Received: 1 October 2021 | Revised: 24 December 2022 | Accepted: 12 January 2023 | Published on: 27 January 2023

DOI: 10.1002/smj.3487

STRATEGIC MANAGEMENT JOURNAL WILEY

RESEARCH ARTICLE

Growing platforms within platforms: How platforms manage the adoption of complementor products in the presence of network effects?

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Abstract

Research Summary: Platform owners often use endorsements to actively manage complementor firms. We argue that the direct network effects of complementors' products play a central role in the platform management by its owner. We test our predictions using data on the Apple's promotion of apps. We find that apps with network effects are more likely to receive an award. This likelihood increases when the app is introduced by a developer with a larger market share but declines when introduced in a concentrated segment. The likelihood decreases further if the app is introduced in a concentrated segment by a developer that holds a larger market share. Further, we observe that in concentrated segments, the "challenger" developer has a higher likelihood of receiving the award relative to the leader.

Managerial Summary: Many products offered through platforms have their own direct network effects. The value of the product for each user grows with the number of other consumers using the product. Many platform owners also actively manage their platforms to ensure platform growth and often use less traditional tools such as product endorsements to achieve this goal.

In the context of video games listed in the iOS App Store and the Editors' Choice Awards as a form of product endorsement, we examine the tradeoffs that products with direct network effects (i.e., multiplayer video games) present to the platform owner (Apple). On the one hand, the platform owner may want to promote apps with direct network effects to help them achieve a momentum in terms of user growth. On the other hand, networked apps may become dominant in the segment with negative implications for future growth of the segment and the platform owner's profitability. We find evidence consistent with this tension and find that it critically depends on the complementor strength and market segment concentration. We also observe that in concentrated segments, the "challenger" developer has a higher likelihood of receiving the award relative to the leader.

KEYWORDS

direct network effects, platform competition, platform management

1 | INTRODUCTION

Given the rising importance of platforms in many industries, scholars have started examining questions related to the management of platforms. Prior work has highlighted that firms that own and manage platforms do not only focus on creating an environment in which platform participants (i.e., complementors) deliver value to users but also actively manage complementors to maximize such value (Boudreau, 2010; Cennamo & Santalo, 2013; Cennamo & Santaló, 2019; Chatain & Kaul, 2021; Claussen, Kretschmer, & Mayrhofer, 2013; Gawer & Henderson, 2007; Rietveld, Schilling, & Bellavitis, 2019; Zhang, Li, & Tong, 2020). Because the contractual relationship between the platform owner and complementors tends to be standardized and specifies few basic parameters, platform owners may not have all the tools at their disposal that are available within traditional organizations.[1] Consequently, platform management presents a unique set of challenges that requires new approaches and explanations (Altman, Nagle, & Tushman, 2022; Jacobides, Cennamo, & Gawer, 2018; Koo & Eesley, 2021; Miller & Toh, 2022). Studies have explored how platform owners manage platform growth, adoption, complementors' incentives, and how platform owners can improve customer discovery by highlighting underappreciated products (Boudreau, 2010; Cennamo & Santalo, 2013; Cennamo & Santaló, 2019; Chu & Wu, 2021; Kapoor & Lee, 2013; Rietveld et al., 2019;

[1]For an example of a standardized agreement, see Apple License and Use Agreements: https://developer.apple.com/support/terms/

Schilling, 2009; Zhang et al., 2020; Zhu & Furr, 2016). Recently, scholars have also started focusing on the distribution of value between platform owners and complementors (Ceccagnoli, Forman, Huang, & Wu, 2012; Chatain & Plaksenkova, 2020; Huang, Ceccagnoli, Forman, & Wu, 2013; Pagani, 2013; Wang & Miller, 2020) and management of competition with other platforms (Miric, Pagani, & El Sawy, 2021).

While prior studies have highlighted how the adoption of complementor products drives platform growth and performance (Katz & Shapiro, 1994; Shankar & Bayus, 2003), extant research tends to treat the complementor products as homogenous when managing the platform (Miric et al., 2021; Rietveld et al., 2019). We know relatively little about a key contingency potentially affecting how platforms manage adoption—*complementor product direct network effects*.[2] When products have positive direct network effects, the utility they create for any user will depend on whether they can create a sufficiently large installed base of users (Rietveld & Ploog, 2022; Shankar & Bayus, 2003). Promoting the adoption of promising products with direct network effects may help to achieve such a critical mass and lead to a momentum while creating a significant value for the users and the platform owner. At the same time, such momentum may become "out of control" from the perspective of the platform owner as well as the users, leading to dominant complementors that stymie growth of the segment or bend rules to shift value away from the platform owner. Consequently, platform owners may find it useful to *balance* the adoption of complementor products with direct network effects to, on the one hand, resolve uncertainty and facilitate product adoption (Moeen, Agarwal, & Shah, 2020) and, on the other hand, mitigate risks associated with complementor dominance (Pagani, 2013). Since the ability to achieve dominance likely depends on the competitiveness of the environment in which the products are introduced and capabilities of the complementor, the nature of the balance may vary across product segments and complementors.

For example, the tension between adoption and dominance is salient in the context of video games. Multiplayer games (offered through a platform) such as Fortnite by developer Epic Games have strong direct network effects because the value of the game for each player critically depends on the number of other players (Boudreau, Jeppesen, & Miric, 2021; Rietveld & Ploog, 2022). Further, many video games like Fortnite are broadening their scope by offering not only a gaming experience but also social interactions (i.e., they are becoming "platforms within platforms"). Developers controlling a successful "platform within platform" may achieve dominance in their segment, and even not adhere to the contractual terms of the platform and impede segment growth.[3]

We develop a conceptual framework to explore how platform owners promote complementor products with direct network effects to achieve the balance between encouraging adoption versus mitigating the risk of complementors' dominance and examine how this effect depends on the characteristics of the segment and the complementor. We focus on a novel tool that platforms use to foster adoption identified in recent work—selective product promotions through awards (Foerderer, Lueker, & Heinzl, 2021; Rietveld et al., 2019; Rietveld, Ploog, & Nieborg, 2020; Rietveld, Seamans, & Meggiorin, 2021). Although awards are traditionally conceptualized as being given to the best products, when the awards are rare and influential (Elfenbien, Fisman, & McManus, 2015), they can be used strategically to grow the platform (Elfenbien et al., 2015;Foerderer et al., 2021; Rietveld et al., 2021) or aid in customer discovery

[2]These effects differ from the platform-level direct and indirect network effects that have been a traditional focus.

[3]For example, Rover (2002) argues that games are the new social platforms (https://medium.com/coinmonks/digital-consumers-spending-more-time-and-money-online-invest-in-these-areas-7c780cab49af).

(Rietveld et al., 2019). Awards are a form of non-pecuniary recognition (Hukal, Henfridsson, Shaikh, & Parker, 2020) that can be used to gently "shepherd" the community (Altman et al., 2022; Foerderer et al., 2021) while, at same time, providing a quality signal about the product. Given the rarity of awards, selecting among different high-quality products can provide sufficient flexibility to use awards strategically. As an important distinction, prior work has examined awards that are given after the platform owner observes the market reaction and conceptualized such awards as aiding in product discovery (Rietveld et al., 2019) or influencing complementor incentives (Foerderer et al., 2021; Rietveld et al., 2021). When the awards are given shortly post release without observing the market (as in our context), they are relevant tools for managing adoption. This is particularly salient when managing the adoption of products with direct network effects as later stage awards may be ineffective in inducing user switching.

To examine the questions, we utilize a detailed dataset on gaming apps (such as Fortnite) listed in the Apple App Store between 2012 and 2016. We focus on the games category because games are heterogeneous in terms of the direct network effects and relatively homogenous in how they interact with the rest of the ecosystem (e.g., games can be typically played on both iPhones and iPads). Further, games typically do not rely on specific hardware such as the Apple Watch.[4] Our dataset contains detailed information about the app features, software, and hardware characteristics and information about developers. Our dependent variable is Editors' Choice Awards—a recognition that Apple gives to apps shortly after they are introduced and that are featured prominently in the app store. The games category also exhibits a significant heterogeneity across product segments in terms of market structure, allowing us to study how the main effects depend on the competitiveness of the environment and complementor strength.

We find that the theorized tensions are present when platform owners manage the adoption of complementor products using awards. Specifically, to promote adoption, and conditional on product quality, platform owners are more likely to give awards to complementor products that have direct network effects (i.e., multiplayer and massively multiplayer games), and particularly those products with network effects that are introduced by complementors that have a proven track record of building an installed based (as indicated by having a larger market share). However, these effects are weaker if the specific product segment is concentrated and dominated by only a handful of complementors. Specifically, complementors with (a) a larger market share, (b) that introduce products with network effects, (c) in concentrated markets, are *less* likely to receive an award relative to when any of these conditions are missing. Further, in segments that are concentrated and where products have network effects, the second complementor in terms of the market share is more likely to receive an award relative to the market leader.

Our theory also implies that the platform owner considers both value appropriation (benefiting the platform owner) and value creation (benefiting both users and the platform owner) when making award decisions. We implement additional analysis to examine these implications. It reveals that products with direct network effects from which the platform owner (Apple) can appropriate more value (as proxied by in-app purchases, utilization of a new processor, or new iOS features) are more likely to receive an award. The analysis also shows that a combination of direct network effects of products in the segment and complementor concentration has negative future consequences for the segment (in terms of lower future entry of

[4]Apple may have strategic reasons to promote apps that have strong hardware complementarities. We leave the examination of such heterogeneity for future work.

new apps and new developers as well as stagnant growth of new users) incentivizing the platform owner to avoid such a situation.

