.03 (0.02)	0.08 (0.02)
Freemium	0.04 (0.05)	0.55 (0.13)	2.02 (1.32)	1.93 (0.28)	−0.41 (0.32)	−0.01 (0.03)	0.13 (0.06)	1.27 (1.23)	−0.31 (0.22)	0.21 (0.18)
Games × Freemium	−1.10 (0.11)	−1.10 (0.20)	−3.29 (1.07)	−2.47 (0.31)	0.05 (0.34)	−0.10 (0.06)	−0.10 (0.08)	0.04 (1.28)	−0.59 (0.27)	−0.13 (0.18)
Post GC × freemium	−0.05 (0.14)	0.07 (0.12)	−0.24 (0.41)	−0.22 (0.08)	−0.14 (0.08)	−0.03 (0.10)	−0.01 (0.08)	0.10 (0.26)	0.24 (0.08)	0.17 (0.07)
Post GC × Freemium × Games	0.44 (0.11)	0.44 (0.21)	3.09 (0.98)	0.69 (0.11)	0.53 (0.12)	−0.08 (0.06)	−0.05 (0.10)	−0.36 (0.63)	−0.15 (0.11)	−0.23 (0.08)
Category FE	Yes	Yes	Yes			Yes	Yes	Yes		
Time trends	Yes	Yes		Yes	Yes	Yes	Yes		Yes	Yes
Constant	2.26 (0.02)	2.22 (0.02)	6.59 (0.09)	2.24 (0.01)	2.35 (0.02)	1.15 (0.01)	1.14 (0.01)	4.48 (0.07)	1.19 (0.01)	1.18 (0.01)
χ^2/F	729.96	13.72	2.87	130.42	88.21	484.91	9.67	0.54	77.55	60.88

Note: DV: *log*(*Daily App Revenue + 1*), unit of observation: *Category-Day or Category—Pre/Post* (*Only Col 3 & 8*). To Address serial correlation within groups (categories), we implement a variety of checks. In Columns 1 and 6, we report bootstrapped *SE*s. In Columns 2 and 7, we cluster *SE*s at the category-week level, allowing for arbitrary serial correlation within these groups. This is similar to the state-year clusters used in Bertrand et al. (2004). In Columns 3 and 8, we repeat the analysis collapsing the data to one observation pre–post the Game Center event. Results remain consistent across these specifications. In Columns 4, 5, 9, and 10, we repeat the analysis but introduce fixed effects at the product level first at the level of the leader firm, and then second on the pair of leader–follower firm. The results are consistent. *SE*s clustered at category-week level, but remain consistent with alternative specifications.

that is critical to the difference-in-differences approach. We perform a number of placebo checks to ensure that the results are not driven by differences between the treatment and the control groups. We report all of these checks in Appendix B1. First, we introduce a placebo shock 35 days (halfway through the pre-shock period) before the actual shock and include this in the regression. Second, we randomize the treatment variable (*Games*). In both cases, the significance of the placebo results suggests that the results are driven by spurious factors rather than the policy change.[11] The results shown in Appendix B1 suggest that this is not the case, further supporting the main results.

5.5.2 | Alternative variable construction

We also perform checks to ensure that the analysis is not driven by the construction of the variables or the data set. First, to ensure that the results are not driven by the construction of the revenue estimates, we repeat the analysis using raw revenue ranking as the outcome variable. The results are comparable with the main results, reported in Appendix B3.

Second, to ensure that these results are not driven by the construction of the categories and the definitions of the market leader and the follower, we repeat the analysis with the 32 categories used by Apple. These are the categories that developers choose when listing their apps, as well as the source of the ranking provided by Apple. These results are reported in Appendix B2.

We also test whether the results are consistent if we construct the freemium measure as a time-invariant variable (genre level) that is an indicator of the categories where “freemium” is used by the majority of the titles prior to the introduction of Game Center, rather than a dynamically changing variable. The results are reported in Appendix B4 and B3 (Table B7, Column 5).

5.5.3 | Accounting for alternative explanations

Unobserved factors may influence companies' revenues. For instance, the companies that use freemium business models may have more sophisticated managers or make larger investments in marketing. This may introduce bias into the analysis as companies with freemium business models may be better able to benefit from the introduction of network effects due to the firms' superior marketing capacity.

