THREE ESSAYS ON HETEROGENEOUS NETWORK EFFECTS: IMPLICATIONS FOR FIRMS AND USERS

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I, Joe Niklas Ploog, confirm that the work presented in my thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

ABSTRACT

In the dissertation “Three Essays on Heterogeneous Network Effects: Implications for Firms and Users,” I examine the impact of network effects across various markets, challenging the notion that these effects uniformly affect all market participants and are always beneficial.

In the first theoretical chapter, I discuss the governance of multi-sided platforms, focusing on balancing openness and curation strategies to enhance match quality. Openness encourages network effects but requires intricate curation due to diverse user needs. In contrast, closed platforms offer higher quality matches with a more homogenous user base but struggle to achieve critical mass. I propose a framework to navigate these challenges, contributing to understanding platform success through strategic governance and curation to maintain high match quality.

In the second chapter, I investigate the strategic choice of firms to incorporate social features in products, highlighting how these features can induce network effects. Analyzing the global board games industry, where collectible network games and traditional games coexist, my results show how social features influence product diffusion due to demand uncertainty. I contribute to the literature on network effects and innovation diffusion, offering strategic insights on when firms should integrate social features into their products.

In the final chapter, I explore how incorporating social features into freemium products can propel and impede market success. Utilizing a sample of 9,700 Steam games, I demonstrate that while social features can significantly enhance a product’s appeal in markets with immense demand potential they can also detract from the product’s value in markets with limited demand potential, thereby undermining network effects. This research enriches our understanding of product-level network effects, freemium strategies, and the dynamics of superstar products.

Collectively, these essays advance our understanding of network effects, advocating a more strategic and context-sensitive approach to leveraging them for competitive advantage.

IMPACT STATEMENT

In this dissertation, I examine the dynamics of heterogeneous network effects, providing a novel perspective that challenges the conventional understanding of how network effects uniformly benefit all market participants. By analyzing digital and traditional market settings, I offer strategic insights for firms navigating the complexities of network effects in varied contexts. My work is beneficial for understanding how firms can exert strategic control over network effects and the broader implications for competitive dynamics.

The research delineates how network effects can be manipulated at the product level, suggesting that firms can strategically induce or mitigate these effects through deliberate product design. As a result, not all products within the same market might be subject to the same network effect. This reconceptualization moves beyond the exogenous view of network effects as a given market condition to a dynamic element that firms can influence. By demonstrating how social product features can propel and impede market success, the dissertation advises managers on the risks and benefits of generating network effects, particularly emphasizing the role of demand uncertainty and market conditions.

Furthermore, the dissertation highlights the impact of non-network factors, such as product novelty and business model choices, on product success in the presence of network effects. For example, the findings indicate that integrating social features in highly competitive markets or alongside novel product designs impedes product success. This insight encourages managers to adopt a more cautious approach, considering network and non-network factors in their strategic decisions.

The research also addresses strategic challenges in achieving and sustaining "winner-takes-most" market positions. It underscores that merely providing social interaction possibilities is insufficient for fostering network effects. Effective strategies must account for the growing heterogeneity of user bases and the evolving competitive landscape.

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Joe Ploog had the idea, collected, structured, analyzed the data, and wrote the first draft. Joost Rietveld helped edit the paper for publication and significantly helped to improve the manuscript throughout the review process. Both authors presented the paper at multiple seminars and conferences.

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Joe Ploog had the idea for the paper, collected, cleaned, structured, and analysed the data, wrote the first draft for the front end, significantly contributed to the theorizing, and presented the work at multiple conferences. The supervisor initially provided strong guidance on all aspects of the paper and helped to significantly edit the paper for journal submission and the respective rounds of revisions. In percentage, it is about 50-50.

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   Joost Rietveld

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INTRODUCTION

Network effects occur when the value of a firm's offering increases with the number of its users. Imagine playing a multiplayer video game like Fortnite alone, ordering a ride on Uber with no drivers nearby, or trying to sell goods on a platform like Amazon without any buyers. These scenarios highlight the importance of network effects. Network effects are not just confined to entertainment and e-commerce but are also prevalent in social media, content streaming, and professional services. Instagram, YouTube, and TikTok thrive as more creators contribute diverse, engaging content that attracts the masses. At the same time, professional tools like Microsoft Office have become more indispensable as more people use them for collaboration. In sum, network effects underpin the success of many technology companies (Adner, Puranam, & Zhu, 2019; McIntyre & Srinivasan, 2017; Rietveld & Schilling, 2020). The more users a firm benefitting from network effects attracts, the more valuable it becomes to each additional user, creating a cycle of growth that leads to dominant market positions (Cennamo & Santalo, 2013; Eisenmann, Parker, & Van Alstyne, 2011).

However, this dynamic can also lead to significant challenges. As these networks grow, they can achieve near-monopoly statuses, making it exceedingly difficult for competitors to convince users to switch to less populated networks, regardless of the potential benefits or innovative features they may offer. The literature refers to this phenomenon as market 'tipping'—where minor advantages in the number of users early on can escalate into a dominant market share, leaving competitors and new entrants locked out (Arthur, 1989; Fang, Wu, & Clough, 2021; Schilling, 1998, 2002). Take the example of WhatsApp, the messaging app. As it became popular, the value of using WhatsApp increased since more people were available on it. This network effect made WhatsApp increasingly indispensable for users seeking convenient, instant communication with friends and family. The more users joined WhatsApp, the less appealing alternative messaging apps became, solidifying WhatsApp's dominance in the market. Competing instant messaging offers struggle to attract users away from WhatsApp, as moving to a less populated platform means losing access to the vast network of established connections. For that reason, much of the literature on network effects has analyzed how firms that compete in the presence of network effects can ensure they acquire large user numbers as quickly as possible (Schilling, 2002; Suarez, 2004).

Furthermore, network effects are not solely a function of the number of users installed but also of network strength, which describes the marginal increase in use value an additional user generates for the entire network (Cabral, Salant, & Woroch, 1999; Shankar & Bayus, 2003). Network strength can vary as a function of an offering’s network structure, the users comprising the network, the offering’s life cycle, and the offering’s features (Afuah, 2013; Binken & Stremersch, 2009; Dou, Niculescu, & Wu, 2013; Gretz & Basuroy, 2013; Panico & Cennamo, 2022; Suarez, 2005; Tucker, 2008). For example, the strength of ties between users in the network and the presence of high-status network members can increase network strength (Suarez, 2005; Tucker, 2008). Similarly, high-quality, exclusive, or superstar complements positively affect the network strength of two-sided platforms (Binken & Stremersch, 2009; Corts & Lederman, 2009; Shankar & Bayus, 2003). Furthermore, research has shown that network effects are stronger earlier in the industry, platform, or product life cycle (Gretz & Basuroy, 2013; Rietveld & Eggers, 2018).

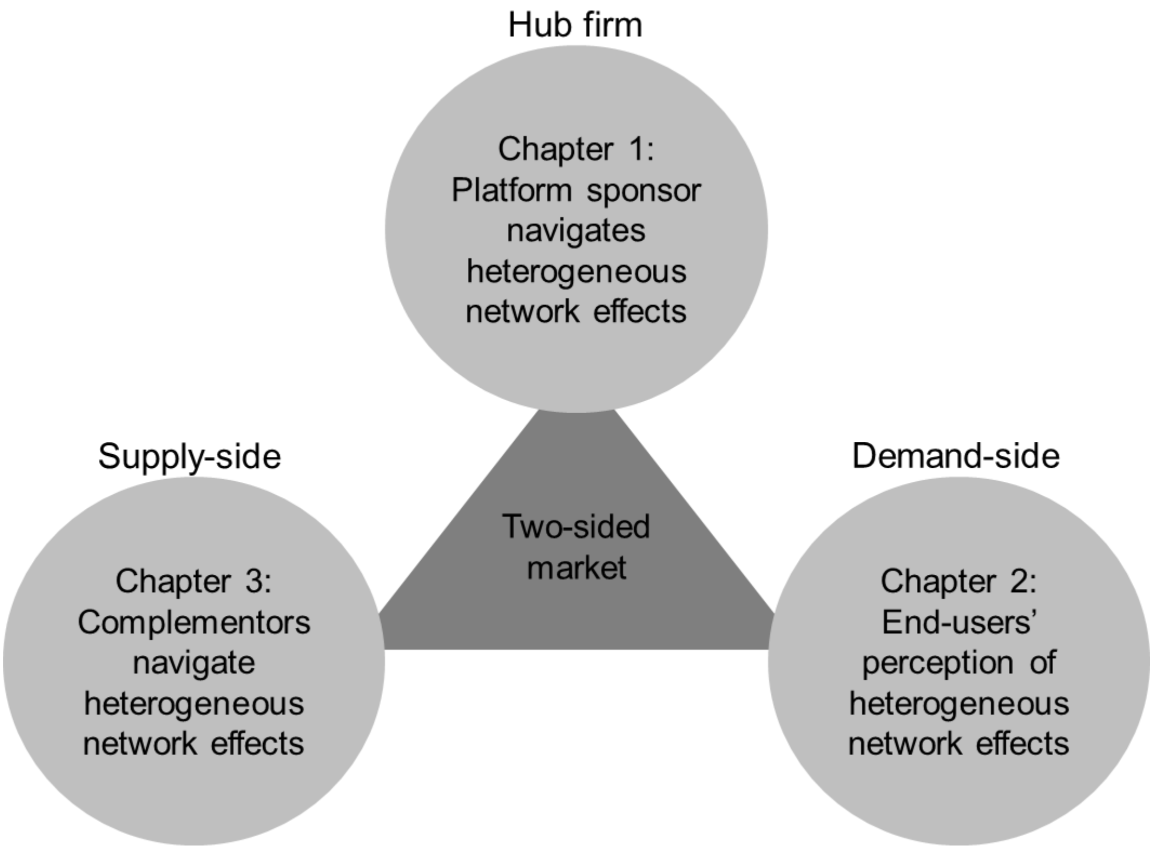
The literature on network effects commonly assumes network effects to be exogenously determined by market-level features, universally affect all market participants, and are unequivocally beneficial for firms able to exploit them (Agarwal, Miller, & Ganco, 2023; Boudreau, Jeppesen, & Miric, 2022; Clements & Ohashi, 2005; Katz & Shapiro, 1992; Zhu & Iansiti, 2012). Some more recent work, however, adds nuance to these assumptions by showing that firms can endogenously modify the strength of their products’ network effects through various actions, including their product design choices (Dou et al., 2013; Niculescu, Wu, & Xu, 2018; Zhu, Li, Valavi, & Iansiti, 2021). For example, a developer can launch a video game with or without multiplayer functionality. In the first case, the developer hopes to acquire a large user base to benefit from network effects, increasing the product's value for other potential users. In the second case, the number of users will have a much smaller impact on the adoption decision of potential users. This shift in perspective injects an element of business strategy into the predominantly economic conversation around network effects. This agency leaves us with several unanswered questions, including: *When should firms design their products for network effects in the first place, and what strategic actions contribute to or impede the success of firms operating in situations characterized by heterogeneous network effects?*

In this dissertation, I add to the burgeoning conversation on network effects by theorizing about and investigating contexts where firms compete under heterogeneous network effects. Drawing from prior work, I argue that in some contexts, firms have the agency to induce network effects by utilizing product (or platform) design choices (Dou et al., 2013; Zhu et al., 2021). For example, a ride-hailing platform provider can decide to offer carpooling, which will create some value for users based on whether they want to carpool and how many other users opt-in to choose that option. This agency leads to situations where products with varying network strengths compete, which, to my knowledge, has not yet been explored by prior work. In doing so, I also further move away from the notion that just installed base size determines the outcome of competition under network effects (Afuah, 2013; Cennamo & Santaló, 2019; McIntyre & Srinivasan, 2017).

Moreover, I explore the role of heterogenous network effects in various settings spanning digital platforms and the non-digital board games industry. By doing so, I reemphasize the importance of direct network effects, which have recently garnered less attention than their indirect counterparts due to their significance in the context of digital platforms (Panico & Cennamo, 2022). Finally, I highlight that network effects by no means always lead to positive results for the firms trying to induce them and that their maintenance over time requires managers to adjust strategies to the given market conditions.