Our study makes multiple contributions. First, in the context of the emerging literature on the strategic management of platforms, we highlight that direct network effects at the level of the complementors' products play an important role when platforms manage complementors (Altman et al., 2022; Ceccagnoli et al., 2012; Huang et al., 2013; Pagani, 2013; Rietveld et al., 2021; Wang & Miller, 2020). Specifically, we provide evidence consistent with the network effects influencing whether and when platform owners promote product adoption. We show that the network effects lead to tensions that platform owners face when balancing product adoption versus complementor dominance and that such tensions critically depend on the characteristics of the product segment and the complementors. Our findings extend prior work showing that novel tools in the management of platforms such as awards can be used to create and maintain a vibrant platform (Foerderer et al., 2021; Rietveld et al., 2019; Rietveld et al., 2020; Rietveld et al., 2021). Second, we contribute to the literature on network effects (Afuah, 2013; Basker & Simcoe, 2021; Katz & Shapiro, 1994; Rietveld & Ploog, 2022) by showing that product-level network effects have implications for how the products will be perceived and managed by platform owners with implications for product performance. The study also has practical implications for both platform owners and complementors. Platforms that do not use awards to manage their complementors may benefit from implementing approaches examined in our study. Further, developers may need to be cognizant of strategic considerations related to awards. These may have implications for their product design and entry choices.

2 | THEORETICAL FRAMEWORK AND HYPOTHESES

Scholars argue that platforms present a unique set of strategic challenges that require new approaches and explanations. Altman et al. (2022), in a recent review article, describe platform owners as using a "translucent hand" to manage ecosystem participants. They also argue that platform management requires new tools for such management since platform owners may not have tools at their disposal that are available within traditional organizations (Jacobides et al., 2018; Koo & Eesley, 2021; Miller & Toh, 2022). Specifically, the contracts between the platform owner and complementors tend to be standardized and often define basic parameters of the relationship such as licensing fees in return for hosting of the product on the platform and use of the platform's development resources. Such contracts may not provide sufficient flexibility for the platform owner to actively manage complementors.

One of the key objectives of platform owners is to achieve platform growth and adoption (Cennamo & Santalo, 2013; Cennamo & Santaló, 2019; Claussen et al., 2013; Gawer & Henderson, 2007). For instance, platforms such as Facebook and Twitter had no profits and unclear monetization models for multiple years post entry and were primarily concerned with user growth. Reflecting this emphasis, scholars have studied how platform owners may achieve early-stage adoption, maximize growth, structure complementors' incentives, and improve user experience (Boudreau, 2010; Foerderer et al., 2021; Rietveld et al., 2019, 2021; Schilling, 2009). While the primary condition of platform survival is its adoption and growth, platform owners eventually face the pressure to introduce monetization models and focus on profitability. The objectives of platform adoption and growth versus value appropriation may conflict, creating management challenges for the platform owner. Less control over complementors and fewer direct tools available for their management make such challenges more pronounced. Consistent with this notion, scholars have started exploring how the value is shared between the platform and the complementors (Ceccagnoli et al., 2012; Huang et al., 2013; Pagani, 2013; Wang & Miller, 2020).

An important consideration in the context of platforms is whether the products introduced by complementors have direct network effects. The presence of product-level network effects has potentially significant implications for the management of complementors by the platform owner. While network effects are not a necessary condition for the platform existence (Altman et al., 2022), prior literature has highlighted the importance of network effects at the level of the platform for the growth of platforms (Afuah, 2013; Katz & Shapiro, 1994; Rietveld & Ploog, 2022). However, we know relatively little about the complementor product-level network effects, particularly as they relate to platform management. Managing network effects at the product level may differ from managing network effects for the entire platform. For instance, a platform such as Facebook has strong direct network effects for users because the value of the platform for users critically depends on the number of other consumers using Facebook. Further, Facebook as a platform has indirect network effects for advertisers because the value of the platform depends on the number of consumers using Facebook. At the same time, advertisers may introduce apps through Facebook, such as a customer survey that may not exhibit direct network effects. In our context of the Apple App Store, some games may have direct network effects while others do not. For instance, in the massively multiplayer game Fortnite, the objective is to survive by defeating other players in real-time while possibly teaming up with friends. The playing experience critically depends on the number of other players using the app at the same time. Other games where players play against computer-generated environments, like the popular game Don't Starve, have low direct network effects because the player experience does not depend on other users and most such games can even be played offline. In our study, we focus on the product-level direct network effects because they affect the calculus of how likely the platform owner may support the adoption of the product.

When competing products with strong direct network effects are introduced, the segment may exhibit significant volatility and low growth. It is because multiple products may be used concurrently but none of them might have enough users to create a valuable experience for the users. In the context of multiplayer games, multiple products in the same segment may coexist while each has an active online userbase that is insufficient to ensure a smooth playing experience (Rietveld & Ploog, 2022).[5] Further, lower quality products may end up dominating the market when temporary fluctuations in the number of users may be amplified into irreversible positions due to high switching costs. These mechanisms have been extensively described in the network effects literature. For instance, in the competition for technological standards, the video standard Betamax was considered superior to VHS while VHS ended up dominating the market (Arthur, 1994; David, 2001; Page, 2006). As a result of these mechanisms, the platform owner may have an incentive to help resolve the uncertainty and tip the adoption toward one of the competing products. Absent other strategic considerations, the platform owner may prefer that the best product is adopted since that may increase the value of the product to the consumers relative to competing products outside of the platform. Generally, value maximization for the users is likely beneficial for the platform due to attracting more users to the platform

[5]Multiplayer games use a queuing system in which the players wait in a "lobby" until enough available players with mutually fast response times (called the ping rate) join, and the match can start. When the pool of active players is low, the wait times increase and players who have slower ping rates may need to join (e.g., from more distant locations), increasing the error rates of the game and lowering the user experience.

and in turn allowing the platform owner to appropriate more value either directly from the users or through indirect network effects at the level of the platform (e.g., by selling advertising).

Although the platform owner may have an incentive to steer the users toward a particular product with network effects to resolve the uncertainty and promote adoption, the tools that it has at its disposal may be limited. One constraint is that all complementors are often subject to the same contractual conditions and overt promotion of some products may be seen as potentially unfair and anti-competitive. Altman et al. (2022) propose that platforms need to gently "shepherd" their communities as opposed to using tools of direct control, and Foerderer et al. (2021) discuss "soft" mechanisms of platform management. Consistent with this view, Rietveld et al. (2019) show, in the context of the gaming consoles PS3 and XBOX360, that platform owners (i.e., console manufacturers) use awards not only to highlight best-in-class video games (given the time period, their study did not include multiplayer online games) but also strategically. They examine awards given to games that are usually at least 6 months post release and achieved at least 300,000 units sold and show that platforms use awards to highlight products with interesting features that may be underappreciated by the market, promote products in categories in which the platform owners do not have their own competing products, promote products introduced by developers with which they have an exclusive relationship, and promote more products during slow periods. Similarly, Foerderer et al. (2021) examine annual awards given by Google to apps listed on the Play Store. The objective of the awards is to reward innovativeness and the authors show that the awards affect complementor incentives by increasing complementor entry, future app quality, and multihoming. Several related studies show that selective promotion of complementors by platform owners in the form of awards, badges or lists improves the performance of the promoted product or the platform (Aguiar & Waldfogel, 2021; Elfenbien et al., 2015; Rietveld et al., 2021).

We extend this work by maintaining that product level network effects play an important role in the strategic calculus. Specifically, awards may be used to resolve the uncertainty associated with the adoption of multiple competing products, but, as we discuss below, the downside of the strong network effects is that the complementors may become dominant and powerful, leading to negative outcomes for the platform owner and the users.

It is important to note that to maximize the strategic impact of awards a number of conditions should be considered. The awards should be rare, impactful, should strongly correlate with product quality and, if they are aimed at driving adoption, be given early in the product life cycle. Awards that are common may lose their information value and may become less influential (Elfenbien et al., 2015). The awards should also be prominently featured by the platform owner to influence consumer behavior. If the award is given too late after the product introduction, it may not influence users who already chose a competing product. The importance of early-stage awards is particularly salient if the platform owner needs to effectively manage the adoption of products with direct network effects. Awards may be insufficient to induce user switching between products after switching costs increase. Importantly, the award must capture product quality (Foerderer et al., 2021). Otherwise, it would lose credibility with product users and lose its information value.[6] Consequently, platform owners' strategic use of awards may be in essence a selection among high quality products that is driven by other strategic considerations that are not necessarily related to quality.

The arguments described above lead us to formulate our first (baseline) prediction:

[6]As we describe below, the awards in our context satisfy all these criteria.