We have designed the analysis to ameliorate these issues. We perform the analysis at the level of a narrowly defined market category. In some categories, freemium business models are used by virtually all firms, while in other categories, these models are not used at all. Thus, in this setting, if the leading company in a particular market category uses freemium business models, then generally, competing firms also use freemium business models. As a result, if companies that used freemium business models were more sophisticated or had better marketing assets, then this would apply to the market leader and the first-ranked follower in a particular market category. Although the introduction of network effects might increase the absolute demand for these products (creating an upward bias in terms of daily revenues), it would not affect the relative demand for these products. Thus, by constructing the outcome variable as a ratio between the leading and the following firms, we help to account for this bias. Finally, we include product and product pair (market leader–follower) fixed effects as a robustness check, which would capture inherent differences across products.

TABLE 4 Results for difference-in-differences regressions for leader and follower revenue gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline results				**Robustness checks**					
	Heteroscedasticity and autocorrelation robust SE				***Pre-trend matched***	***Bootstrap SE***	***Clustered SE***	***Collapsed pre/post***	***Only leader FE***	***Leader + follower FE***
Post GC	0.13 (0.04)	0.18 (0.04)	0.19 (0.04)	−0.13 (0.14)	−0.18 (0.14)	0.19 (0.03)	0.05 (0.03)	−0.00 (0.10)	−0.14 (0.02)	−0.03 (0.02)
Freemium	0.20 (0.10)	0.18 (0.10)	0.25 (0.10)	0.51 (0.09)	(0.71) (0.10)	0.25 (0.10)	0.51 (0.13)	2.16 (1.76)	0.04 (0.13)	−0.24 (0.33)
Post GC × Games		−0.13 (0.10)	−0.16 (0.09)	−0.24 (0.05)	−0.10 (0.05)	−0.17 (0.06)	−0.24 (0.08)	−0.52 (0.29)	−0.16 (0.04)	−0.30 (0.05)
Post GC × Freemium		−0.52 (0.16)	−0.72 (0.17)	−0.17 (0.09)	−0.18 (0.10)	−0.73 (0.15)	−0.18 (0.12)	−0.32 (0.45)	−0.04 (0.08)	−0.04 (0.10)
Freemium × Games		−0.52 (0.16)	−1.26 (0.20)	−1.16 (0.07)	−1.27 (0.20)	−1.26 (0.18)	−1.20 (0.28)	−3.37 (1.33)	−0.62 (0.22)	−0.21 (0.36)
Post GC × Games × Freemium			1.16 (0.23)	1.06 (0.23)	0.91 (0.23)	1.16 (0.23)	1.10 (0.32)	3.12 (1.17)	0.46 (0.17)	0.65 (0.17)
Constant						2.01 (0.03)	1.97 (0.02)	2.06 (0.08)	2.07 (0.01)	2.04 (0.02)
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trends	Yes	Yes	Yes			Yes	Yes	Yes	Yes	Yes
Time FE				Yes	Yes					
χ^2/F	9.74	9.24	10.53	1.61	1.72	220.36	5.77	1.74	21.17	12.07