My dissertation follows the structure of a two-sided market in which a hub firm intermediates interactions between a supply side and a demand side (Parker & van Alstyne, 2005). Each chapter investigates how heterogeneous network effects affect at least one of the three sets of actors within a two-sided market. In the first chapter, I examine how a hub firm (platform sponsor) navigates heterogeneous network effects. In the second chapter, I investigate end-user's perception of heterogeneous network effects. In the final chapter, I analyze how complementors (firms collectively representing a platform's supply side) navigate heterogeneous network effects. **Figure I** illustrates this structure.

Figure I Dissertation Structure



In the first chapter of the dissertation, I explore the pivotal role of match quality in multi-sided platforms, focusing on how platform openness impacts the effectiveness of curation strategies for matching supply and demand platform markets. I begin by establishing the trade-off platforms face between openness and curation. Open platforms, while attracting a larger user base and potentially enhancing network effects, face challenges due to increased user heterogeneity. This heterogeneity increases search costs and complicates the matching process, necessitating more sophisticated curation strategies. Conversely, closed platforms, though they may experience higher average match quality due to a more homogenous user base, risk failing to achieve critical market thickness for generating network effects. I introduce a comprehensive framework that examines how platform openness influences user heterogeneity and market thickness and propose a typology of platform configurations and corresponding curation strategies to ensure high match quality. Furthermore, discussing the dynamic nature of platforms, I argue that as they evolve, their curation must adapt to changes in user heterogeneity to maintain high match quality. I contribute to the platform governance literature by highlighting match quality's central role in sustaining user engagement and network effects. This first chapter provides a theoretical foundation for understanding how platforms can strategically manage user interactions to foster long-term growth and success in competitive digital marketplaces. The insights offer actionable strategies for balancing openness with effective curation to enhance overall platform performance.

In the second chapter, I explore product diffusion in markets where network effects are not uniformly applicable across all products. I investigate the board games industry, comparing products with network-based social features against traditional board games that lack these features. I develop a theoretical framework to examine how social features in products influence consumer demand uncertainty and, consequently, the diffusion of these products in the market. I posit that network products, which rely on social interactions to generate value, experience greater demand uncertainty than standalone products. This uncertainty arises because the value of network products significantly depends on the size of their user base, which is zero at the time of the product launch. Using data collected from boardgamegeek.com, I test several hypotheses regarding how factors like product novelty, early adoption strategies, and competition differentially affect the diffusion of network products versus standalone products. The findings reveal that factors that typically increase demand uncertainty, such as novel product features or intense competition, tend to have a disproportionately negative impact on the diffusion of network products compared to standalone products. Overall, I contribute to the literature on network effects and innovation diffusion by highlighting the unique challenges faced by products in markets characterized by heterogenous network effects. It offers strategic insights for firms considering integrating social features into their products, suggesting that firms must carefully balance the benefits of network effects against the potential for increased market uncertainty and diffusion challenges.

In the final chapter, I focus on the implications of adding social features to freemium products. I identify that while social features like multiplayer functionality can drive network effects, leading to a product becoming a "superstar," these effects are highly contingent on the size of the platform's user base. Specifically, when the user base is large, social features significantly boost a product's likelihood of achieving widespread adoption and generating high revenue through network effects. Conversely, in scenarios where the user base is smaller, these features may detract from the product's appeal, as the expected benefits of network effects are not realized, potentially leading to a decline in user engagement. I explore this duality through a unique dataset of 9,700 games from Steam, the largest distribution platform for digital PC games. The results are particularly relevant for freemium business models on digital platforms where user interaction and engagement can directly influence revenue streams from in-app purchases. I contribute to strategic management literature by highlighting the conditional benefits of network effects in freemium models and offering insights into when and how adding social features can either be a strategic asset or a liability. These insights assist managers in making informed decisions about product features and strategic positioning in digital marketplaces.

With my dissertation, I am opening up space for research to explore the agency firms have in inducing network effects, altering them over time, and adjusting them according to competitive dynamics. Most strategic recommendations advise firms to adapt to network effects by deploying aggressive actions such as price reductions, extensive marketing, or sunk-cost investments, all of which aim at rapidly accumulating a large installed base (Cabral et al., 1999; Katz & Shapiro, 1994; Schilling, 2002). In contrast, exploring the implications of heterogenous network effects shifts the attention to factors traditionally not considered in the discussion of success in the presence of network effects. For example, I highlight (1) the importance of match quality within digital platforms to sustain network effects, (2) how non-network factors such as novelty and competition penalize products with network effects more than those without, and (3) that including network effects into digital products only leads to success when carefully considering the chosen business model and the market's demand potential. **Table I** shows a chapter overview.

Table I Chapter Overview

Chapter	Title	Target Journal	Status
1	Match Quality in Multi-Sided Platforms: Balancing Openness and Curation	AMR	Not submitted
2	Rolling the Dice: Resolving Demand Uncertainty in Markets with Partial Network Effects	AMJ	Accepted
3	On Top of the Game? The Double-Edged Sword of Incorporating Social Features into Freemium Products	SMJ	Published

1. CHAPTER 1

MATCH QUALITY IN MULTI-SIDED PLATFORMS: BALANCING OPENNESS AND CURATION[1]

1.1 ABSTRACT

From prior research, we know governance in multi-sided platforms, including openness and curation strategies, is essential to match supply and demand effectively. High match quality— continuously and effectively connecting users with optimal interaction partners— heightens user engagement and helps to sustain indirect network effects. However, platforms face a trade-off between their openness and curation strategies. On the one hand, an open platform leads to more users but calls for more intricate curation due to the number and heterogeneity of potential interaction partners. On the other hand, on a closed platform, matches tend to be of higher average quality since the more homogenous users are easier to match, but the platform might lack the critical mass needed to kickstart network effects. This trade-off evolves, challenging platforms to secure long-term user engagement and sustain network effects. I propose a comprehensive framework that outlines how platform openness affects the number of users and their heterogeneity, allowing me to (1) develop a typology of platform configurations and (2) identify curation strategies to ensure high match quality. Highlighting match quality's central role in sustained platform success, I contribute to the literature on platform governance and network effects by offering insights into their maintenance and evolution.

Keywords: *Platform Configurations, Match quality, Multi-sided platforms, Network effects, Platform governance*

[1] This chapter is based on a paper with the same current title coauthored with Joost Rietveld. The target journal is *The Academy of Management Review*.

1.2 INTRODUCTION

Platforms serve as intermediaries, connecting two or more distinct user groups (sides) in a (digital) market. These connections result in indirect network effects, where the likelihood of new end-users joining increases as the number of complementors grows and vice versa (McIntyre & Srinivasan, 2017; Stremersch, Tellis, Franses, & Binken, 2007).[2] This interdependence is a primary driver of value creation within these markets, significantly influencing the platform's appeal for all participants (Boudreau, 2010; Parker & van Alstyne, 2005). An organization in control of a platform (further called *platform sponsor*) not only facilitates interactions but governs who can join the platform, as well as how and when interactions take place (Jacobides, Cennamo, & Gawer, 2018; Rietveld, Schilling, & Bellavitis, 2019; Wareham, Fox, & Cano Giner, 2014).[3] A central decision of platform governance is whether and to what extent the platform sponsor restricts who can join the platform – e.g., how open or closed the platform is (Boudreau & Hagiu, 2009; Eisenmann, Parker, & van Alstyne, 2009; Schilling, 2011). Another one is the curation of complementary offers to facilitate end-users' search for these offers (Foerderer, Lueker, & Heinzl, 2021; Rietveld et al., 2019; Rietveld, Seamans, & Meggiorin, 2021). Youtube, for example, is fully open to end-users and complementors by allowing virtually anyone to create an account, consume, and upload content. Youtube curates their platform by employing algorithms to sort and recommend content, navigating users through the vast library to enhance match quality between viewer preferences and videos.

Platforms face a trade-off concerning openness and curation. On the one hand, an open platform leads to increased market thickness[4], strong network effects, and growth. On

[2] I use the term 'users' when speaking about all platform participants meaning complementors and end-users.
[3] Most interactions amongst end-users and complementors within platforms are transactions. However, my theory also applies to non-transactional interactions such as chatting with a potential civil partner on a dating platform. Subsequently, I use the more encompassing term *interactions*.
[4] Market thickness refers to the level of activity within a market, characterized by the number of participants on both sides of an interaction – buyers and sellers in a traditional market, or end users and complementors in a

the other hand, not restricting platform access based on characteristics (e.g., quality or demographics) increases user heterogeneity—vertically and horizontally. This leads to higher user search costs and a lower probability of matches, calling for more intricate curation strategies. In contrast, a closed platform can easily curate its more homogenous market to connect users with optimal counterparts but might struggle to reach the necessary market thickness to generate network effects.

Drawing from matching theory, I consider the platform sponsor a market maker who applies various curation strategies to form matches between supply and demand. I argue that openness directly impacts market thickness and user heterogeneity on both sides of the platform, thereby affecting appropriate curation methods. The existing literature on matching recognizes that the user base's composition (market thickness and user heterogeneity) influences the effectiveness of curation strategies (Dinerstein, Einav, Levin, & Sundaresan, 2018; Shi, 2023) but often overlooks the role of platform openness in shaping this composition. Furthermore, while we know how platform strategies create an indirect network effect (Boudreau, 2012; Parker & van Alstyne, 2005), we know less about how platforms can sustain their network effects over time. For example, in 2014, nobody thought Facebook would struggle to keep its users engaged due to more appealing alternatives like TikTok. Today, user retention, which relies on high match quality, is a commonly used key performance indicator for platforms and their complementors (Gu, Bapna, Chan, & Gupta, 2022; Huang, Jasin, & Manchanda, 2019; van Alstyne, Parker, & Choudary, 2016). Finally, most of our knowledge about platforms comes from a static perspective, not considering how the exchange relationships and the need for their curation evolve over time (see. Wareham et al., 2014; Kyprianou, 2018; and Rietveld, Ploog, & Nieborg, 2020 for exceptions). This is of

platform context (Bennet, Seamans, & Zhu, 2015). A thicker market has a high number of participants, which generally increases the likelihood of interactions taking place market. Thick markets strengthen indirect network effects, as they attract more participants by offering a greater variety of potential interactions.

concern since platforms not only need to attract users to their market but also ensure they stay engaged to uphold the network effects.

Match quality on multi-sided platforms is not only about individual experiences but also reflects the collective satisfaction and value generated across the entire user base. I define it as the extent to which the platform can consistently facilitate interactions that closely match its users' diverse preferences and needs, fostering valuable exchanges (Dinerstein et al., 2018; Fradkin, 2017; Shi, 2023). Whereas network effects attract users to the platform and increase the likelihood of any interactions taking place ex-ante, match quality affects the value of an interaction ex-post. High match quality, therefore, signifies a platform's success in regularly achieving preference alignments, enhancing overall user satisfaction. This consistency, in turn, contributes to higher retention, better reviews, and increased profitability. High match quality at an individual level aggregates to a higher overall market quality, indicating a thriving platform where high-quality interactions become a norm. Inadequate attention to match quality may result in missed opportunities for platforms to differentiate themselves in a competitive market.

Without understanding the mechanisms to enhance match quality, platforms may struggle to sustain long-term growth as user numbers alone won't result in durable network effects (Afuah, 2013; Suarez, 2005). Platforms with low average match quality risk users stop engaging with or leaving the platform altogether (Tiwana, 2015b). Consequently, I ask the following research question: *How should platforms balance openness and curation to ensure high match quality, and how does this relation evolve over time?*

To answer this question, I first develop a comprehensive framework that outlines the causal relationships between platform openness, the heterogeneity of users, and the resulting platform configurations. Highly heterogeneous platform users complicate forming high-quality matches. Subsequently, identifying the underlying mechanisms that affect heterogeneity on both sides allows me to develop propositions about adequate curation strategies to improve match quality in response to specific platform configurations. Afterward, I acknowledge that these relationships are dynamic and discuss how they evolve over time.[5] My efforts lead to the following results: First, I derive a typology of platform configurations considering end-user heterogeneity, complement variety, and interaction type. Second, I propose adequate curation strategies for each platform configuration. Finally, I theorize how evolving platform configurations change adequate curation strategies for high match quality.