Hypothesis 1 (H1). *Conditional on product quality, the platform owner is more likely to promote the adoption of a complementor product that has direct network effects.*

When selecting which product with network effects should receive an award, the platform owner may try to select a product that has a greater chance of adoption to ensure segment growth and long-term viability. Even when comparing two products with comparable network effects and quality, they may have unequal chances of long-term adoption. When products with network effects are introduced by small complementors without resources to quickly scale to a critical mass of users, the products may fail, not due to their inherent low quality but due to low user value driven by limited resources and slow adoption. The game segment is replete with examples of multiplayer games that failed not necessarily because they were poorly executed but because they failed to attract a critical mass of users quickly leading to poor gaming experience (for instance, the failure of multiplayer games such as Gods & Heroes or Tabula Rasa was attributed to a crowded segment of similar games released around the same time even though the games were considered of high quality and received high critical acclaim). Consequently, when platform owners bet on which high quality product with network effects to support through early awards, they may steer away from small complementors and toward larger complementors with more experience, a better track record and greater resources. Consequently, we propose the following:

Hypothesis 2 (H2). *Conditional on product quality, the platform owner is more likely to promote the adoption of a complementor product with direct network effects that is introduced by a complementor with a higher market share (relative to a complementor with a smaller market share).*

In the arguments above, we implicitly assumed that the environment is competitive, and the platform owner is not concerned about the complementors becoming too dominant or accumulating excessive power. Some segments of the market may be dominated by a few powerful players. When selecting which quality products with direct network effects to promote through awards, the platform owner may be more hesitant to give awards in categories in which the award may result in the dominance of a single product. If the segment is concentrated where a small number of complementors compete, promoting the adoption of a new product of one of these complementors may tip the balance of power, leading to one complementor dominating the segment. While having multiple competing products in a segment may be suboptimal from the perspective of segment growth, it may prevent any individual complementor from achieving dominance.

From the perspective of the platform owner, a complementor dominating a segment may have several negative implications. Powerful complementors may threaten the ability of the platform owner to appropriate value from the platform and affect its profitability. Dominant players may have stronger bargaining power to renegotiate the terms of the listing contract or may request other forms of allowances or support from the platform owner (e.g., they may request additional promotion, sharing of marketing costs or tie-ins with hardware). An example of a lawsuit between Epic Games (developer of Fortnite) and Apple, Inc. illustrates this argument. At the time of listing, like any other app listed in Apple's App Store, Epic Games was required to share 30% of in-app purchase revenues with Apple. However, when Fortnite became the #1 video game in the App Store, Epic decided to circumvent the fee by allowing in-app purchases directly from Epic's website. Despite being a top seller, Apple dropped the game from the App Store. Both Apple and Epic filed lawsuits and the current verdict allows developers to use other forms of payment, thereby circumventing paying fees to Apple and resulting in a loss of revenue for Apple as the platform owner.[7]

Even in cases when the complementor dominance does not lead to renegotiation of licensing fees or other contractual changes, it can result in a lower value created in the segment and negative consequences for both users and the platform owner. Complementor dominance may lead to existing users being locked into the leading product (due to network effects and high switching costs), lower entry of new products and new complementors as well as stagnating user growth.

Consequently, we theorize that the platform owner is more likely to avoid promoting the adoption of networked products in segments that may be at risk of becoming dominated by one or a few powerful players:

Hypothesis 3 (H3). *Conditional on product quality, the platform owner is less likely to promote the adoption of a complementor product with direct network effects that is introduced in a segment that is highly concentrated (relative to a more competitive segment).*

It follows from the prior arguments, that the platform owner may be particularly concerned about the complementors that have accumulated power and dominance already. Specifically, complementors holding significant market share in concentrated markets may be at the cusp of dominating the segment, which may create challenges in terms of both value appropriation and creation in the focal segment for the platform owner. Consequently, the platform owner may be particularly unlikely to give awards to powerful complementors already enjoying high market share when they introduce products with network effects in concentrated markets:

Hypothesis 4 (H4). *Conditional on product quality, the platform owner is less likely to promote the adoption of a complementor product with direct network effects that is introduced in a concentrated segment by a complementor with a higher market share (relative to a complementor with a smaller market share in a concentrated segment with direct network effects).*

The logic developed in the preceding hypotheses has an additional implication. In concentrated markets, the platform owner may want to go beyond just not supporting the adoption of products introduced by a dominant complementor. If the threat is deemed excessive, the platform owner may decide to steer the segment *against* the dominant complementor. Specifically, to manage the potential threat of the dominant complementor the platform owner may promote a challenger. When faced with a possibility of a dominant complementor in a segment, the platform owner may decide to encourage more competition by actively promoting a competitor as opposed to just refraining from promoting the dominant complementor:

[7]In response, Apple also lowered the fee to 15% for apps with <$1 million in total sales, while maintaining a 30% fee once sales exceed $1 million. Google followed by implementing an identical fee structure.

Corollary 1. *If the segment has both high concentration and the products have high network effects, the platform owner is more likely to promote the challenger's product rather than the leader's product.*

Our arguments imply that the platform owner considers not only maximizing value for the users and growth of the platform when promoting product adoption, but value appropriation concerns enter its calculus as well. We also maintain that dominance by a complementor in a segment when combined with direct network effects of the products has negative future implications for the segment in terms of the value for users (and indirectly for the platform owner). We implement additional analyses to examine these implications. We explore whether the presence of an appropriation mechanism in the products with direct network effects (such as the presence of in-app purchases) increases the likelihood of the platform owner promoting their adoption. We also explore the implications of high direct network effects and complementor dominance in the segment in terms of the future entry of new apps, new complementors, and user growth.

3 | EMPIRICAL ANALYSIS

3.1 | Context and data

The empirical context for the study is Apple's iPhone platform ecosystem, where Apple is the platform owner and app developers are complementors who participated in the iPhone platform between 2012 and 2016. For many reasons the setting provides a relevant empirical context to study how platform owners use awards to manage complementors. First, the iPhone platform ecosystem represents one of the largest and most valuable business ecosystems, with App Store revenue estimated to be more than $20B in 2016. Second, the concern regarding the dominance of complementors is particularly salient as situations where an app dominates a segment or genre are common and there are also multiple litigations ongoing between Apple and complementors such as Epic Games and Spotify. Third, Apple actively uses the "Editors' Choice" awards. These awards are particularly valuable for app developers as they compete with thousands of other apps. Apple states that the key criteria in the award selection include gameplay, visuals, sound, music, story, and technical performance. Apple gives these awards shortly after an app is launched. Fourth, the setting allows us to systematically observe and measure complementor products with the potential for meaningful direct network effects. Finally, Apple classifies games into 20 categories (which Apple calls sub-genres) that are heterogeneous with respect to the extent of market concentration, which allows us to explore the role of market concentration in shaping platform owners' strategic choices when selecting awards.[8]

The primary source of data is a leading app analytic firm, Online Media Group Inc., that has been systematically archiving app-related data since 2011. The firm provides its data to many large companies such as Amazon, Intel, and Adobe. Through this firm, we were able to access information on all the apps that have entered the iPhone platform since 2011.

[8]The categories are Action, Adventure, Arcade, Board, Card, Casino, Dice, Educational, Family, Kids, Music, Puzzle, Racing, Role Playing, Simulation, Sports, Strategy, Trivia, Word, and Miscellaneous Games. We note that Apple rarely awards apps in the same category on the same day (1.5% of days in our sample) or in the same month (10% of our sample). In most of these cases, these awards were given to games in the Action category. This could indicate that the Action category is too broad, and that Apple may use different subclassifications within Action. We rerun our results excluding the Action category and find robust results.

3.2 | Sample

Our initial sample consists of repeated cross sections of game apps released from 2012 to 2016. We map each app to the month of its release, with a total of 60 months in our sample. Our sample starts in 2012, which leaves sufficient time for Apple to implement routines in the management of the app store.[9] Our sample ends in 2016 because we lack technical data on apps from 2017 to 2021. We observe technical data when the app is released and when it is updated.[10]

In the 2012–2016 period, we have 644,128 game apps, 432,721 of which we do not have full technical information on, due to the lack of usage data from Apple's iOS application program interface (API), Apple software development kits (SDK), and third-party SDKs. Using cumulative reviews between launch and December 2021, we find that apps with missing technical information have on average 88% *fewer* reviews than those with technical information (mean of 20 vs. mean of 163) and are 43% *less* likely to receive an Editorial Award from Apple. Therefore, to have complete data, we focus our analysis on game apps for which we have full API and SDK usage information. Our resulting sample has 211,407 games across 20 categories released during the 60 months between 2012 and 2016. To alleviate concerns that sample selection may be affected by an outcome of awards (i.e., reviews), we examine an alternative specification in which we exclude API and SDK based variables so that we can run our models with the maximum sample size, and we find robust results (see the Appendix S1).

3.3 | Measures

3.3.1 | Dependent variable

Our hypotheses pertain to how a platform owner will promote the adoption of complementor products using awards. In the App Store, Apple promotes apps with an Editors' Choice award. Apps that receive the award will receive a visible badge that will appear under the name of the app for the app's lifespan. Beginning in 2012 (at the beginning of our sample), the app will also appear in a special section of the App Store called the Editors' Choice section.

The Editors' Choice award is an effective tool for the management of the adoption of complementor products for several reasons. First, Editors' Choice is the only official endorsement given by Apple. Second, these awards are rare—0.04% of all apps (1,307 in total) across all genres received an award. Third, the awards are valuable because they are associated with adoption ex-post—regressing the natural log of reviews on receiving an award, time-fixed effects at the monthly level, and category-fixed effects, we find that receiving an award is associated with a 589% increase in total reviews. Fourth, Apple gives the Editors' Choice award early in the app's life (close to release) and before the app has sufficient observable market performance (this is particularly relevant when managing products with network effects, as we describe in the theory section). This suggests that the awards are not used as a form of reward for good performance, but rather to influence consumer adoption. Finally, these awards are highly sought after by both big and small developers as they provide instantaneous visibility to their apps. The importance of these awards for app developers can be seen by the following press release from Electronic Arts (one of the largest game developers) after receiving the award: "*Exciting news to share—Need for Speed Most*

[9]Apple launched the App Store in July 2008.

[10]Because apps get awards soon after release, we use technical information based on the first release.