Note: DV: log(*Daily Revenue Leader*) - log(*Daily Revenue Follower*); unit of observation: *Category - Period* (*Day or Pre/Post*). HAC *SE*s reported in parentheses (calculated with a bandwidth of two periods, robust to alternative specifications) for Columns 1–5. In Column 6, we report results with bootstrapped *SE*s. In Column 7, results reported with *SE*s clustered at the category-week level to allow for arbitrary correlation between observations within groups. This is similar to the state-year clusters used in Bertrand, Duflo, and Mullainathan (2004). In Column 8, we report the results with a collapsed dataset of a single observation pre/post as an additional check suggested by Bertrand et al. (2004). In Columns 8 and 9, we include fixed effects at the leader and leader–follower level, respectively. In Columns 1–4, we report the results for the full sample of categories ($n = 33{,}543$). The results are consistent with the earlier result, with no significant effect for the *Post GC × Games* coefficient (C3: $\beta = -.16$; $z = -1.79$; $p = .073$). However, do we find an effect for the *Post GC × Games × Freemium* coefficient (C3: $\beta = 1.16$; $z = 5.01$; $p = .000$). In Column 5, we repeat the results with a matched sample to ensure a parallel pre trend of the treatment and control groups ($n = 29{,}537$) and find consistent results (C5 *Post × Games*: $\beta = -.09$; $z = -1.89$; $p = .059$; C5 *Post GC × Games × Freemium*: $\beta = .90$; $z = 3.87$; $p = .000$). These results support Hypothesis (H2), but provided limited support of Hypothesis (H1). The results in Columns 6 and 7 report results with alternative *SE*s. These results have slightly higher *SE*s but are consistent in supporting Hypothesis (H2) (C6: $\beta = 1.16$; $z = 5.71$; $p = .00$; C7 $\beta = 1.09$; $z = 3.38$; $p = .001$). In Column 8, we repeat the analysis but for a collapsed sample to account for possible serial correlation in the data ($n = 486$). While the coefficients are larger as we are looking at total revenue over the period of the pre/post period, but provide support for Hypothesis (H2) (C8: $\beta = 3.13$; $z = 2.67$; $p = .008$). In Columns 9 and 10, we repeat the analysis include fixed effects at the product (market leader and leader–follower pair level). The results here should be interpreted as the difference in revenues when the same leader, or leader follower pair are in competition before/after the strengthening of network effects. While the coefficients are smaller (given that it is within group), it continues to provide support for Hypothesis (H2) (C9: $\beta = .45$; $z = 2.69$; $p = .007$; C10: $\beta = .64$; $z = 3.87$; $p = .000$).
Abbreviation: HAC, heteroscedasticity and autocorrelation robust.

There might be various revenue streams that we do not account for in this analysis. For instance, we do not capture revenues from advertising or indirect revenues. Although these business models are widespread in the App Store, companies with these business models were typically not among the top-ranked titles examined in this article, especially in 2010, which is the focus.

Additionally, there may be a concern that because freemium strategies were used by developers at a time of a new Game Center feature, Apple could have promoted freemium titles at the time of this event (Rietveld, Schilling, & Bellavitis, 2019). Although Apple may have featured freemium titles, it typically uses this "featured" content as a way to promote lower-ranked titles, as top-ranked titles often receive enough exposure on their own, which would counter our results.

6 | DISCUSSION AND CONCLUSION

In this article, we have investigated how the strengthening of direct (same side) network effects affects the revenues of market leaders and followers, in both settings where freemium and paid-only settings are used. The appeal of freemium strategies is often tied to the presence of network effects around the underlying product (demand-side economies of scale). However, empirical research into the impact of network effects, particularly where freemium strategies are used, is limited.

The results from our empirical analysis show that stronger network effects have a limited impact on the revenues of both market leaders and followers when paid-only strategies are used (only one version of a product for a single price). However, when freemium strategies are used, stronger network effects considerably increase the revenue of the leader and decrease the revenue of the follower. These results suggest that network effects may not lead to market dominance where paid-only strategies are used but only in cases where freemium strategies are used.

6.1 | Implications for theory

This study's results contribute to the literature that has examined the impact of network effects on market outcomes (Kretschmer & Claussen, 2016; Panico & Cennamo, 2020; Schilling, 2002; Shankar & Bayus, 2003; Suarez, 2005). We build on and extend these studies by considering the role of freemium pricing strategies (an extremely important business model for digital products) in influencing the impact of network effects on market outcomes. As the results show, these strategies greatly amplify the impact of network effects on performance and are vital for explaining the market structure of digital industries. This highlights the need to jointly consider network effects and the business strategies that may be more or less favorable to these conditions.

Second, this article contributes to the literature on freemium strategies by providing empirical evidence of how network effects shape the effectiveness of freemium strategies. Much of the literature on freemium strategies is based on analytical modeling, and few studies have considered the use of freemium in a competitive setting. The studies that do so (Pang & Etzion, 2012; Zhang et al., 2016) highlight how competitive interactions can be intensified when network effects are strong, as freemium strategies can increase the user base of companies but may lead them to cannibalize their paying customers, leading to lower revenues. The empirical studies that investigate freemium strategies emphasize how these may influence revenues (Rietveld, 2018; Tidhar & Eisenhardt, 2020). However, existing studies have not considered the role of network effects, as well as the difference between leaders and followers. This article's results highlight the complex interactions among network effects, freemium strategies, and the positions of a market leader and a follower. The findings also emphasize the need to take into account these various aspects when considering whether and how network effects influence firm revenues and market outcomes.