I make several theoretical contributions. First, I contribute to the literature on platform design and strategy by outlining the complex interplay of mechanisms that lead to various platform configurations as a function of end-user heterogeneity and complement variety (Cennamo & Santaló, 2019; Eisenmann et al., 2009; Jacobides, Cennamo, & Gawer, 2024). Doing so allows me to develop a typology of platform markets, each of which calls for different curation strategies to ensure high match quality. Furthermore, most of the literature on matching in two-sided platforms implicitly assumes that a platform has many (homogenous) users (Fradkin, 2017; Halaburda, Jan Piskorski, & Yıldırım, 2018). I add nuance by proposing that platform openness is an antecedent of both user base size and user heterogeneity. Second, I contribute to a recent stream of studies that acknowledge the evolutionary nature of platforms and their governance (Kyprianou, 2018; Rietveld et al., 2020; Wareham et al., 2014). I highlight that platform markets change over time as new users and complementors join the platform. Evolving platform configurations require changing curation strategies to ensure high match quality and durable network effects. Finally, I

[5] Verbal theorizing is especially suited to answer my research question due to the complex causal relation between constructs and the difficulty of measuring them—e.g., user preferences and the quality of matches between platform users (Mitsuhashi & Greve, 2009; Shi, 2023).

contribute to the literature on network effects by highlighting match quality as an integral driver of network strength and long-lasting network effect. My insights contribute to a recent stream on network effect heterogeneity and the strategic agency firms have in designing for and sustaining their network effects (Clough & Wu, 2022; Gregory, Henfridsson, Kaganer, & Kyriakou, 2021; Rietveld & Ploog, 2022; Zhou, Zhang, & van Alstyne, 2021; Zhu et al., 2021).

1.3 THEORETICAL BACKGROUND

1.3.1 Matching theory

Matching theory provides a framework for understanding how agents in a (two-sided) market find suitable (interaction) partners based on their preferences and needs. The theory was first introduced in the context of marriage (Becker, 1973; Gale & Shapley, 1962) and has since been extensively applied in labor economics (Dustmann, Glitz, Schönberg, & Brücker, 2016; Jovanovic, 1979; Roth & Xing, 1994). Matching theory outlines that agents in a market have preferences for potential matches, possess complete information to rank these preferences and seek stable matches where no pair would prefer a different partnership (Gale & Shapley, 1962; Roth & Sotomayor, 1992). Additionally, choices are made based on individual evaluations without regard to others' preferences within a finite set of options. In management, the theory has been used to explain matching processes in the context of the formation of alliances (Greve, Mitsuhashi, & Baum, 2013; Mitsuhashi & Greve, 2009), partnership choices of entrepreneurs and firms (Haas, Criscuolo, & George, 2015; Mindruta, 2013; Vissa, 2011), and knowledge sharing activities of organizations (Haas et al., 2015).

1.3.2 Matching in platform markets

In multi-sided platforms, interactions—ranging from transactions and information exchanges to social connections—are the core mechanism for value creation (Cennamo & Santaló, 2019; Kanoria & Saban, 2021). To engage in any interactions, users must first join the platform (Rietveld & Ploog, 2022). The likelihood of new users joining increases with the number and variety of users on the opposite side, called indirect network effects (Parker & van Alstyne, 2005). Indirect network effects are self-enforcing, meaning the attractiveness of a platform increases with its user base, which in turn increases the likelihood of new users joining (Eisenmann et al., 2011). However, an increasingly large user base leads to search frictions that hinder the formation of satisfactory matches amongst many potential interaction partners (Bakos, 1997; Kanoria & Saban, 2021; Petrongolo & Pissarides, 2001). On top of that, the more users join a platform, the more heterogeneous they will be (Boudreau, 2010; Rietveld & Eggers, 2018). Platform users are heterogeneous on both vertical and horizontal dimensions. First, users have horizontally distributed preferences, any given one of which does not necessarily align with every potential interaction partner (Einav, Farronato, & Levin, 2016; Liu, Lou, Zhao, & Li, 2023). Secondly, platform users also differ regarding vertical dimensions such as quality, responsiveness, reliability, and their threshold for accepting interaction partners on that dimension (Boudreau, 2010; Romanyuk & Smolin, 2019). User heterogeneity changes over time since late adopters often vastly differ in their preferences from early adopters (Rietveld & Eggers, 2018).

Consequently, adequately matching platform users is a central task for platform sponsors (Rochet & Tirole, 2006), which becomes increasingly more challenging with market thickness (Bennett, Seamans, & Zhu, 2015; Dinerstein et al., 2018). As the market thickens, the diversity in user preferences and requirements grows, complicating the matching process. Fradkin (2017) finds that optimal match quality varies significantly between end-users and complementors in platforms like Airbnb, largely dependent on the number of available offers. His findings illustrate the complexity of maintaining high match quality in thicker markets, especially when there is an asymmetry in user preferences across both sides. Similarly, Halaburda et al. (2018) show that restricting user choices in dating platforms can paradoxically enhance value by reducing the likelihood of rejection in a crowded market. Finally, Li and Netessine (2020) note that increased market size can exacerbate search frictions and lower matching rates, particularly when matches must occur quickly. These insights collectively highlight platforms' nuanced challenges in balancing market thickness with adequate match quality. Finally, by focusing on user preferences, Shi (2023) proposes that suitable matching strategies are a function of how easily complementor and end-user preferences are observable and describable. The author suggests that platforms should let end-users search and match (decentralized matching) if complementor preferences are easily describable, complementors search and match (decentralized matching) when end-user preferences are easily describable, and platforms should handle the matching themselves (centralized matching) when both are easy to describe.

While all the studies above acknowledge the importance of market thickness and user heterogeneity for match quality, they do not identify antecedents of those. The platform governance literature provides insights into how a platform sponsor controls how and who joins their platform, profoundly affecting market thickness and user heterogeneity.

1.3.3 Platform governance, market thickness, and user heterogeneity

Platform governance refers to the frameworks, rules, and processes established by platform owners to control access, manage participant interactions, and facilitate value creation and capture within a platform (Boudreau, 2010; Jacobides et al., 2018). It involves determining how complementors and end-users interact within the platform, the degree of openness or restriction in participation, and how resources and information are shared and controlled (Rietveld et al., 2019; Rietveld et al., 2020; West, 2003). Effective governance strategies are crucial for balancing diverse stakeholder interests, ensuring platform stability, and fostering growth (Wareham et al., 2014). Since a platform's user base composition, needs, and value creation capabilities change over time, platform governance is not static (Rietveld et al., 2020; Tiwana, 2015a; Tiwana, Konsynski, & Bush, 2010). Instead, a platform sponsor must balance stability and flexibility by dynamically orchestrating value across multiple sides to ensure the platform participants stay engaged (Kyprianou, 2018; Wareham et al., 2014; Yoffie & Kwak, 2006). Whereas platforms can potentially create far more value than traditional organizations, poor governance can quickly erode value and lead to market failures (Jacobides et al., 2024; Reeves, Lotan, Legrand, & Jacobides, 2019).

Platform openness. One central governance choice for platform sponsors is to decide how open each side is for users to join. Platform openness refers to the degree to which a platform allows access and contributions from external users. It encompasses policies and mechanisms governing how third parties interact with the platform, including creating content, developing complementary products or services, and accessing platform resources or data (Boudreau, 2010; Boudreau & Hagiu, 2009; Eisenmann et al., 2009; Schilling, 2011; West, 2003). Platform sponsors decide about the openness of their platform on both the demand side (end-users) and the supply side (complementors) (Boudreau & Hagiu, 2009; Parker & Van Alstyne, 2018). An open demand side invites a broad user base, enhancing diversity, while on the supply side, openness fosters a wider and more varied range of offerings. For example, GitHub, as an open platform on both the demand and supply sides, allows developers to share code and collaborate on projects while a broad range of users can access and contribute to these repositories. This openness enriches the ecosystem with diverse software solutions and collaborative opportunities.

Platform openness comes with a trade-off. On the one hand, fully open platforms lead to more users joining the platform, thickening the market, and strengthening indirect network effects. On the other hand, they also attract more heterogeneous (horizontally and vertically) users, who crowd the market, increase search costs, and potentially lower the average quality offered on the platform (Boudreau, 2010; Eisenmann et al., 2009; Schilling, 2011). In contrast, closed platforms that attract only users with specific characteristics host fewer, more homogenous users of higher quality, ensuring a tighter fit between both sides of the market and reducing search costs (Boudreau, 2010; Eisenmann et al., 2009; West, 2003). At the same time, closed platforms might struggle to generate network effects since reaching the necessary market thickness takes longer than on an open platform. A platform's market thickness is additionally affected by complement type. Complements can be of two types—stock or flow. Generally, stock complements refer to products or services that remain available on the platform over an extended period, such as product listings for sale on Amazon. Flow complements, on the other hand, are consumed or provided in real-time or are only available on the platform for a limited duration, such as a ride in a ride-hailing app like Uber or a project on Kickstarter. The distinction between stock and flow complements mainly affects the importance of interaction timing (Li & Netessine, 2020). Interaction timing is critical for flow complements because their availability or relevance is time-sensitive. Like perishable goods, flow complements' relevance (value) disappears from the platform after their duration date (time) expires (Janssen, Claus, & Sauer, 2016). Subsequently, unlike stock complements, which remain accessible indefinitely, flow complements, such as rides or crowdfunding projects, require immediate or timely consumption. This urgency necessitates matching mechanisms to connect users with complements at the right moment.

I illustrate the impact of platform openness in the context of academic publishing (McCabe & Snyder, 2018). Research Gate is an open-access repository where researchers freely submit preprints across fields, facilitating rapid dissemination of research without the gatekeeping of peer review. Its openness accelerates the adoption and spread of new ideas, leveraging strong network effects as the variety of submissions attracts a broad academic audience. However, the diversity in research quality and relevance can complicate user search and discovery processes, potentially impacting the average quality of content. INFORMS, in contrast, offers a curated collection of peer-reviewed academic journals. Access is restricted to institution-affiliated users or those who pay for access, making it a more closed platform. This controlled environment ensures high uniformity and quality of academic materials. While this might slow down the new user acquisition rate, it simplifies content discovery and provides a consistent user experience, aligning closely with the institution's academic rigor and reliability standards.

Platform curation. Another central governance strategy is the curation of offers. Platform curation involves selecting and organizing content, products, services, and user interactions within a platform. It aims to enhance the user experience, maintain content quality, and facilitate effective matches between supply and demand (Burks, Cowgill, Hoffman, & Housman, 2015; Rietveld & Schilling, 2020). Curation strategies can be categorized into algorithmic and manual. Algorithmic curation relies on data-driven rules and automated processes to sort and present offerings based on user behavior and preferences (Bhargava et al., 2020; Dzyabura & Hauser, 2019; Horton, 2017). This method can efficiently handle vast amounts of data to deliver personalized user experiences but may lack the nuanced understanding of content quality and cultural context that human curators provide. In contrast, manual curation involves human curators making deliberate choices about which content to feature based on subjective assessments of quality, relevance, and diversity (Gawer, 2014; Rietveld & Schilling, 2020). Manual curation is more labor-intensive, albeit more straightforward, for a platform sponsor to establish. In contrast, algorithmic curation is more complex to set up and maintain due to the need for data, coding, and analytical capabilities. In sum, manual curation adopts a top-down approach, serving as an orchestration tool that applies a more uniform editorial perspective on what content to highlight and can help to nudge platform users to behave in specific ways (Rietveld et al., 2021). Conversely, algorithmic curation excels at accommodating a thick market and user heterogeneity, utilizing data to tailor recommendations that align with individual preferences.

Effective curation strategies are pivotal for platforms, as they ensure that users are matched with services or products that best fit their needs and preferences, enhancing overall satisfaction and engagement (Foerderer et al., 2021; Rietveld et al., 2019; Tiwana et al., 2010). Prior research on platform curation has shown that sponsors do not just provide more visibility to the highest quality complementors. Instead, they tend to promote complementors that are (1) of high quality but not market leaders, (2) in segments that are underappreciated by end-users, and (3) at times when not many new complements are being released (Rietveld et al., 2019). Curation strategies affect how and when interactions occur and shape the behavior of complementors aligned with the curation strategy's purpose. For example, Rietveld et al. (2021) show that complementors on a micro-financing platform aligned their product offering following the reward immediately after receiving it from the platform. As such, algorithmic curation can enhance match quality with the right balance of supply and demand. In contrast, manual curation can direct the market towards specific trends or segments, influencing future user characteristics.