Wanted recently secured Apple's prestigious 'Editor's Choice' [sic] *placement the week of launch on the iTunes App Store. The game was also featured on the iPhone and iPad store fronts*." Similarly, a small firm named Wolt shared the news about getting the Editors' Choice award: "*The Wolt app gets Apple's prestigious Editors' Choice award for its UX, immediately after launching*." Our dependent variable, *Award*, takes the value of 1 if the app gets an Editors' Choice award and 0 otherwise.

3.4 | Independent variables

3.4.1 | Direct network effects

To measure if an app has meaningful direct network effects, our main measure is based on whether the app uses Apple's Game Center (Boudreau et al., 2021). Apple describes the Game Center as a service that allows users to play online multiplayer social networking games and includes a set of tools for developers of such games. The service allows consumers to play with multiple players, share in-game achievements, challenge friends to play, and discover what games their friends are playing (see https://developer.apple.com/game-center/). It was first released by Apple in September of 2010 with the launch of the iOS 4.1 operating system.[11] Being Game Center enabled is a strong proxy for the potential for direct network effects because Game Center allows implementation of multiplayer functionality and cross-user information sharing—features that are essential for games where the utility for a user is derived from other users adopting the game (Boudreau et al., 2021). The Game Center also fosters building the installed base by allowing users to observe what games their friends play.

While the presence of Game Center functionality provides a reasonable broad proxy for direct network effects, it does not capture differences in the relative strength of network effects. Specifically, the network effects may be stronger (i.e., the user experience is more dependent on the number of other users) for massively multiplayer games than for other Game Center enabled games (for which having many active participants playing at once is less vital for the gaming experience). Consequently, we implement several alternative ordinal measures that account for these differences, which we discuss later and in the Appendix S1.

3.4.2 | Developer market share and market concentration

We cannot observe app-level revenue for the apps on the platform. Instead, we can access a daily, platform-wide rank of the top 500 apps by revenue, and, like prior literature, we use this as a proxy (Garg & Telang, 2013; Kapoor & Agarwal, 2017). To proxy for revenue, we code the top-ranked app as 500, the second-ranked app as 499, and so on and use these values in place of revenue. To measure *Developer Market Share* in category *c*, for each developer *k*, we take the summation of the daily revenue for a 3-month period, then divide this total by the total revenue proxy for apps in category *c*, and then lag the value by 1 month. The measure thus captures differences in revenue

[11]Prior to the release of Game Center, the iOS platform lacked a unified multiplayer infrastructure. Multiplayer functionality is a key feature of the gaming experience for some games. As a result, many third-party companies such as OpenFeint, Plus, AGON Online, and Scoreloop started providing multiplayer infrastructure on the iOS platform. However, the solutions by third-party providers often varied in quality and experience for users and app developers. Apple launched the Game Center to address these issues.

within each category. We measure the *Concentration* for each category using the Herfindahl index on our revenue proxy across developers for a 3-month period and then lag the value by 1 month.

While the above measure is simple, it may not capture the skewness of the revenue distribution. As an alternative measure, we create the revenue proxy using the inverse of the app's rank, which approximates the pareto distribution. Pareto distribution has been shown to capture the skewed nature of the revenue distribution in some online markets (Brynjolfsson, Hu, & Smith, 2003; Chevalier & Goolsbee, 2003; Garg & Telang, 2013; Kapoor & Agarwal, 2017). We report these results later and in the Appendix S1.

3.5 | Control variables

3.5.1 | App-level controls

To account for the technical sophistication of the app and its quality, we control for a variety of variables. To control for the extent that the app uses the iOS platform (*ln*(*Platform Usage*)), we take the natural log of the count of the number of Apple iOS API configuration keys used by the app.[12] Apps that use more APIs may by more functionally complex. An app can link to other apps on the platform (e.g., Apple Maps, Google Maps, Facebook) via software developer kits (SDKs). We control for how the app links to other applications on the platform by taking the natural log of the number of SDKs that the app uses (*ln*(*SDKs*)). We control for the app's hardware usage (*Hardware Usage*) by counting the number of required hardware capabilities (camera, accelerometer, etc.) necessary for the app to function appropriately. To control for device interoperability, we count the number of Apple devices (iMac, iPhone, iPad) that the app runs on (*Device Total*) and whether the app supports the *Apple Watch*, which takes the value of 1 if the app supports the watch and 0 otherwise. Because larger apps may be more complex, we control for download size, measured as the natural log of the download size in megabytes (*ln*(*Download Size*)).

To account for how the app generates revenue, we include two variables. To account for price (*ln*(*Price*)), we take the natural log of 1 plus the app's price. *In-app Purchase* takes the value of 1 if the users can make purchases within the app and 0 otherwise. We note that the factors that influence Apple's decision to award a free game might differ than that of a paid game and simply controlling for a continuous price may not sufficiently account for these differences. We do not believe this will significantly affect our main results as only 1.7% of all games use a paid business model. Including a control variable for free games or running the analysis only using free games both yield robust results. We discuss these analyses further in the Section 5.

3.5.2 | Developer-level controls

To account for developer quality beyond market share, we include several variables. For each app, we have all ratings and reviews received on each day since the app's release. We use this data

[12]An application programming interface (API) is a type of software interface, connecting applications to platforms or computer programs to computers. It simplifies programming by abstracting the underlying implementation and only exposing objects or actions which the developers need as they build applications. It usually consists of different parts acting as tools or services available to the developers, who access these parts using subroutines, methods, requests, or endpoints. It comes with a document or a standard, called API specification, describing how to build or use the connection or interface.

to account for developer quality and visibility. To account for the developer's quality, we take the average of all the ratings across all the developer's apps' ratings up until the month prior to the focal apps release (*Developer Rating*). Ratings per app can range from 0 to 5. To control for developer visibility and prior user adoption of its apps, we include the developer's cumulative number of reviews across all its apps up until the month prior to the focal app's release (*Developer Reviews*). It is possible that some developers are better at gaining awards than others due to a closer relationship with Apple or some unobserved capability. To control for this, we include the cumulative total of prior awards received by the developer in the category up until the month prior to the focal app's (*Prior Awards*). We also control for whether the app comes from a developer based in the United States, as these apps might be valued higher by Apple.

3.5.3 | Environment-level controls

To control for entry into the category, we include the prior month's total number of new apps in the category (*New Apps*). To account for the unobserved effects in the environment correlated with time, we include year fixed effects. Seasonal factors may influence app releases and Apple's awards decisions, so we control for seasonal fixed effects at the monthly level.

In our base models, we assume that Apple monitors each of the 20 game categories and will allocate the scarce awards within each category as needed to meet its goals. Therefore, we include category-fixed effects in the models and cluster the standard errors by category. However, Apple may instead allocate only so many awards each period and apply them across the categories as necessary. To estimate this decision model, we want to exploit cross-category variance within each period. In this alternative specification, we include fixed effects for each period (i.e., each of the 60 months in the sample) instead of a category fixed effect to capture between-category variation in our estimates. In these models, we cluster the standard errors by period. We report these analyses in the Additional Analysis section.

4 | RESULTS

4.1 | Market structure and category dynamics in the presence of direct network effects

Our theoretical framework implies that Apple is trying to avoid creating a dominant complementor in a segment as this may have negative implications for the segment (both in terms of value for users and Apple's revenues). We put this conjecture to the test by examining how market structure affects factors such as entry, user adoption, and user satisfaction. To conduct our analysis, we create a category-period sample comprised of the 60 periods (months) in 2012–2016 and the 20 game app categories.[13] To measure market structure, we use the category's market concentration over the past 3 months (*Concentration*). To measure when apps with direct network effects are dominant, we calculate the total market share of these apps within category c over the prior 3 months (*Direct Network Effect App Market Share*); we report the descriptive for both variables in the table notes. To assess the consequences of concentration as the dominance of apps with direct

[13] We lose 151 observations because the category lacked games that ranked on the top 500 list in the prior 5 months, and, therefore, we are unable to calculate category concentration.

TABLE 1 Implications of concentration and direct network effect app market share on value creation

	Model 1	Model 2	Model 3	Model 4
Dependent variable	**ln (New Apps)**	**ln (Developers)**	**ln(Total Reviews)**	**Average Rating**
Concentration	−1.282 (.000)	−0.778 (.000)	−2.419 (.000)	−0.389 (.001)
Direct Network Effect App Market Share	−0.195 (.003)	0.402 (.000)	0.672 (.000)	−0.372 (.000)
Concentration × Direct Network Effect App Market Share	−0.882 (.000)	−1.718 (.000)	−1.019 (.003)	0.514 (.001)
Observations	1,049	1,049	1,019	1,019
R-squared	.184	.203	.313	.018
Period FE (60 months)	Yes	Yes	Yes	Yes
R-squared	.038	.044	.038	.018
DV mean	5.78	5.37	5.01	4.17
DV standard deviation	1.16	1.01	2.87	0.61

Note: *Direct Network Effect App Market Share* has a mean of 0.48 and standard deviation of 0.29. *Concentration* has a mean of 0.24 and standard deviation of 0.26. In parentheses we include *p*-values calculated from robust standard errors.

network effects varies, we run linear regressions with *Concentration*, *Direct Network Effect App Market Share*, the interaction between the two, and period fixed effects as regressors.

We begin by analyzing app-level and developer-level entry. To measure app-level entry, we use the natural log of new apps in the month; to measure developer-level entry, we use the natural log of developers releasing an app in the month. We display the results in Table 1. We find a strong negative effect of *Concentration* on both app-level entry (Model 1: −1.282, $p = .000$) and developer-level entry (Model 2: −0.778, $p = .000$). We also find that the negative effect of Concentration is amplified when *Direct Network Effect App Market Share* is higher (Model 1: *Concentration × Direct Network Effect App Market Share* = −0.882, $p = .000$; Model 2: −1.718, $p = .000$).