Although not the main contribution of this article, we find an interesting parallel between our work and that on product companies offering services (; Cusumano, Kahl, & Suarez, 2015). This literature highlights how offering services may increase sales but dampen profitability. Interestingly, much of the game-theory literature that we draw on in this article (Pang & Etzion, 2012; Zhang et al., 2016) uses the analogy of a company offering a product and a service. The present results show how offering a free product may allow a market leader to acquire a large user base and gain an advantage over followers. However, this advantage is based on offering a free product and is therefore not guaranteed to increase profitability. In fact, it may drastically reduce the profitability of the follower, while not guaranteeing that the market leader will generate higher revenues.

This also spurs questions of the long-run equilibria that would emerge in this competition between products with network effects. For instance, Halaburda, Jullien, and Yehezkel (2020) study the dynamics of competition in a market with network externalities and study the dynamics of competition between a low quality or high-quality product. In the long run, it may be that products in the marketplace began adapting the types of products they created, to adapt them to freemium strategies or distinguish themselves if they are using paid-only strategies. While this is beyond the scope of our data and the focus of this article, there may be many opportunities to explore this issue in future research.

6.2 | Implications for practice

This article's findings also have implications for managers and for a competitive strategy in the context of network industries. There is a prevailing logic that freemium models and network effects may be mutually beneficial and lead to favorable market outcomes. The present results show that when that might be the case, it would be so only for the market leader. Follower firms would ultimately suffer in a market with network effects and freemium strategies. Additionally, as the results highlight at various points, even market leaders may also suffer in settings where network effects exist and freemium strategies are used. This partly calls into question whether firms should focus on strategies that might amplify their advantage in network industries, as this might lead to market dominance (advantage over followers) but might lower profitability.

These results also have implications for platform owners that control digital marketplaces. Owners of platforms, such as the App Store, often aim to devise policies to benefit complementors and customers. However, as the present results show, this may lead to unforeseen consequences. Recent studies have shown how the market structure may influence the innovativeness of complementors on the platform (Boudreau & Jeppesen, 2015). These results suggest

[11] Point estimates for the randomized treatment are much smaller ($\beta = .28$, $SE = 0.16$) and not statistically significant in comparison to the magnitude with the actual treatment (i.e., games) variable ($\beta = 1.16$, $SE = 0.19$).

that freemium strategies, more than just network effects, may end up creating a market structure dominated by a single firm. This has potential implications for the health of that ecosystem, for instance, in terms of revenue generation and incentives for innovation. These potentially broader consequences create a further need for platforms to consider such issues when fostering network effects on products or allowing the use of tools that enable network effects and freemium strategies.

6.3 | Limitations

The results of this article provide evidence for the relationship between direct network effects and market outcomes, both when freemium strategies are used and when they are not. Part of the empirical contribution of this article is its research design which allows us to exploit a policy intervention which was associated with stronger direct network effects. However, that brings with it its own limitations. In our setting, firms did not have time to adapt their business models. Over time, there was a greater shift to freemium strategies. While many of the same forces may have existed under those conditions, there may be other factors that influenced how network effects and freemium strategies impacted market outcomes. Another limitation of this study is that many of our empirical findings emerge from the subset of firms which did use freemium strategies in this very early period of the app store. Our results provide evidence that freemium strategies did provide a greater advantage to leaders over followers when network effects were strengthened, across several categories and many products. That said, these results are based on that specific subsample and future work should look for other settings where we can look for evidence of similar patterns.

ACKNOWLEDGEMENTS

The authors are grateful to participants of the DRUID 2016 Conference, Seminar participants at the Institute for Strategy, Technology and Organization (ISTO), USC Marshall Junior Faculty Brownbag, USC Research Day and College of Management of Technology—EPFL. Thomas Rønde, Juan Santalo, Carmelo Cennamo, Martin Schreier, H. C. Kongsted, and Andrea Fosfuri provided helpful comments. The authors also want to thank the editor and two reviewers for the helpful comments and advice throughout this process. The authors finally mention that all errors are their own.