1.4 THEORY DEVELOPMENT

I consider platform sponsors matchmakers for their respective markets based on matching theory. Without platform intervention (curation), user matches would form randomly. Following this assumption, the more heterogenous user preferences on both sides, the less likely random matching would lead to satisfactory outcomes (high match quality) since the probability of randomly drawn users aligning on their preferences decreases with the variance of user preferences. Platforms can decide about their openness on both sides. An open platform means the sponsor offers unrestricted entry to whoever wants to join the platform. No selection at the gate has the following consequences: First, the user base tends to be large(r) since any interested user can join without restriction, meaning the market is thick, network effects are strong, and interactions are likely to occur. Second, no selection at the gate means users are heterogeneous on horizontal and vertical dimensions. Complementors differ in type and quality. End-users differ regarding their preferences of offering type and the minimum quality a given offer must meet to be considered. Users on the platform incur high search costs, screening many heterogeneous, potential interaction partners. Without any curation by the platform sponsor, a match forms randomly and is not likely to be of high quality due to the large variance of user preferences. Subsequently, in this context, a platform's market curation is essential to ensure high match quality.

A closed platform means the platform sponsor restricts access to that side somehow. For example, sponsors could select based on a quality screening or charge a fee to users to join and use the platform. Such a filtering mechanism has two consequences: First, the platform's user base is smaller, the market is thinner, network effects are weaker, and the probability of interactions occurring is lower than in the open case. Second, entry restrictions mean users are more homogenous. In this context, a random match is less likely to occur than in the open scenario. However, if an interaction takes place, they are likely to be of higher match quality due to the lower variance of user preferences based on the selection criteria of the platform sponsor at the gate.

In sum, while open platforms lead to thicker markets with strong network effects, they face challenges in maintaining match quality due to increased user heterogeneity and search costs. Conversely, closed platforms cultivate a more homogenous user base by restricting access, simplifying the matching process. However, they have weaker network effects and risk slower growth. Consequently, platform sponsors adjust their curation strategy depending on how open their platform is. The more open a platform is, the more the sponsor focuses on curation that enhances match quality and vice versa. While the literature on matching in two-sided platforms has advanced our understanding of the interplay between market thickness and match quality, the antecedents for market thickness are less clear. In the following, I investigate the trade-off between platform openness and the quality of matches it can curate, a crucial yet underexplored aspect that directly impacts user experience and platform sustainability. Open platforms may struggle with maintaining match quality due to increased user heterogeneity, while closed platforms may hinder growth and network effects by limiting market thickness. Addressing this gap is essential for developing strategies that balance attracting a broad user base and ensuring high-quality interactions within platforms.

1.4.1 Boundary Conditions

Following matching theory, I consider platform sponsors to be the matchmakers of their own market, facilitating the formation of interaction pairs between supply and demand. I disregard situations in which platform sponsors might oppose maximizing match quality to exploit, for example, information asymmetries vis a vis their users or avoid their complementors to strictly compete on price (Bakos, 1997; Bennett et al., 2015). Instead, I assume platform sponsors focus on value creation by consistently ensuring high match quality.[6] High match quality directly affects value creation by ensuring that interactions meet or exceed user expectations, fostering a positive experience that enhances user satisfaction and loyalty. By prioritizing match quality, platform sponsors enhance individual user experiences and contribute to the overall attractiveness of the platform, creating a virtuous cycle of engagement and growth.

Furthermore, my theory applies to multi-sided platforms on which interactions across sides occur, including all interaction and information platforms but only some innovation platforms (Cennamo, 2021; Gawer, 2021). While my theory applies to those innovation

[6] While one could argue that complementors on an interaction platform do not necessarily care who adopts their products, I argue the platform sponsor does care since they want to ensure all market participants to be satisfied and continue to interact on or return to the platform.

platforms that allow for direct interactions between supply and demand, it does not apply to innovation platforms in which complementors use a technology provided by a sponsor, with no direct interaction between innovators and end-users. Microsoft's Windows Operating System is an example of an innovation platform where complementors and end-users do not directly interact. Here, software developers (complementors) use the platform's APIs and SDKs provided by Microsoft to create applications. However, these developers do not interact directly with the end-users who purchase or use their applications. Finally, I present all my arguments in the context of two-sided platforms as the most accessible representation of a multi-sided market. I expect my theory to hold in contexts with more sides.

1.4.2 Conceptual Framework

Platform sponsors strategically determine the openness of their platform on both the demand side (end-users) and the supply side (complementors) (Boudreau & Hagiu, 2009; Parker & Van Alstyne, 2018). An open demand side invites a broad user base, enhancing diversity, while on the supply side, openness fosters a wider range of offerings. In contrast, a closed approach on either side allows for greater control over the platform, ensuring alignment with strategic objectives and maintaining a consistent quality standard across users and complementors. This strategic dichotomy leads to four possible configurations of platform openness:

1. Open-Open: Maximizes diversity among both users and complementors.
2. Open-Closed: Allows diverse user participation while controlling the supply side for quality.
3. Closed-Open: Targets a specific user demographic while encouraging complementor variety.
4. Closed-Closed: Restricts users and complementors to maintain the highest control and quality.

These configurations can be applied to both platforms with stock complements (remain on the platform indefinitely) and flow complements (stay on the platform for a limited time). User heterogeneity and complement type lead to eight different platform configurations. For example, one configuration is an open demand side with many heterogeneous users and an open supply side with a large variety of stock complements. Sponsors can apply different curation strategies depending on the resulting platform configurations. From the literature, I identified the following curation strategies that represent the levers platform sponsors have to manage platform configurations. First, curation can be manual or algorithmic. When applying manual curation, the sponsor assigns a human editorial team to screen the platform market for offers that fulfill specific criteria, which will be prominently featured. Apple's "Editor's Choice" is an example of manual curation within the iOS App Store. Algorithmic curation, on the other hand, represents an automated curation effort based on user characteristics and behavior. TikTok's algorithm is a notorious example of algorithmic curation that suggests short video clips based on past user behavior. Importantly, manual and algorithmic curation are not mutually exclusive, and platform sponsors can apply a mix of both.

Furthermore, Platform sponsors can apply centralized curation, meaning the sponsor matches interaction partners without allowing them to search for and initiate interactions with potential partners themselves. Alternatively, the sponsor can apply decentralized curation, meaning users search and initiate interactions. Uber represents an example of a platform that applies centralized matching to assign drivers to users looking for a ride. AirBnB, on the other hand, applies decentralized matching by allowing end-users to search for and initiate an interaction with a listed housing post. Importantly, central and decentral curation are mutually exclusive, meaning a platform sponsor applies either or and never both simultaneously (Shi, 2023). **Figure 1.1** displays the logic outlined in this paragraph.

Insert Figure 1.1 here.

1.4.3 A typology of platform configurations

Abstractly speaking, I consider six levers in the hands of the platform sponsor. First, they decide about the openness on both sides (two levers—one on each side, which can be either open or closed) and the complement type of the platform (one lever—either stock or flow complements). Second, following the openness and complement type decision, sponsors have three curation strategies: manual, algorithmic, and centralized or decentralized curation (three levers, with manual and algorithmic curation levers, can be either on or off, while the third lever can be centralized or decentralized). Generally, algorithmic curation is better suited for more extensive user bases due to the availability of more data and the increased difficulty of screening and evaluating all users manually. Manual curation is better suited in the presence of fewer users on both sides, which allows the platform sponsor to guide the market in the desired direction (Rietveld et al., 2021). Centralized curation is best suited when user preferences on both sides are homogenous (Shi, 2023). In the following, I go through all eight possible platform configurations, given my conceptual model. Platform sponsors decide whether individual sides are open or closed and the type of complements (stock or flow). Based on the resulting platform configuration, I discuss the effectiveness of the identified curation strategies. I start by considering stock complements, meaning the interaction timing is less critical.

Stock complements with both sides open. Both sides being open leads to many heterogeneous end-users facing a wide variety of horizontally and vertically differentiated complementary offers. The platform enjoys high market thickness, and network effects materialize based on the number of users on both sides. However, the large user base increases the likelihood of mismatches due to heterogeneous user preferences and the sheer variety of complementary offers, both of which increase search frictions (Cullen & Farronato, 2021; Li & Netessine, 2020). In this scenario, interaction volume is less of an issue than users being satisfied with interactions to ensure they will return to or continue interacting on the platform. Due to the heterogeneity on both sides, decentralized curation is necessary to achieve high match quality (Einav et al., 2016; Shi, 2023). Since it is difficult for the sponsor to accurately match heterogeneous preferences on both sides, it is more effective to let end-users and complementors, who best know their preferences, search and initiate interactions. On top of that, due to the large number of users, algorithmic curation is more effective than manual curation. In summary, in this configuration, the critical interaction volume is easily achieved but difficult to sustain due to frequent mismatches that lead users to stop engaging and potentially leave the platform.

The dating app Tinder represents an example of such a platform. On Tinder, all users are also complementors. Users are encouraged to provide information about their preferences and expectations upon signing up, which forms the basis for Tinder’s suggestion algorithms. However, the depth and detail of this information can vary widely among users. Some may craft detailed profiles with extensive descriptions, while others prefer to let their photos speak for themselves. This variability presents a challenge for Tinder’s algorithms, which must navigate these diverse expressions of user identity to suggest potential matches. The innovative swipe feature is central to Tinder’s matching mechanism, allowing users to express interest (swipe right) or disinterest (swipe left) based on a relatively quick assessment of another’s profile. Users on both sides can initiate transactions. However, a match is only made when both users have swiped right on each other’s profiles, introducing a mutual consent mechanism that is pivotal for initiating contact. This system ensures communication can only commence once both parties have indicated a mutual interest, thereby enhancing the user experience by filtering out unwanted interactions. The effectiveness of this model relies on the algorithmic processing of user preferences, behaviors, and characteristics. Tinder's algorithm has pooled users of similar attractiveness, attempting to limit rejections[7].

Stock complements with demand-side open and supply-side closed. In this scenario, many but less heterogeneous end-users face homogenous complementary offers. When the variety of offers is limited and clearly defined, users who do not find these offers appealing are less likely to join or remain active on the platform. Thus, the user base tends to consist of individuals with similar preferences or needs that align with the offers selected at the gate, leading to a more homogenous group of end-users. The platform enjoys moderate market thickness, and network effects materialize partially based on the number of end-users and partially on the fit between their preferences and the homogenous complementary offers. Subsequently, mismatches are relatively unlikely. Since the complementary offers are homogenous and easy to understand, end-users usually initiate interactions (Shi, 2023). As such, the platform chooses decentralized curation strategies that facilitate interactions by helping end-users in their search process. Adequate curation strategies in this scenario include providing sales rankings, allowing end-users to rate and comment on complementary offers, and selectively promoting best-in-class complements (Rietveld et al., 2019). Selective promotion can occur manually due to the relatively low number of complementors. The platform sponsor tries to satisfy match quality in this scenario since they must balance interaction volume and user engagement.

In its early years, the PC game distribution platform Steam was an example of a platform with an open demand side and a closed supply side, where the complementary offers were games from Valve and a select number of third-party developers. This selective approach resulted in a homogeneous selection of games, closely matching the preferences of

[7] See https://www.theverge.com/2019/3/15/18267772/tinder-elo-score-desirability-algorithm-how-works last accessed 15/04/24

a focused user base (hardcore gamers). Users engaged in the search and discovery process through features like sales rankings, user reviews, and manual curation, including selective promotion of titles on the storefront. These curation strategies facilitated effective matching by highlighting high-quality games and enabling users to make informed decisions. This setup maximized the visibility of selected games and ensured a high-quality user experience, balancing interaction volume with user satisfaction in the platform market.

Stock complements with demand-side closed and supply-side open. In this configuration, a few homogenous end-users join the platform and face many complements. End-users are homogenous since restricted access limits the platform to a specific group of users with similar characteristics or needs, homogenizing the user base. This homogeneity among end-users allows complementors to tailor their offerings more closely to the user group, enhancing the relevance and appeal of the platform's complements while leading to less variety. The platform enjoys moderate market thickness, and network effects materialize partially based on the number of complementary offers and partially on the fit between the offers and homogenous end-user preferences. Mismatches are relatively unlikely, and since end-user preferences are homogenous, complementors engage in search and initiate contact. The platform focuses on the occurrence of interactions by decentrally facilitating complementor search. An adequate curation strategy in this scenario includes allowing complementors to rate end-users based on communication or the time it took to receive payment. Due to the low number of end-users, manual curation of end-users by the platform's editorial team is feasible. The platform sponsor tries to satisfy match quality in this context since they balance interaction volume and user engagement.