To proxy for use adoption, we use the natural log of total reviews for apps in category c during the period. We find a strong negative effect of *Concentration* (Model 3: −2.419, $p = .000$), which is amplified when *Direct Network Effect App Market Share* is high (*Concentration × Direct Network Effect App Market Share* = −1.019, $p = .003$).

To proxy for user satisfaction, we use the average rating across apps rated in category c during the period. We find a strong negative effect of *Concentration* (Model 4: −0.389, $p = .000$), but that the interaction (*Concentration × Direct Network Effect App Market Share*) has a strong positive effect (0.514, $p = .001$).[14]

To summarize, we find that concentration stymies value creation, with adoption and entry (in terms of products and complementors) declining as concentration increases. Increasing the market share of apps with direct network effects accentuates the negative effect of concentration on adoption and entry but has a positive effect on satisfaction. These results point to an important tradeoff faced by the platform owner that lies at the heart of our theory. The platform wants to shepherd the market toward apps with direct network effects because doing so may increase satisfaction, which should associate with more intense

[14]We find robust results for Table 1 using our inverse revenue rank proxy for calculation of concentration and market share.

TABLE 2 Descriptive statistics

Descriptive statistics				
Variable	**Mean**	**SD**	**Min**	**Max**
Awards	0.001	0.035	0	1
Direct Network Effect	0.237	0.425	0	1
Developer Market Share	0.000	0.008	0	1
Concentration	0.139	0.190	0.027	1
ln(Platform Usage)	4.140	0.773	2.940	11.716
ln(SDKs)	2.525	0.730	0	5.361
Hardware Usage	0.717	0.905	0	7
Device total	2.759	0.635	0	4
Apple Watch	0.001	0.035	0	1
ln(Download Size)	3.658	1.044	0.055	8.334
In-app Purchase	0.511	0.500	0	1
ln(Price)	0.017	0.166	0	9.093
Developer Rating	0.510	1.324	0	5
Developer Reviews	514.598	6,164.505	0	220,909
Prior Awards	0.004	0.120	0	9
USA	0.179	0.384	0	1
New Apps	1,066.999	809.147	16	5,739

usage and, thus, greater revenues from in-app purchases. However, such apps can grow to dominate the category, which can stymie category growth. The results in this section provide support for the underlying tension that we explore in our theorizing and suggest it is both realistic and relevant. We test our hypotheses related to how the platform manages this tension in the following section.

4.2 | Descriptive statistics for hypothesis tests

Table 2 displays the descriptive statistics; correlations can be found in the Appendix S1.[15] Approximately 24% of the games have the potential for direct network effects.[16] In our sample,

[15]Multicollinearity is not a problem (condition index = 22.7, maximum variance inflation factor = 1.37).

[16]Variance in our main independent variable, *Direct Network Effect*, comes from the creative cycle of developers. Across various levels of both of our moderating variables, we expect to observe enough game apps in either state of *Direct Network Effect* so that we can draw inference on the hypothesized relationships. One concern is that the developer's prior market share or the concentration in the category may influence the development cycle such that we do not observe enough variation in *Direct Network Effect* within the various levels of the contingency variables. To test whether our contingency variables determine developers' propensity to release games with direct network effects, we run a logit model with *Direct Network Effect* as the dependent variable and all the other variables (per Table 2) as controls and find that neither *Developer Market Share* (p = .513) nor *Concentration* (p = .913) have the power to predict *Direct Network Effect* well.

0.1% of applications receive an award. We appear to have enough within-category variation to use category-fixed effects.[17]

4.3 | Tests of Hypotheses 1–4

To test our hypotheses, we run a set of linear probability models (LPM) in Table 3 and test our contingency hypotheses using interactions as well as logit models and taking a segmented sample approach to the contingency hypotheses (see Table 4). We describe both sets of results below.

To test H1, we begin by running a univariate logit model of *Award* on *Direct Network Effect* (not shown). We find an average partial effect (APE) of 0.003 (p = .000), suggesting that an app with the potential for direct network effects is 0.3 percentage points (pp) more likely to receive an award than an app without such potential. Although this may seem small, note that the unconditional probability of receiving an *Award* is only 0.1%, therefore it is a 3× increase over the baseline. To formally test H1, we include all control variables and find similar results using a logit model (Table 4 Model 1: APE = 0.003, p = .000) and LPM, (Table 3 Model 1: 0.002, p = .000).

To test H2, the moderating effect of *Developer Market Share* on the *Direct Network Effect–Award* relationship, we do the following tests. In our LPM test, we interact the two variables and find a positive relationship (Table 3 Model 2 *Direct Network Effect* × *Developer Market Share*: 0.445, p = .087). The estimate suggests that a 10 pp increase in *Developer Market Share* will increase the probability of receiving an *Award* by about 5 pp more when the game has the potential for direct network effects than when it does not.[18] To test H2 using logit models, we split the sample into two segments based on an appropriate level of *Developer Market Share* and run two separate regressions. A natural split point is the median, but since the median is 0, we begin by splitting the sample into two segments based on whether *Market Share* for the developer is >1% or <1%.[19] We find having a *Direct Network Effect* associates with a 6.1 pp increase in the probability of receiving an *Award* in the high *Developer Market Share* segment (Table 4; Model 2: APE = 0.061, p = .000) and a 0.1 pp increase in the low *Developer Market Share* segment (Table 4; Model 3: APE = 0.001, p = .000). To test H2, we compare the two estimates across models using Welch's t-test and find evidence consistent with our hypothesis (6 pp, p = .000). Rerunning the tests using the median yields robust results (Difference in APE = 2.8 pp, p = .000).[20]

[17]To examine if we have enough within-category variation in our three independent variables to use category fixed effects, we calculate the within-category coefficient of variation for *Direct Network Effect* (186%), *Developer Market Share* (2,533%), and *Concentration* (54%). There appears to be enough variation to include category fixed effects. Not surprisingly, *Concentration* has a between-category variation that is about four times higher than its within-category variation. As robustness, we also report the results excluding category fixed effects.

[18]Most developers do not have an app in the top 500 in the prior 3 months, for those with *Developer Market Share* >0, the mean plus one standard deviation is 8.6%. Thus a 10 pp increase should be interpreted as a movement from being a typical complementor to a top tier complementor in terms of market share.

[19]This cutoff is justified by the fact that the revenue measure is based on the list of 500 ranked apps across all categories, including non-game genres to measure market share within a category. *Developer Market Share* >1%, on average, indicates the developer is in the top five developers in terms of market share in the category.

[20]It is possible that complementors with large portfolios are more likely to receive awards because the platform owner is more dependent on them as a source of revenue. To help rule this out, we calculate the total apps released by each developer until the month prior to the focal month. We then cut the top 50% of developers in terms of total portfolio size and rerun our test for H2. Using the logit models from Table 3, we find similar results (*Developer Market Share* = High, APE = 0.103, p = .001; *Developer Market Share* = Low, APE = 0.001, p = .001; difference = 0.102, p = .000).

TABLE 3 Linear probability model of awards (tests of Hypotheses 1–4)

DV = selective promotion through awards	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
H1: Direct Network Effect	0.002 (.000)	0.001 (.000)	0.002 (.000)	0.002 (.000)	0.002 (.000)	0.002 (.000)	0.002 (.000)	0.002 (.000)
Developer Market Share	0.170 (.052)	−0.011 (.698)	0.171 (.051)	0.011 (.847)	0.168 (.012)	−0.012 (.737)	0.168 (.012)	0.001 (.904)
Concentration	0.001 (.280)	0.001 (.435)	0.001 (.134)	0.00161 (.117)	−0.00001 (.955)	−0.0001 (.839)	0.001 (.004)	0.001 (.001)
H2: Direct Network Effect × Developer Market Share		0.445 (.087)		1.229 (.000)		0.446 (.016)		1.229 (.000)
H3: Direct Network Effect × Concentration			−0.004 (.027)	−0.003 (.052)			−0.004 (.000)	−0.004 (.001)
Concentration × Developer Market Share				−0.023 (.728)				−0.023 (.813)
H4: Direct Network Effect × Concentration × Developer Market Share				−1.349 (.000)				−1.348 (.000)
All control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
Year fixed effect	Yes	Yes	Yes	Yes	No	No	No	No
Seasonal fixed effect (monthly)	Yes	Yes	Yes	Yes	No	No	No	No
Period fixed effect (60 months)	No	No	No	No	Yes	Yes	Yes	Yes
Observations	211,407	211,407	211,407	211,407	211,407	211,407	211,407	211,407
R-squared	0.038	0.040	0.038	0.045	0.038	0.040	0.038	0.045

Note: In parentheses we include *p*-values calculated from robust standard errors clustered at the category level for Models 1–4, and *p*-values calculated from robust standard errors clustered at the month-year level for Models 5–8. The full table is in the Appendix S1.

To test H3, the moderating effect of *Concentration* on the *Direct Network Effect–Award* relationship, we examine the interaction in the LPM and find a negative and significant effect (Table 3; Model 3: *Direct Network Effect* × *Concentration* = −0.004, $p = .009$). This estimate suggests that one standard deviation increase in *Concentration* reduces the likelihood of a game with direct network effects receiving an award by 7.6 pp relative to a game without direct network effects. Taking the segment sample approach using logit models, splitting the sample at the median of *Concentration*, we find support for H3 (Table 4; Difference in APEs: −0.001, $p = .009$).