DATA AVAILABILITY STATEMENT

Data on product rankings are collected from Apple daily rankings. These are available on various platforms or may be licensed from vendors. The app categorization data was provided by Priori LLC. These data are restricted because they are protected by an NDA.

ORCID

Kevin J. Boudreau https://orcid.org/0000-0003-2787-9599
Lars Bo Jeppesen https://orcid.org/0000-0001-8705-0112
Milan Miric https://orcid.org/0000-0002-8318-9288

REFERENCES

Adner, R., Puranam, P., & Zhu, F. (2019). What is different about digital strategy? From quantitative to qualitative change. *Strategy Science*, *4*(4), 253–261.

Afuah, A. (2013). Are network effects really all about size? The role of structure and conduct. *Strategic Management Journal*, *34*, 257–273.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, *119*(1), 249–275.

Boudreau, K. J., & Jeppesen, L. B. (2015). Unpaid crowd complementors: The platform network effect mirage. *Strategic Management Journal*, *36*(12), 1761–1777.

Brynjolfsson, E., & Kemerer, C. F. (1996). Network externalities in microcomputer software: An econometric analysis of the spreadsheet market. *Management Science*, *42*(12), 1627–1647.

Cabral, L. (2011). Dynamic price competition with network effects. *The Review of Economic Studies*, *78*(1), 83–111.

Caves, R., & Ghemawat, P. (1992). Identifying mobility barriers. *Strategic Management Journal*, *13*(1), 1–12.

Caves, R. E. (2003). Contracts between art and commerce. *Journal of Economic Perspectives*, *17*(2), 73–83.

Cennamo, C., & Santalo, J. (2013). Platform competition: Strategic trade-offs in platform markets. *Strategic Management Journal*, *34*(11), 1331–1350.

Chellappa, R. K., & Shivendu, S. (2005). Managing piracy: Pricing and sampling strategies for digital experience goods in vertically segmented markets. *Information Systems Research*, *16*(4), 400–417.

Cheng, H. K., & Liu, Y. (2012). Optimal software free trial strategy: The impact of network externalities and consumer uncertainty. *Information Systems Research*, *23*(2), 488–504.

Cheng, H. K., & Tang, Q. C. (2010). Free trial or no free trial: Optimal software product design with network effects. *European Journal of Operational Research*, *205*(2), 437–447.

Clements, M. T., & Ohashi, H. (2005). Indirect network effects and the product cycle: Video games in the U.S., 1994–2002. *The Journal of Industrial Economics*, *53*(4), 515–542.

Corts, K. S., & Lederman, M. (2009). Software exclusivity and the scope of indirect network effects in the U.S. home video game market. *International Journal of Industrial Organization*, *27*(2), 121–136.

Cusumano, M. A., Kahl, S. J., & Suarez, F. F. (2015). Services, industry evolution, and the competitive strategies of product firms. *Strategic Management Journal*, *36*(4), 559–575.

Datta, H., Foubert, B., & Van Heerde, H. J. (2015). The challenge of retaining customers acquired with free trials. *Journal of Marketing Research*, *52*(2), 217–234.

Davies, S. W., & Geroski, P. A. (1997). Changes in concentration, turbulence and the dynamics of market shares. *The Review of Economics and Statistics*, *79*(3), 383–391.

Deneckere, R. J., & Preston McAfee, R. (1996). Damaged goods. *Journal of Economics & Management Strategy*, *5*(2), 149–174.

Dey, D., Lahiri, A., & Liu, D. (2013). Consumer learning and time-locked trials of software products. *Journal of Management Information Systems*, *30*(2), 239–268.

Dou, Y., Niculescu, M. F., & Wu, D. J. (2013). Engineering optimal network effects via social media features and seeding in markets for digital goods and services. *Information Systems Research*, *24*(1), 164–185.