Toptal, the elite job network, is an example of such a platform. The platform connects a select group of professionals (the open supply side) with exclusive, often high-profile employers (the closed demand side) who pay for the platform's service. The nature of these portals means that the end-users (employers) are homogenous regarding their high standards and specific requirements for talent. At the same time, the professionals offer a broad range of skills and expertise. On Toptal, employers can screen and initiate contact with promising potential employees. The platform applies a combination of algorithmic curation based on preferences and demographics as well as manual curation of highly competent professionals.

Stock complements with both sides closed. With both platform sides closed, few homogenous end-users face a low variety of complementary offers. The market is thin, and network effects are weak. Mis-matches are highly unlikely, and the platform focuses on scaling interaction volume for indirect network effects to materialize. Subsequently, platform curation aims to facilitate interactions. Manual curation is feasible, and the platform sponsor centrally handles the matching to increase the number of interactions. In this scenario, the platform sponsor minimally focuses on match quality and mainly tries to scale interaction volume.

Stitch Fix is a platform that fits this description, an online personal styling service that only offers products from its partnering clothing brands (complementors). End-users who sign up provide detailed information about their style preferences, sizes, and budget. The platform then uses a combination of algorithmic and human curation to provide a personalized clothing selection for each user, effectively matching them with clothing items without requiring the end-user or the available clothing brands (complementors) to engage in search activities themselves.

1.4.4 The case of flow complements

Flow complements remain (available) on the platform for a limited time. Consequently, the interaction timing is of much greater importance than in the context of stock complements (Halaburda et al., 2018; Janssen et al., 2016; Jovanovic, 1979; Li & Netessine, 2020). Since the end-user and complementor number and heterogeneity will be the same as in the configurations above, I will refrain from repeating them in full. Instead, I focus on how matching strategies change when interaction timing is essential.

Flow complements with both sides open. This configuration is arguably the most demanding for achieving match quality since the platform deals with many heterogeneous users and a wide variety of complements while matching timing is crucial. Subsequently, the right curation strategy involves satisfying interaction value and timing. This scenario calls for decentralized curation by the platform sponsor, which lets both user sides search for and initiate interactions. Additionally, the sponsor needs to gather information about users to apply algorithmic curation to deal with the large number of potential interactions and the need to time them correctly.

TaskRabbit is the closest real-world example. TaskRabbit is a platform that connects individuals seeking to outsource small jobs and tasks with “Taskers” willing to complete them. The platform achieves high match quality through an algorithmic curation system that relies on detailed information from task posters and Taskers, including skills, availability, and location. The platform uses sophisticated algorithms to suggest suitable matches, ensuring tasks are completed efficiently. This system allows TaskRabbit to manage the complexity of matching diverse functions with the appropriate Taskers in real time.

Flow complements with demand-side open and supply-side closed. In this configuration, mismatches are less likely because the homogenous offers attract end-users with specific, immediate needs. This self-selection process leads to a user base that closely aligns with the available complements, reducing the heterogeneity of end-user preferences. Platforms, therefore, focus on facilitating timely interactions by enhancing the visibility of flow complements at critical moments, ensuring end-users can easily find and engage with offers that match their needs. Strategies such as real-time notifications and highlighting urgent or expiring offers help maintain engagement and match quality by aligning end-user search behavior with the availability of complements. Due to the lower number of complementary offers, the sponsor can conduct some curation manually. End-users engage in search and initiate the interaction, while the platform actively curates the discoverability of complements at the right time.

Kickstarter is a fitting real-world example of such a platform. Kickstarter is a crowdfunding platform for creative projects that connects creators offering unique project ideas with a broad audience of potential backers. The platform restricts entry on the supply side by only granting access to projects from creative industries that pass an algorithmic quality screening. The platform sponsor encourages end-users to search and actively select projects to support. At the same time, Kickstarter curates project visibility and timing, ensuring that new and promising projects are discoverable at the right moment. This curation is crucial for aligning the interests of project creators with potential backers and facilitates successful funding campaigns.

Flow complements with demand-side closed and supply-side open. This configuration is similar to the one above. Users are filtered on specific demographics and attract complementors who can serve their needs. Subsequently, the average match quality of any randomly formed match would be relatively high. The platform sponsor allows complementors to search and initiate interactions and can manually curate end-users to match them with complementor preferences. Curation strategies should focus on interaction timing and occurrence while satisfying match quality.

Project-based platforms like Fiverr are examples of this configuration. It provides a platform where freelancers (complementors) offer their services across various categories to a targeted audience of businesses and individuals seeking those services. In this scenario, freelancers can actively search for and respond to specific project requests posted by users, allowing them to initiate interactions based on their skills and availability. Fiverr facilitates these connections by curating user profiles and project listings, ensuring freelancers can quickly discover opportunities matching their expertise.

Flow complements with both sides closed. In this configuration, platform sponsors centrally match users and maximize interaction timing to ensure high interaction volume and user engagement. This can be achieved by collecting information on user preferences, notifying potential interaction partners directly when the potential for an interaction arises, and allowing users to rate their interaction partners. Generally, platforms with flow complements where both sides are relatively closed and need to maximize interaction timing and user engagement are rare due to flow complements requiring real-time or near-real-time interactions. However, specialized professional services or exclusive event ticketing platforms might adopt such strategies to match particular user preferences with available offers, ensuring engagement through direct notifications and comprehensive rating systems.

An example of such a platform is Zocdoc, which operates in the healthcare industry by connecting patients with healthcare providers for appointments. Zocdoc facilitates a scenario where patients (demand side) and healthcare providers (supply side) are relatively closed groups; patients seek specific healthcare services, and providers offer limited appointment slots. The platform focuses on real-time interactions and maintaining user engagement through direct notifications.

Table 1.1 summarizes the typology outlined in this section.

Insert Table 1.1 here.

1.5 AN EVOLUTIONARY PERSPECTIVE ON MATCH QUALITY

So far, I have established that platform configurations do not form randomly. Instead, they are a function of the platform's openness, directly affecting adequate curation strategies for ensuring high match quality. One underlying assumption of my typology of platform configurations is that the sponsor successfully populates both sides so that interactions can occur. However, the number of users, end-user preferences, and complementor variety are not static. Instead, they evolve, necessitating the need to adjust governance accordingly (Rietveld et al., 2020; Wareham et al., 2014). Therefore, I take an evolutionary perspective to explain how platform user compositions change over time. I assume the platform successfully populates both sides over all its life cycle stages. I do not theorize how platforms die.

I start by outlining evolutionary dynamics that hold regardless of the platform configuration. As platforms evolve, they experience an increase in market thickness: initially, they start with a few homogenous users, which makes early matches less complex and curation straightforward. Over time, this user base grows and becomes more heterogeneous, complicating the matching process (Li & Netessine, 2020; Rietveld & Eggers, 2018). Concurrently, the rate at which complementors join the platform accelerates, particularly in the later stages, further increasing the need for nuanced curation strategies (Boudreau, 2012; Boudreau & Jeppesen, 2015). This shift from a homogenous to a heterogeneous user pool and the rapid addition of complementors necessitate evolving and more sophisticated curation approaches to sustain match quality and user satisfaction. Simultaneously, increasing user numbers strengthens the indirect network effect and causes a constant data stream about consumer preferences that the sponsor can use for algorithmic curation (Gregory et al., 2021). This trajectory generally applies to all platform configurations but differs in the extent to which user numbers and their heterogeneity increase. Notably, on an open platform side, many heterogeneous users accumulate much more quickly than on a closed one. The speed at which user numbers and heterogeneity increase affects how long specific curation strategies remain viable. That speed is also affected by the complementor type. On the one hand, stock complements remain on the platform indefinitely, thereby increasing the congestion of the platform. On the other hand, flow complements come and go, which considerately slows down congestion.

Figure 1.2 displays user compositions' evolution dependent on openness and complement type. The number of heterogeneous users joining open platforms grows every period due to network effects, but it stays more constant over time on closed platforms. It further shows how stock complements remain on the platform, whereas some flow complements leave each period. Albeit a simple representation, **Figure 1.2** captures the most essential dynamics affecting user heterogeneity and effective curation strategies.

Insert Figure 1.2 here.

1.5.1 The role of curation in facilitating match quality over time

In the following, I apply an evolutionary perspective to my typology of platform configurations and their effect on the efficacy of curation strategies— manual and algorithmic and central or decentralized curation.

Manual and algorithmic curation. Manual curation by the platform sponsor is most effective when it is feasible to manually screen and evaluate all users on at least one given side. That means the most crucial consideration for the efficacy of manual curation is the number of users per side. Given that the number of users on both sides is limited in the nascent stage of a platform, manual curation proves to be effective early on, regardless of the platform configuration. However, the effectiveness of manual curation over time varies across configurations. If the platform is open on both sides, user numbers grow continuously or exponentially, thereby quickly eroding the feasibility and effectiveness of manual curation.

In a situation where one side is open, and one is closed, manual curation of the open side becomes increasingly less effective. Manual curation of the closed side remains effective for much longer due to the slower increase in user numbers. A configuration where both sides are closed has the slowest user increase over time. Consequently, manual curation remains feasible for both sides for the longest time in this scenario. The more closed a platform configuration is, the longer and more viable manual curation is.

The effectiveness of algorithmic curation relies on the availability of data and the time the platform sponsor and users can learn about user preferences (Bhargava et al., 2020; Dzyabura & Hauser, 2019; Horton, 2017). Regardless of the platform configuration, data availability and the time to learn about preferences increase over time. Conversely, a lack of substantial data renders algorithmic methods less effective in the platform's early stages. However, as user numbers grow, particularly on open platforms, the wealth of data increases rapidly, making algorithmic curation more feasible and effective. Closed platforms accumulate data at a slower pace, delaying the effectiveness of algorithmic curation. Thus, while the scale of data underpins the success of algorithmic curation, the rate at which this scale is achieved varies with the platform's openness. While the effectiveness of algorithmic curation increases regardless of the platform configuration, an open platform on which the number of users grows at higher rates will be able to apply algorithmic curation quicker than a closed platform effectively.

Proposition 1. *The effectiveness of manual (algorithmic) curation for ensuring high match quality decreases (increases) over time.*

Proposition 2. *The more open a platform configuration, the shorter manual curation remains, and the quicker algorithmic curation becomes effective for ensuring high match quality.*

Centralized and decentralized curation. Central curation, meaning the platform sponsor directly matches supply and demand without allowing users to search and initiate transactions, is most effective when user preferences are easily observed (Shi, 2023). Regardless of the platform configuration early in the life cycle, the market is thin, which means users struggle to find interaction partners due to the low absolute number of potential partners. However, they are also more homogenous since they all are early adopters of the specific platform. The platform sponsor, who oversees the whole market and has access to much more information than its participants, will be more effective in matching users. Subsequently, centralized matching ensures higher match quality in this stage and helps to scale interaction volume to kickstart indirect network effects. Centralized matching is less effective if the sides are heterogeneous since it will be difficult for one matchmaker to consider all intricate heterogeneous preferences on both sides. With time, any successful platform becomes more heterogeneous, regardless of its platform configuration, due to the increasing share of late adopters. This process happens quicker when the platform configuration is open.

Decentralized curation means one or both user sides search for and initiate interactions. It is most efficient when users on one platform side are heterogeneous and, therefore, are better off looking for matches themselves (Shi, 2023). Early on, platform users tend to be homogenous but become more heterogeneous over time (Rietveld & Eggers, 2018). Subsequently, decentralized curation strategies become more effective over time, and the more open the platform configuration, the quicker decentralized curation becomes effective.