To test H4, we examine the triple interaction between *Direct Network Effect* × *Concentration* × *Developer Market Share* and find a negative and significant effect (Table 3; Model 4: −1.349, $p = .000$). To perform our hypothesis test using the logit models, we split the sample of observations with high *Concentration* into two segments: high and low *Developer Market Share*. We find that the impact of *Direct Network Effect* on receiving an award is 9.4 pp lower when developers have high market share than when they have low market share, consistent with H4 (Table 4 Difference in APEs = −0.094, p = .000).[21] To add a graphical interpretation, we estimate the fully specified logit model with all interactions and plot the predicted probabilities (see Figure 1).

4.4 | Tests of Corollary 1

To test Corollary 1, we restrict the sample to apps with *Direct Network Effect* = 1 and that are released in a month in which the category has high (above median) *Concentration*. We then create the following binary variables: *#1 Developer* = 1 if the developer has the top market share in the category over the past 3 months, *#2 Developer* = 1 if the developer holds the second market share position, and similarly for *#3 Developer* and *#4 Developer*. The omitted category is all non-top four developers. Per Corollary 1, we should observe that the challengers (e.g., *#2 Developer–#4 Developer*) are more likely than *#1 Developer* to receive the award. We note that in our entire sample, the *#1 Developer*'s share typically exceeds the *#2 Developer*'s share by a substantial margin (mean: 10% vs. 1.2%; 90th percentile: 30% vs. 3.8%).

In Table 5; Model 1, we find a statistically insignificant effect for *#1 Developer* (APE = 0.002, p = .297), a positive effect for *#2 Developer* (APE = 0.026, p = .068), and insignificant effects for *#3 Developer* and *#4 Developer*. Comparing each of challengers to the *#1 Developer* using a Wald Test, we find that the *#2 Developer* has a significantly larger effect (one-sided p-value of .001). This result is consistent with our prediction—when faced with a concentrated market dominated by a developer, the platform owner will more likely award one of the challengers: in this case, the top challenger.

We also check whether a platform promoting non-leading firms to draw adopters' attention to lesser-known high-quality producers may explain our results (Rietveld et al., 2019). This does not appear to be the case. If we examine a sample of apps with *Direct Network Effect* = 1 and that are released in a month in which the category has low *Concentration*, we do not find that the platform promotes unknown developers on average (see Model 2). Instead, we find that all four leading developer variables are positive and significant at the 10% level, with the *#1 Developer* having the APE with the largest magnitude.[22] These results are consistent with H2, that Apple chooses the strongest developers to spur direct network effects.

[21]This result should be interpreted with caution. Our logit model on the high *Concentration*–high *Developer Market Share* segment does not converge using the standard Newton–Raphson algorithm for maximizing the likelihood. We switch to the Berndt–Hall–Hall–Hausman (BHHH) algorithm (see Berndt, Hall, Hall, & Hausman, 1974) as it will more likely converge under certain conditions or at least recover the parameter estimates and standard errors (it avoids estimating the full Hessian Matrix, instead it uses the outer product of the gradient). Although we do not achieve full convergence, we recover estimates and standard errors for a small portion of the sample (see Table 4; Model 6).

[22]Models 3 and 4 report the same analysis but using an indicator for third through tenth ranked developers in place of the third and fourth ranked developer indicators. We also rerun the analysis using LPMs and find that all challengers are significantly more likely than the *#1 Developer* to receive awards (see the Table A3).

TABLE 4 Logit analysis of awards (tests of Hypotheses 1–4)

DV = selective promotion through awards	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Sample	**Full sample**	**High dev. market share**	**Low dev. market share**	**High concentration**	**Low concentration**	**High conc. and high dev. market share**	**High conc. and low dev. market share**
Average partial effects shown							
H1: Direct Network Effect	0.001 (.000)	0.061 (.000)	0.001 (.000)	0.0006 (.001)	0.001 (.000)	−0.093 (.000)	0.001 (.005)
		H2: 0.060 (.000)		H3: −0.001 (.009)		H4: −0.094 (.000)	
Developer Market Share	0.006 (.000)	−0.033 (.737)	0.162 (.000)	0.002 (.000)	0.026 (.000)	−0.450 (.441)	0.210 (.000)
Concentration	0.001 (.507)	−0.251 (.490)	0.001 (.059)	0.001 (.362)	−0.016 (.601)	−1.273 (.421)	0.0001 (.155)
ln(Platform Usage)	0.001 (.000)	0.024 (.000)	0.001 (.000)	0.001 (.000)	0.001 (.000)	0.036 (.212)	0.0004 (.000)
ln(SDKs)	−0.0004 (.050)	−0.017 (.050)	−0.0003 (.053)	−0.001 (.2427)	−0.001 (.064)	−0.119 (.071)	−0.0001 (.655)
Hardware Usage	0.0001 (.176)	0.012 (.089)	0.000 (.804)	0.0001 (.093)	0.0001 (.642)	0.036 (.349)	0.0001 (.498)
Device total	0.001 (.000)	0.043 (.032)	0.0012 (.000)	0.001 (.000)	0.002 (.007)		0.001 (.004)
Apple Watch	−0.001 (.006)		−0.001 (.001)	0.001	−0.001 (.038)		
ln(Download Size)	0.001 (.000)	0.032 (.000)	0.0001 (.000)	0.001 (.000)	0.002 (.000)	0.129 (.002)	0.001 (.000)
In-app Purchase	0.001 (.000)		0.001 (.000)	0.001 (.003)	0.002 (.000)		0.001 (.004)
ln(Price)	0.001 (.000)		0.001 (.000)	0.001 (.000)	0.001 (.000)		−0.0001 (.000)
Developer Rating	0.0003 (.667)	−0.007 (.427)	−0.000 (.885)	−0.001 (.600)	0.001 (.091)	−0.156 (.012)	0.001 (.501)
Developer Reviews (000,000)	0.001 (.001)	0.032 (.583)	0.001 (.001)	0.001 (.003)	0.001 (.281)	0.063 (.165)	0.001 (.002)
Prior Awards	0.0003 (.102)	0.002 (.706)	0.0003 (.006)	0.002 (.000)	0.001 (.310)	0.118 (.000)	0.0001 (.000)
USA	0.001 (.022)	0.009 (.661)	0.001 (.001)	0.002 (.190)	0.001 (.000)	0.410 (.000)	0.0001 (.474)

TABLE 4 (Continued)

DV = selective promotion through awards	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Sample	**Full sample**	**High dev. market share**	**Low dev. market share**	**High concentration**	**Low concentration**	**High conc. and high dev. market share**	**High conc. and low dev. market share**
New apps (000)	−0.0001 (.500)	0.0001 (.001)	−0.001 (.009)	0.0001 (.733)	0.00001 (.712)	0.001 (.025)	−0.0002 (.736)
Category fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal fixed effect (monthly)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	207,799	731	206,670	97,804	100,863	93	97,443
Pseudo R-square	.44	.38	.41	.49	.43	.99	.45
Log pseudolikelihood	−1,170	−137	−976	−353	−779	−12	−293

Note: In parentheses we include p-values calculated from robust standard errors clustered at the category level. (.) indicates that the variable is absorbed or dropped because it predicts success or failure perfectly.

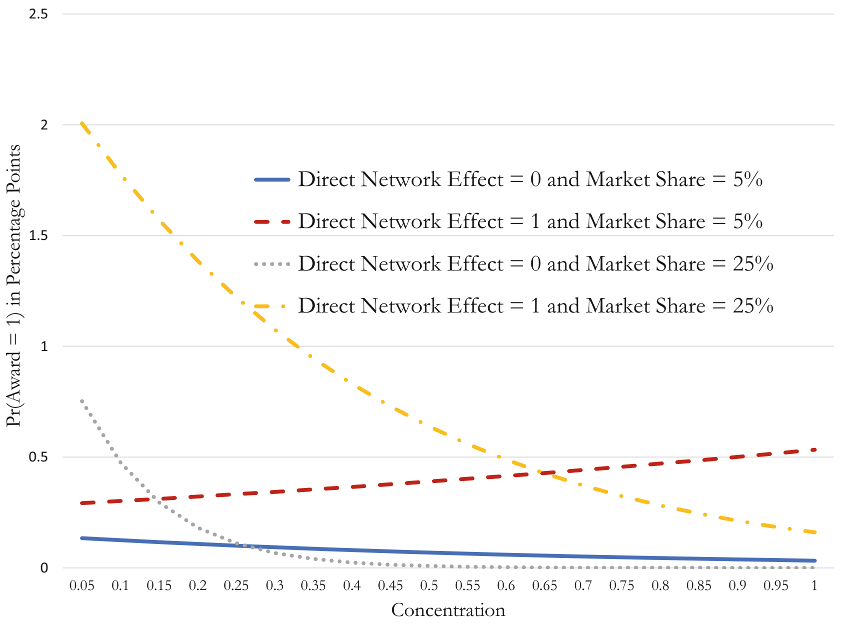

FIGURE 1 Margin plots of interactions.

4.5 | Extensions and further analysis

4.5.1 | Apple's decision calculus

In developing our theory, we maintain that the platform owner considers both value creation and appropriation when making award decisions. We also postulate that the platform owner will want to shepherd users toward a subset of apps that can benefit from direct network effects, as doing so can enhance user utility, which should translate into higher revenues. In this section, we conduct three tests that provide corroborating evidence that both value creation and appropriation considerations enter Apple's calculus when considering awarding products with direct network effects (we report the results in the Appendix S1). We begin by examining the contingent effect of in-app purchases. Apple is more likely to award apps with direct network effects when the app also has in-app purchases because driving customers to such apps will likely increase total revenue (i.e., Apple can benefit more from creating a momentum in adoption due to network effects).[23] Free apps that do not allow for in-app purchases make money through in-app advertising. Apple may only receive a cut if the developer uses Apple's advertising platform, and, on iOS, advertising platforms offered by Google, Facebook, and others tend to be the most popular.[24] To test this conjecture, we examine *Direct Network Effect* × *In-app Purchase* in our LPM and find a positive and significant effect (0.003, $p = .001$). Testing the conjecture using logit models and splitting the sample into apps with and apps without *In-app*

[23]Apple receives 30% of in-app purchases.