Dranove, D., & Gandal, N. (2003). The DVD-vs.-DIVX standard war: Empirical evidence of network effects and preannouncement effects. *Journal of Economics & Management Strategy*, *12*(3), 363–386.

Dubé, J. P. H., Hitsch, G. J., & Chintagunta, P. K. (2010). Tipping and concentration in markets with indirect network effects. *Marketing Science*, *29*(2), 216–249.

Etzion, H., & Pang, M. S. (2014). Complementary online services in competitive markets: Maintaining profitability in the presence of network effects. *MIS Quarterly*, *38*(1), 231–248.

Farrell, J., & Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. In *Handbook of industrial organization* (Vol. 3, pp. 1967–2072). North-Holland. https://www.elsevier.com/books/handbook-of-industrial-organization/schmalensee/978-0-444-70435-1

Farrell, J., & Saloner, G. (1986). Installed base and compatibility: Innovation, product preannouncements, and predation. *The American Economic Review*, *76*(5), 940–955.

Ferrier, W. J., Smith, K. G., & Grimm, C. M. (1999). The role of competitive action in market share erosion and industry dethronement: A study of industry leaders and challengers. *Academy of Management Journal*, *42*(4), 372–388.

Gallaugher, J. M., & Wang, Y. M. (2002). Understanding network effects in software markets: Evidence from web server pricing. *MIS Quarterly*, *26*(4), 303–327.

Gandal, N. (1994). Hedonic price indexes for spreadsheets and an empirical test for network externalities. *The RAND Journal of Economics*, *25*(1), 160–170.

Garg, R., & Telang, R. (2013). Inferring app demand from publicly available data. *MIS Quarterly*, *37*(4), 1253–1264.

Gawer, A. (2014). Bridging differing perspectives on technological platforms: Toward an integrative framework. *Research Policy*, *43*(7), 1239–1249.

Godes, D., & Mayzlin, D. (2009). Firm-created word-of-mouth communication: Evidence from a field test. *Marketing Science*, *28*(4), 721–739.

Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, *57*(1), 3–43.

Greenstein, S., Lerner, J., & Stern, S. (2013). Digitization, innovation, and copyright: What is the agenda? *Strategic Organization*, *11*(1), 110–121.

Greenstein, S., & Markovich, S. (2012). Pricing experience goods in information good markets: The case of e-business service providers. *International Journal of the Economics of Business*, *19*(1), 119–139.

Greenstein, S. M. (1993). Did installed base give an incumbent any (measurable) advantages in federal computer procurement? *The RAND Journal of Economics*, *24*(1), 19–39.

Halaburda, H., Jullien, B., & Yehezkel, Y. (2020). Dynamic competition with network externalities: How history matters. *The RAND Journal of Economics*, *51*(1), 3–31.

Hannigan, T. R., Haans, R. F. J., Vakili, K., Tchalian, H., Glaser, V. L., Wang, M. S., … Jennings, P. D. (2019). Topic Modeling in Management Research: Rendering New Theory from Textual Data. *Academy of Management Annals*, *13*(2), 586–632. https://doi.org/10.5465/annals.2017.0099

Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, *124*(5), 1423–1465.

Katz, M., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *American Economic Review*, *75*(3), 424–440.

Katz, M. L., & Shapiro, C. (1986). Technology adoption in the presence of network externalities. *Journal of Political Economy*, *94*(4), 822–841.

Kretschmer, T., & Claussen, J. (2016). Generational transitions in platform markets—The role of backward compatibility. *Strategy Science*, *1*(2), 90–104.

Kretschmer, T., & Loh, J. (2021). Platform competition and online communities: Evidence from game wikis (Working Paper). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3846218

Kretschmer, T., & Peukert, C. (2020). Video killed the radio star? Online music videos and recorded music sales. *Information Systems Research*, *31*(3), 776–800.

Lee, Y. J., & Tan, Y. (2013). Effects of different types of free trials and ratings in sampling of consumer software: An empirical study. *Journal of Management Information Systems*, *30*(3), 213–246.

Li, H., Jain, S., & Kannan, P. K. (2019). Optimal design of free samples for digital products and services. *Journal of Marketing Research*, *56*(3), 419–438.