> ***Proposition 3.*** *The effectiveness of centralized (decentralized) curation for ensuring high match quality decreases (increases) over time.*
>
> ***Proposition 4.*** *The more open a platform configuration, the shorter central curation remains, and the quicker decentral curation becomes effective for ensuring high match quality.*

1.5.2 Closing down and opening up

While the openness decision is central, platform sponsors can change their initial choice later on, which means an open side can be closed down, and a closed side can be opened up. The platform market typology establishes that an open side generally has more heterogeneous users, whereas a closed side has fewer homogenous users. However, the dynamic differs across complementor types. Due to their indefinite presence on the platform, stock complements, on the one hand, enhance market thickness and strengthen network effects. On the other hand, over time, heterogeneous stock complements congest the market and complicate match quality. Subsequently, the importance of effective curation strategies on stock platforms increases. Conversely, flow complements, on the one hand, lead to a thinner market and weaker network effects due to their temporal availability. On the other hand, platforms with flow complements have an easier time ensuring high match quality due to the lack of congestion on the supply side. Considering heterogeneity complicates achieving high match quality for platform sponsors, closing down the supply side to keep match quality at satisfactory levels seems particularly useful for platforms with stock complements. In contrast, opening up will be attractive for flow platforms to benefit from the remaining users on the demand side, who do not share the temporary availability of the platform's complements.

An example of a platform with stock complements that started with an open approach and later decided to close one of its sides is Airbnb.[8] Initially, Airbnb allowed virtually anyone to list their property on the platform, and anyone seeking accommodation could book these spaces. This openness was crucial for Airbnb's rapid growth, as it amassed a vast inventory of unique accommodations worldwide, attracting a broad user base due to strong indirect network effects. As Airbnb grew, the company faced challenges related to trust, safety, and quality control. In response, Airbnb began to implement more stringent measures to close off the supply side of its platform by (1) implementing a verification process for listings requiring professional photographs of the accommodation, (2) establishing higher standards for hosts, including cleanliness, accuracy of listings, and communication responsiveness, (3) requiring hosts to comply with local laws and regulations, including obtaining necessary permits and paying local taxes, and (4) enhancing its safety protocols for both hosts and guests, including a 24/7 support line. These steps represent a strategic decision by Airbnb to close the supply side of its platform to some degree, prioritizing match quality over the sheer volume of listings.

In contrast, opening up helps increase market thickness, network effect strength, and interaction volume, which will be particularly useful for platforms with flow complements. Kickstarter, known for its crowdfunding of creative projects, initially employed strict manual curation to maintain high project quality, carefully selecting projects to ensure they met stringent criteria. Kickstarter transitioned to a more lenient algorithm-based approach to increase market thickness and encourage more interactions, broadening its supply side. This shift allowed more projects to launch on the platform, significantly enhancing its diversity and volume of creative endeavors. Opening up the supply side in such a way significantly

[8] See https://news.airbnb.com/about-me/ and https://news.airbnb.com/an-update-on-my-work-to-empower-hosts-to-deliver-high-quality-stays/ last accessed 02/04/24

increased Kickstarter's interaction volume. Still, it simultaneously decreased the average funding success and the amount of funds raised (Rietveld et al., 2020), which hints at the difficulty of keeping satisfactory match quality on open platforms even in the context of flow complements.

In total, closing down represents an attractive option for a platform with stock complements to counteract congestion, as seen in the example of Airbnb. On the other hand, opening up works better for platforms with flow complements to counteract complements, constantly leaving the market and keeping it thin.

Proposition 5. *Closing down (Opening up) a platform's supply side is more effective for ensuring high match quality in the case of stock (flow) complements.*

In reality, platforms with stock complements are more likely to start out relatively closed and open up over time (Eisenmann et al., 2009; Rietveld et al., 2020). Facebook, for example, started as a tight network famously accessible only to Harvard students and opened up over time by granting access to other Universities before fully opening up the demand side. Similarly, while being ad-free initially, Facebook granted advertisers access to its API over time. Another example is Steam, which started out closed on the supply side by offering only its own video games on the platform. Later in their lifecycle, they opened the platform to third-party providers. Simultaneously, they shifted their initially centralized curation to end-user-led curation and later to fully automated algorithmic curation (Rietveld et al., 2020). However, aligned with the arguments above, opening up their platforms in this way has hurt FaceBook's and Steam's match quality and the platforms as a whole. Both are in decline and struggle to keep their users engaged in the case of FaceBook or keep the quality of their complements at satisfactory levels in the case of Steam.[9]

[9] See https://www.forbes.com/sites/ryanerskine/2018/08/13/study-facebook-engagement-sharply-drops-50-over-last-18-months/ and https://www.ccn.com/valve-quality-control-hot-trash-games/ last accessed 02/04/2024

1.6 DISCUSSION

I explore the balance between openness and curation in multi-sided platforms regarding their effect on match quality. While an open platform leads to a thicker market and stronger network effects, it also contains more heterogeneous users whose preferences are more challenging to match effectively. I develop a comprehensive framework that assesses how openness affects effective curation strategies. I demonstrate that achieving optimal match quality depends on balancing user heterogeneity and interaction volume. I propose that platforms (must) adapt their curation efforts to navigate these challenges. I identify strategies the platform sponsors have at their disposal to curate interactions—manual, algorithmic, central, and decentral curation. Acknowledging that platform configurations evolve, I derive propositions that outline the effectiveness of these curation strategies as functions of user heterogeneity and market thickness.

My theory has its limitations. For example, it fails to say anything about when specific curation strategies in a platform's lifecycle become effective, nor does it allow for the prediction of when platforms will die. Moreover, my framework exclusively considers match quality as an outcome of interest, which might not always be the priority for platform sponsors. Past research even showed that in some situations, platform sponsors are better off purposefully withholding information that would increase match quality to improve profits for complementors and themselves (Dinerstein et al., 2018; Kanoria & Saban, 2021; Liu et al., 2023). Finally, while I explicitly make heterogeneity a central construct of my conceptual framework, actual heterogeneity is much more complex. For example, end-users might be homogenous in their preference for many heterogenous offers. I simplified this reality by only considering horizontal and vertical preference heterogeneity.

I make several contributions, first, to the literature on platform design and strategy (Boudreau, 2010; Parker & Van Alstyne, 2018; Rietveld & Schilling, 2020) by outlining the mechanisms that give rise to diverse platform configurations shaped by end-user heterogeneity and the variety of complements. To my knowledge, I am among the first to take a holistic view of how the decision about platform openness affects the platform market, including user numbers, heterogeneity, and complement type. My framework not only helps to inform adequate curation strategies to achieve high match quality but also informs platform governance to create value more broadly. The platform market typology opens up fertile ground for future research trying to find answers to questions such as: *Which platform configuration is least vulnerable to disintermediation or multi-homing? What is the effect of exclusive or superstar software in different platform configurations? Which configuration is best to defend a dominant market position, and which is best to attack one?* Amongst others.

Second, I contribute to the burgeoning conversation on platform evolution by developing normative theory of adequate curation strategies according to evolving platform configurations (Kyprianou, 2018; Rietveld et al., 2020; Tiwana, 2015a; Wareham et al., 2014). I propose platform sponsors have six levers that affect match quality: (1) supply-side openness, (2) demand-side openness, (3) stock or flow complements, (4) manual, (5) algorithmic, (6) centralized or decentralized curation. Identifying these levers enhances our understanding of platform governance and curation over time by (1) outlining how neglecting one of the levers in empirical analysis can lead to contradicting empirical results (2) showing how the correct position of each lever evolves with the platform configuration. These insights into sustaining high match quality over time are crucial in our understanding to avoid platform failures (Jacobides et al., 2024; Van Alstyne, Gu, & Finger, 2023).

Finally, I contribute to the literature on network effects, especially a recent stream that discusses firms' agency in designing for network effects (Rietveld & Ploog, 2022; Zhou et al., 2021; Zhu et al., 2021). My theory differentiates between network effects—the force that attracts new users to join a platform—and match quality, which is the force that keeps users engaged and, therefore, sustains the network effect. Doing so represents a first step in theoretically disentangling network effects from network strength (Shankar & Bayus, 2003). I provide a theoretical foundation for why not only network size but also keeping users engaged matters (Afuah, 2013; Cennamo & Santaló, 2019; Claussen, Kretschmer, & Mayrhofer, 2013). This insight also has implications for platform competition. Strategically considering match quality might help stay in the market when it becomes evident that dominance based on user numbers is impossible. This approach ensures maximum value from the existing user base. Focusing on match quality over sheer market dominance underscores the importance of creating a sustainable competitive advantage through superior user experiences, thereby retaining a loyal user base and potentially attracting new users who value quality matches over the breadth of options.

I also offer several practical implications for platform sponsors. For once, I outline how focusing on match quality enables platform sponsors to sustain the indirect network effects. Second, my theory implies that manual curation offers platform sponsors the flexibility to steer user behavior toward the platform's strategic goals by rewarding and incentivizing specific actions, fostering a shared purpose among users (Cennamo, 2021; Rietveld et al., 2021). The evolutionary perspective reveals this approach is particularly efficient in the early stages of a platform when the user base is smaller and more homogenous. Over time, as the user base grows and becomes more diverse, manual curation becomes challenging, especially on more open platforms. At this stage, algorithmic curation becomes more suitable due to its ability to handle large volumes of data and complex interactions, although it may offer less control over aligning user behavior with the platform's strategic goals. Put differently, open platforms that rely on strong network effects will experience more inertia in steering their user base than closed platforms on which manual curation remains effective for longer. Third, my findings hint at a significant challenge for platforms with stock complements, such as gaming consoles. In those settings, users often have a continued preference for older, established offers, which can overshadow newer offerings (Rietveld & Eggers, 2018). For example, users purchasing a Nintendo Switch today are still likely to buy older, well-known games like Mario Kart. This preference can create a competitive disadvantage for newer games, potentially leading to a market failure for these late-arriving complements as they struggle to gain traction (Jacobides et al., 2024).

I examined the critical balance between openness and curation in multi-sided platforms, focusing on how these factors affect user diversity and match quality. My theory highlights the pivotal role of match quality in enhancing user engagement and sustaining network effects, contributing to platform governance and network effects literature.

Table 1.1 A Typology of Platform Configurations

Supply-Side	Demand-Side: Open	Demand-Side: Closed
Open	**Stock Complements** Platforms experience high market thickness with diverse users, facing various complementary offers. The sponsor focuses on decentralized, algorithmic curation to navigate high search frictions, emphasizing match quality to sustain user engagement due to the low average quality of random matches. *Example: Tinder*	**Stock Complements** Fewer, more homogenous users encounter a range of heterogeneous complements. The platform facilitates decentralized complementor search, potentially allowing ratings of users to ensure interactions align with user preferences. *Example: Toptal*
	Flow Complements Platforms face the challenge of matching diverse users and complements within tight timing constraints. Given the high curation efforts required, decentralized and algorithmic curation is essential to satisfy interaction value and timing. *Example: Task Rabbit*	**Flow Complements** With the decent quality of random matches, the focus shifts towards facilitating interactions and ensuring timely matches. Complementors take the initiative in interactions. Platforms curate end-user preferences more actively to meet complementor offerings in a timely manner. *Example: Fiverr*
Closed	**Stock Complements** Less heterogeneous users meet homogenous offers with moderate market thickness. Curation strategies support decentralized user searches with features like sales rankings and reviews to facilitate matches, balancing interaction volume with user satisfaction. *Example: Steam*	**Stock Complements** A thin market in which few similar users face a low variety of offers. The focus shifts towards scaling interaction volume, with minimal manual and centralized curation needed to achieve high match quality. *Example: Stitch Fix*
	Flow Complements With less likely mismatches, the focus shifts towards facilitating interactions and ensuring timely matches. Platforms apply decentralized curation and enhance the discoverability of complements, with end-users initiating interactions. *Example: Kickstarter*	**Flow Complements** Maximizing interaction timing becomes critical for engagement and interaction volume. Platforms might need to gather extensive information on preferences and enable algorithmic, direct notifications for potential matches, centrally managing interaction partners and timing. *Example: Zoc Doc*