[24]AdMob, which was acquired by Google, tends to have the dominant share on iOS (https://appfigures.com/top-sdks/ads/all).

TABLE 5 Logit analysis of Corollary 1

	Model 1	Model 2	Model 3	Model 4
DV = selective promotion through awards	**Network effects and high concentration**	**Network effects and low concentration**	**Network effects and high concentration**	**Network effects and low concentration**
Average partial effects shown				
#1 Developer	0.002 (.297)	0.013 (.011)	0.002 (.266)	0.017 (.006)
#2 Developer	0.026 (.068)	0.008 (.024)	0.030 (.065)	0.011 (.012)
#3 Developer	0.0002 (.961)	0.001 (.042)		
#4 Developer	0.005 (.527)	0.010 (.092)		
#3–#10 Developers			0.005 (.366)	0.008 (.000)
All controls	Yes	Yes	Yes	Yes
Category fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes
Observations	12,822	31,931	12,822	31,931
Pseudo R-square	.57	.45	.57	.45
Log pseudolikelihood	−99	−502	−0.98	−495
Wald test (one-sided p-values)				
#2 Developer > #1 Developer	.001	.806	.001	.180
#3 Developer > #1 Developer	.645	.848		
#4 Developer > #1 Developer	.334	.685		
#3–#10 Developers > #1 Developer			.312	.959

Note: The p-values included in parentheses. The full table is in the Appendix S1.

Purchase and comparing the APEs for *Direct Network Effect*, we find similar results (Difference in APE = 0.002, p = .000).

Next, we conject that apps that more heavily use advanced features, such as a new processor or iOS features will create more value for customers. This will, in turn, increase customers' willingness to pay for Apple's products and strengthen the indirect network effect, which will allow Apple to enhance their ability to appropriate value in the future. To test this conjecture, we first interact *Direct Network Effect* with *ln*(*Platform Usage*), which will increase as the app uses more iOS platform features. We find a positive and significant interaction effect (0.008, p = .001) and a similar result using logit models and splitting the sample at the median of *ln*(*Platform Usage*) (Difference in *Direct Network Effect* between high and low samples: 0.002, p = .000).

As a second test of the conjecture, we examine whether an app with *Direct Network Effect* = 1 will more likely receive an award when it also requires an advanced microprocessor. Apps requiring a more advanced processor will encourage customers to upgrade their devices. In our sample, we use an indicator of whether the app requires a processor based on ARMv7, which would force customers to upgrade to Apple iPhones that used Apple's own-system-on a chip design.[25] Results show positive and significant effect of *Direct Network Effect* × *ARMv7* (0.003, p = .000). Using the logit models and splitting the sample, we find similar results (Difference in APEs: 0.001, p = .069).

5 | ALTERNATIVE SPECIFICATIONS AND ROBUSTNESS ANALYSIS

In this section, we provide additional analyses to address several concerns related to our sample, developer quality, Apple's decision model, the app's business model, measurement of the independent variables, and modeling of rare events.

5.1 | Sample selection

We use all game apps released in the 2012–2016 period on Apple iOS to test our hypotheses. However, we lose many apps because we lack information on API and SDK usage. To assess if our results differ if we use the excluded apps, we rerun our tests but drop the API- and SDK-based variables *ln*(*Platform Usage*), and *ln*(*SDKs*). This increases the sample size from 211,407 to 601,796 observations. Our results remain robust (see Online Appendix Table B1).

5.2 | Developer quality

We theorize that the platform wants to promote apps with the potential for direct network effects more than those without because the platform can benefit more from complementors that have strong direct network effects. Alternatively, apps with direct network effects may on average exhibit higher quality than other apps, and despite our rich controls for technical quality and developer quality, Apple may award apps based on app-level quality unobservable to us. We take several steps to address this issue. First, to account for unobserved developer-level quality, we include developer-level fixed effects in our LPM models and find robust results (see Online Appendix Table B2).

Second, we run the LPM models only on higher quality developers in each category. To assure that the developer has enough apps in the category to assess quality, we exclude any developer that has not released at least five apps in the category. To identify high quality, we include only apps from developers if their *Developer Rating* (average rating across prior apps in the category) falls above the 75th percentile in our entire sample. Rerunning our main model on this sample, we find robust results (see Online Appendix Table B3).

[25]This would require customers to upgrade to at least an iPhone 4 or the first-generation iPad (both introduced in 2010).

Third, to more closely control for developer quality, we employ a matching framework with *Direct Network Effect* as the treatment. To account for an app's business model, quality, category, and release date, we block on period (each of the 60 months), category, free apps,[26] *In-app Purchase*, and *Developer Average Rating* (*rounded*).[27] Within these blocks, we then use the Mahalanobis distance nearest neighbor matching algorithm to match each treated app to one or more control apps using all the other control variables from Table 3 and a measure of the number of prior apps the developer has released. To estimate the average treatment effect on the treated (ATET), we compare the outcome of the treated app to the average of the control apps, then we take the average across these values and calculate the standard errors using Abadie and Imbens (2005) method to adjust for matching bias. We find robust results for H1, ATET equal 0.18 pp ($p = .000$, $n = 175{,}826$). To test H3, we split the sample by high and low *Concentration* and reran the matching model on each subsample (High Subsample: ATET = 0.13 pp, $p = .000$; Low Subsample: ATET = 0.22 pp, $p = .000$). Comparing the ATET across models using Welch's *t*-tests, we find support for H3 (Difference in ATET = 0.09 pp, $p = .017$). Because of the small sample of developers with high market share, we do not have enough treatment and control apps in each block to employ the above matching procedure to test H2. Instead, to test H2, we loosen the matching requirements by blocking on year rather than on period and keep the rest of the procedure the same. Results support H2 (High *Developer Market Share*: ATET = 9.12 pp, $p = .058$; Low *Developer Market Share* ATET = 0.16 pp, $p = .000$; Difference in ATET = 8.9, $p = .064$). We do not have enough observations in the High *Developer Market Share*–High *Concentration* subsample to appropriately employ our matching model to test H4.

5.3 | Platform owner's decision model

Our choice of using within-category or within-period variation to estimate our parameters should align with our assumption on Apple's decision-making process. In our main analysis, we assume Apple mostly manages awards within-category. Alternatively, Apple may allocate only so many awards each period and apply them across the categories as necessary. Switching our specification and error clustering from category fixed effects to month-year (period) fixed effects yields robust results (see Table 3; Models 5–8).[28]

5.4 | Game monetization model

Free and paid games may differ in important dimensions such as consumer trial and the formation of the installed base (Rietveld, 2018), which could have implications for Apple's intent to manage the direct network effects and may not be sufficiently controlled for using price. Excluding paid games (1.7% of the sample) or including a free app indicator as a control yields robust results (see Online Appendix Table B4).

[26]Free app equals 1 if the app is free and 0 otherwise.

[27]To block on *Developer Average Rating*, we round the rating to the nearest tenth (e.g., 4.1 stars).

[28]Note that including both category and period fixed effects yields very similar results to our main logit and LPM results (e.g., Table 2; Models 1–4 and Table 3). Results are available on request.

5.5 | Measurement of market share and concentration

To calculate our two contingency variables, we proxy for revenue using the top 500 apps in revenue and reverse coding the rank so that the top app has a value of 500. This means that the top app has twice the weight as the 250th app. In this section, we discuss several alternative measures.

First, we use an alternative measure from prior literature (Garg & Telang, 2013; Kapoor & Agarwal, 2017) that approximates a pareto distribution by using $(\text{rank})^{-1}$. This measure puts much more weight on the top few ranked apps (e.g., top app has 100 times the weight of 10th ranked app and 250 times the weight of the 250th ranked app). Using this value in our models, we find robust results for all our findings except for H3, for which we lack significant statistical support. Table B5 of the Online Appendix displays the base LPM results with the alternative measures.

Second, to capture "high-performing products" that likely generate substantial revenue, we focus on the number of days that a developer has products in the top 10. For each category, we use the Apple App Store's daily platform ranking to identify any apps in that category ranked in the top 500 on that day, and then we identify the top 10 (if there are 10) in the category. We then calculate Developer's Days in Top 10 as the number of days that developer i has a game in category c in the top 10 in category c over the prior 3 months. We calculate *Concentration of Top 10 Days* for each category using the Herfindahl index of the developer top 10 count across all developers over the prior 3 months. Using these two measures, we find robust results (see Online Appendix Table B6).

Third, to capture only the highest performing apps in the platform, we use the Apple App Store's daily platform ranking to identify the top 10 apps in the overall 500 on each day. We then calculate *Developer's Days in Top 10* as the number of days that the developer i has a game in category c in the overall top 10 over the prior 3 months. We calculate *Concentration of Top 10 Days* for each category using the Herfindahl index of the developer top 10 count across all developers over the prior 3 months. Using these two measures, we find robust results (see Online Appendix Table B6).

5.6 | Modeling rare events

Awards are a rare event in our sample. Maximum Likelihood Estimation in the logit model can suffer from small sample bias when an outcome occurs very infrequently. We rerun our hypotheses tests using the rare event logit (King & Zeng, 2001) and find robust results (see the Online Appendix Tables B7 and B8).