Liu, C. Z., Au, Y. A., & Choi, H. S. (2014). Effects of freemium strategy in the mobile app market: An empirical study of Google play. *Journal of Management Information Systems*, *31*(3), 326–354.

Markovich, S., & Moenius, J. (2009). Winning while losing: Competition dynamics in the presence of indirect network effects. *International Journal of Industrial Organization*, *27*(3), 346–357.

Mussa, M. (1979). The two-sector model in terms of its dual: A geometric exposition. *Journal of International Economics*, *9*(4), 513–526.

Nan, G., Wu, D., Li, M., & Tan, Y. (2018). Optimal freemium strategy for information goods in the presence of piracy. *Journal of the Association for Information Systems*, *19*(4), 266–305.

Niculescu, M. F., & Wu, D. J. (2014). Economics of free under perpetual licensing: Implications for the software industry. *Information Systems Research*, *25*(1), 173–199.

Pang, M. S., & Etzion, H. (2012). Research note—Analyzing pricing strategies for online services with network effects. *Information Systems Research*, *23*(4), 1364–1377.

Panico, C., & Cennamo, C. (2020). User preferences and strategic interactions in platform ecosystems. *Strategic Management Journal*. https://doi.org/10.1002/smj.3149

Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management Science*, *51*(10), 1494–1504.

Rietveld, J. (2018). Creating and capturing value from freemium business models: A demand-side perspective. *Strategic Entrepreneurship Journal*, *12*(2), 171–193.

Rietveld, J., & Ploog, J. N. (2021). On Top of The Game? The Double-Edged Sword of Incorporating Social Features into Freemium Products. *Strategic Management Journal*. https://doi.org/10.1002/smj.3362

Rietveld, J., Schilling, M. A., & Bellavitis, C. (2019). Platform strategy: Managing ecosystem value through selective promotion of complements. *Organization Science*, *30*(6), 1232–1251.

Rochet, J. C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990–1029.

Rysman, M. (2004). Competition between networks: A study of the market for yellow pages. *The Review of Economic Studies*, *71*(2), 483–512.

Saloner, G., & Shepard, A. (1992). *Adoption of technologies with network effects: An empirical examination of the adoption of automated teller machines* (Working Paper No. w4048). National Bureau of Economic Research.

Schilling, M. A. (2002). Technology success and failure in winner-take-all markets: The impact of learning orientation, timing, and network externalities. *Academy of Management Journal*, *45*(2), 387–398.

Shankar, V., & Bayus, B. L. (2003). Network effects and competition: An empirical analysis of the home video game industry. *Strategic Management Journal*, *24*, 375–384.

Shapiro, C., Carl, S., & Varian, H. R. (1998). *Information rules: A strategic guide to the network economy*. Boston, MA: Harvard Business Press.

Shi, Z., Zhang, K., & Srinivasan, K. (2019). Freemium as an optimal strategy for market dominant firms. *Marketing Science*, *38*(1), 150–169.

Stremersch, S., Tellis, G. J., Hans Franses, P., & Binken, J. L. (2007). Indirect network effects in new product growth. *Journal of Marketing*, *71*(3), 52–74.

Suarez, F. F. (2005). Network effects revisited: The role of strong ties in technology selection. *Academy of Management Journal*, *48*(4), 710–720.

Tidhar, R., & Eisenhardt, K. M. (2020). Get rich or die trying… finding revenue model fit using machine learning and multiple cases. *Strategic Management Journal*, *41*(7), 1245–1273.

Tucker, C. (2019). Digital data, platforms and the usual [antitrust] suspects: Network effects, switching costs, essential facility. *Review of Industrial Organization*, *54*(4), 683–694.

Yang, Z., & Peterson, R. T. (2004). Customer perceived value, satisfaction, and loyalty: The role of switching costs. *Psychology & Marketing*, *21*(10), 799–822.

Zhang, Z., Nan, G., Li, M., & Tan, Y. (2016). Duopoly pricing strategy for information products with premium service: Free product or bundling? *Journal of Management Information Systems*, *33*(1), 260–295.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Boudreau, K. J., Jeppesen, L. B., & Miric, M. (2021). Competing on freemium: Digital competition with network effects. *Strategic Management Journal*, 1–28. https://doi.org/10.1002/smj.3366