Figure 1.1 Conceptual Framework

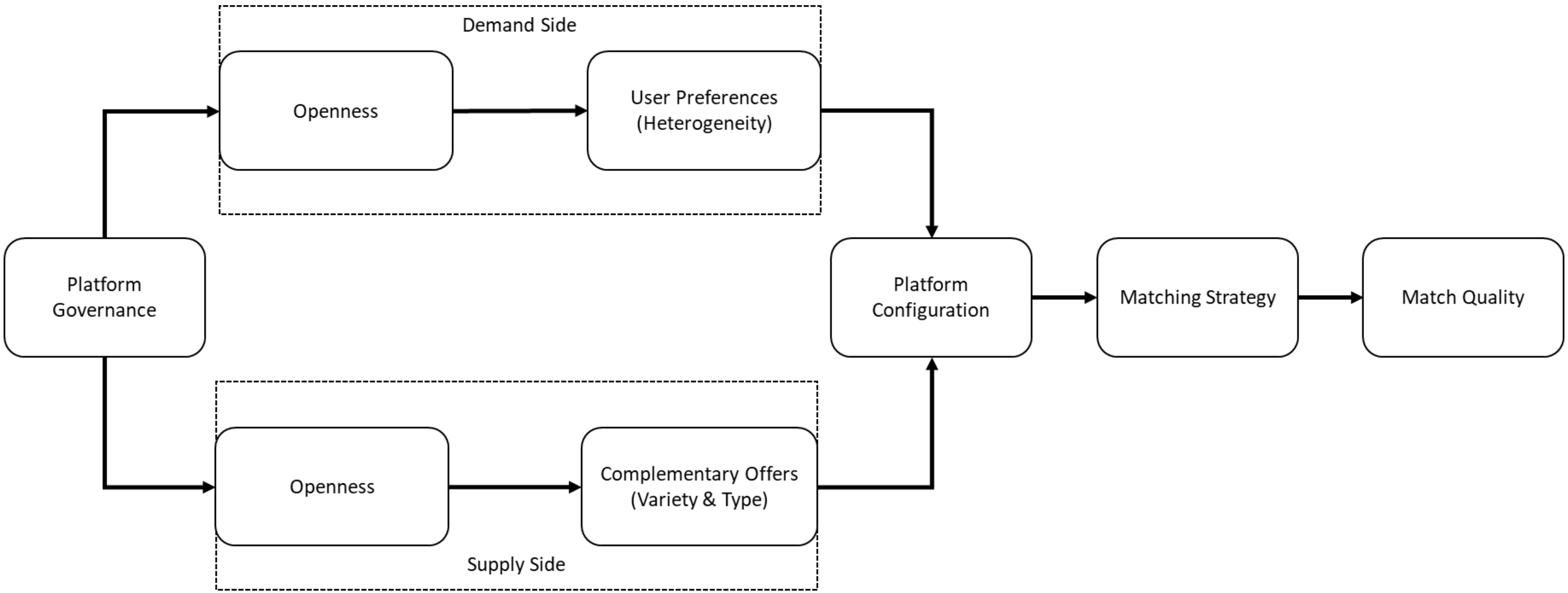
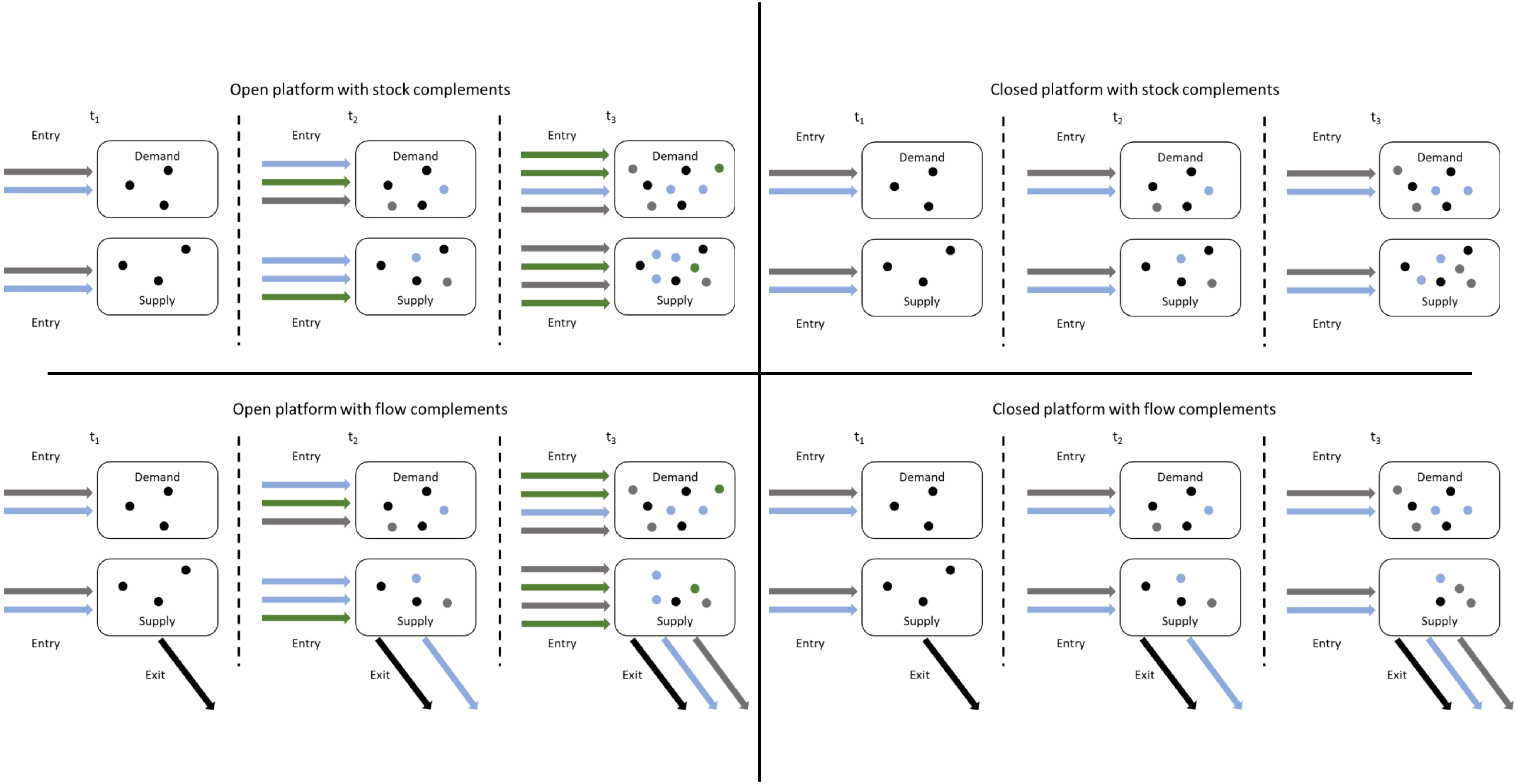


Figure 1.2 User Composition Evolution



2. CHAPTER 2

ROLLING THE DICE: RESOLVING DEMAND UNCERTAINTY IN MARKETS WITH PARTIAL NETWORK EFFECTS[10]

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[10] This chapter is based on a paper with the same title coauthored with Joost Rietveld. We submitted the paper to *The Academy of Management Journal* on 09/02/23 where it was accepted after three rounds of revisions on 01/05/24.

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3. ON TOP OF THE GAME? THE DOUBLE-EDGED SWORD OF INCORPORATING SOCIAL FEATURES INTO FREEMIUM PRODUCTS[25]

3.1 RESEARCH SUMMARY

Freemium products require widespread diffusion for their success. One way to do this is by incorporating social features (e.g., multiplayer functionality, virtual collaboration, ridesharing), which can generate network effects and result in a product becoming a *superstar*. However, social features can be a double-edged sword: When demand potential for freemium products is large, social features can significantly boost a product's appeal resulting in more adoption, more usage, and more in-app purchases; but when demand potential is constrained, network effects might fall short and users may feel they are missing out on key aspects of the product. I test this on a sample of 9,700 games on Steam. Findings contribute to our understanding of network effects, freemium strategies, and superstar products in platform markets.

3.2 MANAGERIAL SUMMARY

Freemium has become a popular business model among firms competing on digital platforms. Freemium products require widespread diffusion because most consumers do not pay for premium upgrades. One way to stimulate a product's diffusion is by incorporating social features (e.g., multiplayer functionality, virtual collaboration, ridesharing). Social features can boost a product's appeal resulting in more adoption, more usage, and more in-app purchases. My analysis of 9,700 digital PC games on Steam reveals that the efficacy of incorporating social

[25] This chapter is based on a paper with the same title coauthored with Joost Rietveld. We submitted the paper to *Management Science* and *Informations System Research* prior to submitting it to *Strategic Management Journal* where it was published online after three rounds of revisions on 18/11/2021. It appeared in print in June 2022.

features importantly depends on the number of users on the platform itself. Social features can help freemium products become a *superstar* when the platform's installed base is large, but they hinder a freemium product's success when the platform's installed base is small.

3.3 INTRODUCTION

The freemium business model—where a firm offers a base product for free and users can pay for premium content and features after they have adopted the base product—has gained widespread popularity on digital platforms (Rietveld, 2018; Tidhar & Eisenhardt, 2020). The share of freemium apps on Apple's App Store, for example, increased from 25% of all apps in 2009 to over 75% in 2018. Freemium's popularity is further signified by a handful of extremely successful products, including the telecommunications program *Skype* and the online dating application *Tinder*. Users can download and use these products free of charge and have the option to make in-app purchases, including Skype's credit for making calls to mobile phones and landlines and Tinder's Super Likes for signaling interest to romantic partners.

Freemium products require widespread diffusion for their success: Only a small portion of freemium users spends money on premium upgrades, and there exists substantial variation in the amount paying users spend. Freemium products must thus attract a disproportionately large user base compared to paid products to generate revenues and capture value.

Firms that operate the freemium business model therefore need to devise strategies to maximize their products' diffusion. One such strategy is to incorporate social product features, such as multiplayer functionality in video games, virtual collaboration tools in productivity software, and carpooling in ride-hailing applications. Social features can enhance social referral and stimulate a product's diffusion by adding network functionality to a product's standalone functionality (Cabral et al., 1999; Lee & O'Connor, 2003). Products that incorporate social features—*and which also manage to attract a large user base*—generate network effects (Aral & Walker, 2011; Dou et al., 2013). Freemium's low barriers to adoption paired with strong network effects from social features can create a virtuous cycle resulting in a product's widespread diffusion, which may ultimately lead to a product becoming a "superstar" (Parakhonyak & Vikander, 2019; Shi, Zhang, & Srinivasan, 2019).

Incorporating social product features, however, could be a double-edged sword. When demand potential for freemium products is large (Lilien & Yoon, 1990), social features can indeed significantly boost a product's appeal, resulting in more adoption, more usage, and more in-app purchases. On the other hand, when demand potential for freemium products is constrained—because, for example, a product is launched on a platform with a small installed base—network effects likely fall short and users may feel they are missing out on key aspects of the product. In this case, users derive more benefits from products that are less reliant on network functionality and focus more on standalone functionality. Thus, social product features raise the stakes: They might both increase and decrease the chances of a product becoming a superstar. Given the uncertain results of incorporating social features, I ask: *How and when do social product features affect the likelihood of a freemium product becoming a superstar?*

I explore this question by analyzing a sample of 9,700 products released between 2011 and 2016 on Steam; the market-leading distribution platform for digital PC games. Freemium—or, free-to-play—and paid games compete side-by-side on Steam. Free-to-play games generate revenues exclusively from in-app purchases (e.g., cosmetic enhancements, additional content, etc.) and represent about 10% of all observations. Social product features include whether a game can be played jointly by multiple players simultaneously (e.g., online multiplayer, local cooperative play, cross-platform multiplayer). A game's demand potential is defined by the number of registered users on Steam—the platform's installed base—at the time of release. After controlling for a firm's decision to operate the freemium business model and the timing of a game's market launch, I find support for my arguments: When the platform's installed base is large, free-to-play games with many social features have a 49 percentage points higher probability of becoming a superstar than free-to-play games without any social features, whereas when the platform's installed base is small, free-to-play games with many social features have a 26 percentage points lower probability of becoming a superstar.

I further argue and find that the mixed effects of incorporating social features and a product's demand potential on becoming a superstar are specific to freemium products (i.e., do not apply to paid products). Freemium products enjoy stronger social referral than paid products because consumers are more inclined to recommend products that exhibit low risks to adoption, such as those that are free (Bond, He, & Wen, 2019; Lin, Zhang, & Tan, 2019). Freemium products additionally have different use dynamics than paid products. Paid products exhibit strong lock-in mechanisms given that paying consumers "want to get their money's worth". This means that freemium products will diffuse more quickly, but also that freemium users are less engaged than paying users (Bapna, Ramaprasad, & Umyarov, 2018; Rietveld, 2018). Taken together, these considerations suggest that the effect of a product's demand potential on generating network effects from social features is stronger for freemium products.