5.7 | Measurement of direct network effects

All apps in the Game Center seem to benefit more from the same side user participation than do game apps that do not use the Game Center. However, some of the Game Center-enabled apps may exhibit greater potential to benefit from direct network effects. Specifically, direct network effects may be more important for the massively multiplayer online games (MMOs) because they tend to provide more satisfaction for users when there are many players actively playing the game, and, therefore, we many need to distinguish between these games and the other Game Center enabled games. We calculate an ordinal direct network effects measure that takes MMOs into account using two separate methodologies. First, we use data from the game description to identify multiplayer games. However, many games do not provide sufficient detail in their description, so we predict multiplayer status using information on the APIs, graphics programs, and SDKs that the games utilize. Second, we use information on the categories to code which games are more likely subject to strong direct network effects. In both cases, we find robust results. We describe this process in detail and provide the results in Section C of the Online Appendix.

6 | DISCUSSION

There is a growing interest in the strategy research regarding how platform owners actively manage complementors (Altman et al., 2022; Boudreau & Hagiu, 2009; Koo & Eesley, 2021; Miller & Toh, 2022; Miric et al., 2021; Rietveld et al., 2020, 2021; Wang & Miller, 2020; Wareham, Fox, & Cano Giner, 2014). Importantly, many products introduced on modern platforms have their own direct network effects and are thus "platforms within a platform." However, we know relatively little about how the network effects at the complementors' product level affect the management of complementors by the platform owner.

This article offers a novel perspective on how platform firms manage the adoption of complementor products with direct network effects to balance the tension between achieving product growth and avoiding potential complementor dominance and explores how this tension depends on complementor and market segment characteristics. On the one hand, platform owners have an incentive to navigate the market toward one or a few high-quality networked products to resolve uncertainty and ensure adoption and growth. On the other hand, this effort may encourage the emergence of complementors that dominate the segment. Having one or a few complementors dominating the segment may stymie dynamism and growth of the segment, and, in extreme cases, dominant complementors may try to circumvent the rules set by the platform owner. We explore how platform owners navigate this tension using a novel tool—selective product promotion through awards (Foerderer et al., 2021; Rietveld et al., 2019). Although awards are traditionally conceptualized as a performance incentive given to the best product, they can also be used as a strategic tool to shape adoption when they are rare and given early in the product life cycle.

We argue that platform owners are more likely to give an award to a complementor product with network effects to resolve uncertainty and tip the market toward a product with a greater chance of adoption and long-term viability. This effect tends to be stronger for a complementor with a greater market share as small complementors may have limited resources to scale their product to a critical mass of users. Further, we account for how the market concentration impacts platform owners' choice of an award. Market concentration increases the risk of dominance by the smaller number of players that can threaten both the platform owner's value appropriation in the future and the growth of the segment. The platform owners are, thus, more likely to steer away from awarding a complementor's product with direct network effects in market segments that are highly concentrated, and this negative effect is stronger for complementors with greater market share.

We test our framework with the game apps that participated in the iPhone's platform between 2012 and 2016. Apple promotes the adoption of apps by giving them an Editors' Choice award shortly post release, which is a visible badge that appears under the name of the app in the App Store. We find that an app with direct network effects is more likely to receive the award than the app without any direct network effects. We also find that this effect tends to be stronger for apps introduced by developers with greater market share but is lower for concentrated market segments. Further, we find that, while the leading developer with the largest market share has a higher likelihood of receiving the award in markets with low concentration, the challenger developer with the second-largest market share is more likely to receive an award in markets with higher concentration (relative to the leader and other developers competing in the same segment).

Exploring the theorized mechanisms, we also find that apps with network effects that also offer in-app purchases or use the most recent hardware or iOS features by Apple have a higher likelihood of receiving an award (consistent with the argument that value appropriation considerations influence award decisions). Examining the implications of both concentration and direct network effects in a segment, we find that segments that are concentrated and in which networked products have a large market share tend to subsequently have a lower entry of new products and complementors as well as a lower growth of users. This implies that the platform owner may have incentives to avoid such a situation to maximize value both for users as well as for itself.

Our study's findings make several contributions to the emerging perspective of strategic management of platform ecosystems (Altman et al., 2022; Boudreau & Hagiu, 2009; Koo & Eesley, 2021; Rietveld et al., 2019, 2021; Wareham et al., 2014). The focus of the literature on platform management was to understand how platform owners can attract complementors and users and how the value is distributed among different actors (Ceccagnoli et al., 2012; Huang et al., 2013; Pagani, 2013; Wang & Miller, 2020). We contribute to this literature by highlighting that the "shepherding" of complementors (Altman et al., 2022; Foerderer et al., 2021) in the context of modern platforms often entails managing "platforms within a platform," complementor products with their own direct network effects. The presence of such network effects incentivizes platform owners to act both in support of the products with network effects and against them when the complementors introducing them pose risks for the platform.

Our findings also contribute to the prior work that showcased the usage of awards as a novel tool used by platform owners to manage complementors (Foerderer et al., 2021; Rietveld et al., 2019). In this line of work, to our knowledge, we are first to show that awards can be used to manage a complementor's dominance by influencing product adoption. Our findings also contribute to the literature on network effects that have highlighted the role of network effects at the level of the platform in driving platform adoption and performance (Afuah, 2013; Katz & Shapiro, 1994). We showcase that the network effects are not just confined to the platforms but can also be present in the complementors' products with important implications for platform management. Moreover, we highlight that understanding complementors' direct network effects is relevant for the platform owners. Network effects can help platform firms resolve uncertainty and drive adoption but can also facilitate the emergence of dominant complementors.

By focusing on the network effects present in the complementors' products, the study also contributes to the prior work that has brought attention to product-level network effects (Boudreau et al., 2021; Rietveld & Ploog, 2022; Shankar & Bayus, 2003). While the prior work has demonstrated that the network effects are heterogeneous across products in the same industry and how they can facilitate product adoption and performance, the findings from the article highlight that the efficacy of the product-level network effects can be contingent on the firm's resources and market characteristics. Future research can further explore the trade-offs associated with designing products with network effects and explore differences between products with direct and indirect network effects.

Finally, our study offers several practical implications for both the platform owners and complementors. Our findings highlight how platform owners can use awards as a tool to manage complementors, especially the dominant ones. More specifically, it sheds light on the conditions when platform owners should promote the adoption of a leading complementor and when to promote a challenger. Platform owners may benefit from understanding these nuances in using awards as a tool to manage adoption. Further, we highlight various strategic considerations regarding product design and entry decisions relevant for complementors.

The findings of this study are subject to several limitations that provide opportunities for future research. First, the empirical context for the study is a single platform. While the iOS platform is one of the most valuable platforms globally, with Apple being one of the most successful platform owners, the validity of our findings may need to be explored in other settings. Second, the observation period of our study starts from 2012, which excludes the initial 4 years of platform growth. While we start our observation from 2012 because Apple began awarding complementors only then, we might not be fully capturing all the considerations of management as the strategies may have evolved during the initial period around the platform launch. Future work can thus shed more light on how the management of complementors with networked products differs across different phases of the platform's growth and study its implications on the platform's management. Third, our measure for products with direct network effects is based on the usage of the Game Center and our alternative measures are based on the API usage or use of keywords related to multiplayer features. It will be fruitful for future work to explore measures that directly capture user benefits as they depend on the number of other users actively using the app. Such efforts may require the development of datasets that measure real-time use of the apps while also capturing real-time user experience. Despite these and other limitations, our study is the first to inform how platform firms use selective promotion via awards to manage the adoption of complementor products with direct network effects. We hope that such a perspective yields valuable insights on platform management for platform owners and complementors.

To conclude, we hope to stimulate research in several areas. We highlight that network effects are not confined to the platform level. Complementary products with their own network effects affect how platforms manage complementors. Future research can build on this by exploring other differences between complements with and without network effects, tradeoffs associated with developing complementary products with both direct and indirect network effects and how such differences shape complementors' innovation trajectory and their performance. While we showcase the use of awards for management of product adoption, we know relatively little about how awards shape complementors' strategies. Receiving an award provides recognition, but it is unclear whether complementors should continue investing into the product that received the award or focus on developing new products. Finally, there could be heterogeneity in terms of how different platform owners use awards to manage complementors. Future work may look across platforms to explore how the use of awards is shaped by platform-level characteristics. We hope that our study facilitates these and other research directions in the growing research on platform management.

ACKNOWLEDGEMENTS

We would like to thank the editor Sendil Ethiraj and two anonymous reviewers for their helpful comments during the revision process. We would also like to thank Carmelo Cennamo, J.P. Eggers, Aseem Kaul, Tim Simcoe, and Brian Wu for helpful comments on early versions of the paper. The paper was presented at INSEAD, The Ohio State University, University of North Carolina Chapel Hill, Organizations, Markets, Platforms, & Regions Conference, 2022 Strategy Science Conference, 2021 Consortium on Competitiveness and Cooperation Innovation Brownbag, and the Consortium on Competitiveness and Cooperation Industry Dynamics Brownbag. We appreciate the helpful comments from these seminar and conference participants.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Online Media Group Inc. Restrictions apply to the availability of these data, which were used under license for this study. Contact, Online Media Group Inc. for information on licenses.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Agarwal, S., Miller, C. D., & Ganco, M. (2023). Growing platforms within platforms: How platforms manage the adoption of complementor products in the presence of network effects? *Strategic Management Journal*, *44*(8), 1879–1910. https://doi.org/10.1002/smj.3487