My study aims to make three contributions. First, I offer two important insights about network effects. One of these insights—which requires relaxing the common assumption that network effects are a market-level construct (e.g., McIntyre and Srinivasan, 2017; Schilling, 2002; Suarez, 2004; Zhu and Iansiti, 2012)—is that firms can add network functionality to their products by incorporating social features (also see: Aral and Walker, 2011; Dou et al., 2013). Competing products might thus vary in strength of network effects as a function of their user base *and* their design features (Shankar and Bayus, 2003). The other insight is that social features are not unequivocally associated with a product's superior performance. When a product's demand potential is limited, firms will, in fact, decrease their chances of becoming a superstar if they overly depend on network functionality. Combined, these insights imply that firms must think strategically about network effects: Products can be designed to have stronger or weaker network effects, but the efficacy of these choices depends on external factors.

Second, I show how and when freemium products can take advantage from network effects. I document that incorporating social features to boost a freemium product's diffusion is especially effective on platforms with a larger installed base, while it is detrimental on platforms with a smaller installed base. By doing so, I contribute to our understanding of when the freemium business model works (Kumar, 2014), and how freemium strategies differ from strategies for paid products (Bapna et al., 2018; Bond et al., 2019; Eckhardt, 2016; Lee & Csaszar, 2020; Pauwels & Weiss, 2008; Rietveld, 2018; Shi et al., 2019; Tidhar & Eisenhardt, 2020).[26] My research relates to work by Boudreau, Jeppesen, and Miric (2020), who study how a change in market-level network effects impacts the performance of freemium versus paid market leaders. I

[26] Related literatures in marketing and information systems look at feature-limited software applications that act as a free trial or sampling instrument for paid software applications. These literatures study whether offering a free trial version benefits the paid application, and what makes this more effective or less (e.g., Arora, ter Hofstede, and Mahajan, 2017; Cheng and Liu, 2012; Gu, Kannan, and Ma, 2018; Lee, Zhang, and Wedel, 2021).

complement their work by identifying product design features as an important—and strategic—predictor of which freemium products become market leaders.

Third, I add to a growing literature on superstar products in platform settings. Superstars are the very best-performing products which enjoy exponentially superior performance (e.g., downloads or revenues) compared to the products they compete with (e.g., Benner & Waldfogel, 2020; Brynjolfsson, Hu, & Smith, 2010; Rosen, 1981).[27] Scholars are increasingly interested in superstar products given their important role in digital platforms, both as drivers of an ecosystem's overall value (Binken & Stremersch, 2009; Gretz et al., 2019; Yin et al., 2014) and as drivers of value for products' commercializing firms (Cox, 2014; Yin et al., 2014). I propose a novel measure for operationalizing superstar products in platform markets that accounts for variation in a product's demand potential and for the extent of competition a product faces.

3.4 THEORETICAL BACKGORUND

3.4.1 Freemium and Social Product Features

Facilitated by the Internet, the freemium business model has gained widespread popularity among firms competing on digital platforms including mobile app stores and video game consoles.[28] Freemium departs from the traditional paid model by introducing novel transaction structures and novel transaction content (Amit & Zott, 2001; Rietveld, 2018). First, instead of offering a bundled product, freemium products offer users a menu of paid items in the form of

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[27] The literature has referred to such products interchangeably as "superstars", "blockbusters", and "killer apps". I follow the predominant convention by using the term superstars (see Appendix 3A for a review).

[28] The term "freemium" was coined in 2006 by Fred Wilson, who used it to describe a novel business model where firms "Give your service away for free, possibly ad supported but maybe not, acquire a lot of customers very efficiently through word of mouth, referral networks, organic search marketing, etc, then offer premium priced value added services or an enhanced version of your service to your customer base." See: https://avc.com/2006/03/my_favorite_bus/; https://avc.com/2006/03/the_freemium_bu/ (accessed February, 2021)

in-app purchases (*product bundle decomposition*). In the freemium video game *Fortnite*, for example, players can purchase cosmetic items such as virtual clothing and accessories for their avatars as well as unlock entire game modes through in-app purchases. Second, users can download and perpetually use freemium products before making any in-app purchases (*temporal decoupling*). For example, *Fortnite* players can play the base game for as long as they want before potentially committing to any of its premium content. Firms operating the freemium model must therefore develop distinct capabilities in such areas as user engagement, data analytics, price menu design, and product life cycle management (Kumar, 2014; Lee and Csaszar, 2020; Tidhar and Eisenhardt, 2020). That is, the activities required for successfully developing and commercializing freemium products are distinct from paid products.

There are three main reasons why freemium products require more widespread diffusion than paid products to generate revenues and capture value. First, because freemium products can be adopted free of charge, the user base of freemium products is characterized by substantial demand heterogeneity. A lack of adoption barriers entices users with a wide range of willingness-to-pay to download and use freemium products. Second, product bundle decomposition allows heterogeneous users to mix-and-match a combination of premium items that closely reflects their willingness-to-pay. This implies that the majority of freemium users will spend very little—if anything—on in-app purchases while a fraction of avid users (so-called 'whales') spends large amounts on freemium products. In the video game industry, for example, it is well-known that between two and five percent of a freemium game's player base spends money on in-app purchases (Luton, 2013; Seufert, 2013). Third, temporally decoupling a product's use from optional payments for premium content or features negatively impacts users' perception of value

(Datta, Foubert, & van Heerde, 2015; Gourville & Soman, 1998). Put differently, keeping all else equal, users are willing to pay more for the same product bundle when it is commercialized with a paid business model than a freemium business model.

To overcome these challenges and stimulate a product's diffusion, firms often incorporate social features into freemium products. Social product features enable user interactions, which, when present, generate value in use. These features range from multiplayer functionality in video games to online collaborative tools in productivity software and carpooling functionality in ride-hailing apps. In *Fortnite*'s Battle Royale mode, for example, up to one hundred players can play both cooperatively and competitively to accomplish a common objective (e.g., be the last players standing). If a product manages to attract a large user base, social features add network value to a product's standalone value (Cabral et al. 1999; Lee and O'Connor, 2003). Such products generate network effects, where a user's benefits increase with the total number of users of the same product (Farrell and Saloner, 1986; Katz and Shapiro, 1985). Products that exhibit strong network effects have increased chances of becoming a superstar (Cennamo and Santalo, 2013; Shankar and Bayus, 2003; Suarez, 2004). Indeed, the network effects literature has long asserted that a single product or technology can end up dominating an entire market in the presence of network effects.

Incorporating social product features is particularly beneficial for freemium products, because freemium products enjoy stronger social referral through word-of-mouth than paid products (Cheng & Liu, 2012; Shi et al., 2019). Consumers are more inclined to recommend products that exhibit low risks to adoption, such as those products that are free to use, and they are also more likely to reciprocate any benefits that they receive for free by endorsing a firm's products (Bond et al., 2019; Lin et al., 2019). In sum, freemium products are advantageously positioned to generate network effects by incorporating social product features because they enjoy lower barriers to adoption and stronger social referral compared to paid products.

3.5 HYPOTHESES

3.5.1 The Mixed Effects of Incorporating Social Features on Becoming a Superstar

Superstars are the top-performing products in a market, which enjoy exponentially superior performance—often expressed in terms of downloads or revenues—compared to the products they compete with (Rosen, 1981). Superstar products are highly salient in digital platforms where the distribution of performance (at the market level) tends to be skewed (Benner and Waldfogel, 2020; Brynjolfsson et al., 2010). These contexts are characterized by marked differences between the performance of the few products ranked at the very top of the market (i.e., superstars) and of the numerous products at lower performance ranks (i.e., the long tail).

Social product features can help freemium products become a superstar by setting in motion a self-reinforcing network effect. It should be noted, however, that network effects fail to materialize in the absence of a large user base. That is, a product's network value, or the network externalities it generates, is a function of its social features *and* the size of its active user base (Shankar and Bayus, 2003). Given that products on digital platforms can only be adopted by those users who have first adopted the platform itself (i.e., the platform's installed base), I argue that freemium products will be more likely to benefit from incorporating social features when they are launched on a platform with a large (rather than a small) installed base.

Products launched on a platform with a small installed base are constrained in their demand potential (Lilien and Yoon, 1990), whereas products launched on a platform with a large installed base can potentially reach a much wider audience (Rietveld and Eggers, 2018). Even though all products launched at the same time can be offered to an equisized installed base, the extent of a product's value creation through social features will be greater the larger the platform's installed base. That is, the likelihood of a product becoming a superstar from incorporating social features will be higher when the product's demand potential is larger.

Consider the stylized example of a consumer who is deciding between two products—one that relies exclusively on network functionality for its value proposition (i.e., many social features) and another that relies exclusively on standalone functionality (i.e., no social features). If the consumer is the only one that has adopted the platform these products are launched on (i.e., the platform has an installed base of one), she will anticipate no benefits from social features. In this case, the consumer will be more inclined to adopt the product without social features, anticipating (greater) benefits. When the consumer considers the same two products but this time on a platform that has been adopted by other users (i.e., it has an installed base greater than one), she may expect to derive some benefits from the product's social features. This is true even if she does not know the exact size of the product's user base, given that consumers often *anticipate* the size of a product's user base in the presence of network effects (e.g., Farrell and Saloner, 1986; Parakhonyak and Vikander, 2019; Schilling, 2003).

Note that my stylized example holds even when I allow a product to offer any combination of standalone functionality and network functionality, so long as there is some (either perceived or actual) tradeoff between a firm's investments in standalone functionality and its investments in social features. In the aggregate, it is intuitive that a product's demand potential can hinder or help a product's market performance if it relies on network functionality for its value proposition: When a product's demand potential is large, consumers may anticipate the product to have a larger user base, which makes the inclusion of social features valuable to some extent. When a product's demand potential is constrained, however, consumers will anticipate a smaller user base, which makes the inclusion of social features less beneficial or even detrimental to the extent that it compromises the product's value proposition.

Social features therefore can be a double-edged sword: If firms are to fully exploit the benefits conferred by the freemium business model, they must carefully consider their products' demand potential. On the one hand, when a platform has a small installed base, freemium products have limited potential to create value from social features. In this case, users will anticipate greater benefits from those products that fully depend on standalone functionality, which will offer benefits in the absence of a (large) user base. On the other hand, when a platform does boast a large installed base, freemium products will be in an opportune position to take advantage from network functionality. In this case, users will derive greater benefits from freemium products that incorporate social features than from those that do not. The combination of freemium's social referral *and* potentially strong network effects generated by social features can boost a product's diffusion to the point where it becomes a superstar:[29]

[29] I do not hypothesize about the main effect of incorporating social features because I do not expect a main effect given the strong contingency of a freemium product's demand potential on becoming a superstar.

Hypothesis 1: *Platform installed base size moderates the effect of incorporating social features on becoming a superstar, such that freemium products with many social features will be more likely to become a superstar when the platform's installed base is large.*

3.5.2 Freemium vs. Paid Superstars

There are two reasons why this dynamic is specific to freemium products (i.e., does not apply to paid products). First, the potential benefits of a large demand potential are more pronounced. Low barriers to adoption and strong social referral allow freemium products to diffuse more quickly and more widely than paid products. A product that incorporates social features, has low barriers to adoption *and* strong social referral can quickly capture a large share of the market (Cheng and Liu, 2012; Shi et al., 2019). This happened, for instance, with the free-to-play game *Dota 2*. Released in 2013 by publisher Valve, *Dota 2* quickly became the all-time most downloaded game on Steam with over 112 million downloads. *Dota 2* was highly rated among gamers and its online multiplayer and cooperative play modes generated strong network effects, which set in motion a virtuous cycle further amplifying the game's popularity.

Second, there exist qualitative differences between how freemium and paid products are used. First, given that consumers must spend money before they can use a paid product, only those users who *ex ante* anticipate sufficient benefits will adopt a given paid product (Rietveld, 2018). Second, upfront payments for paid products create a sunk-cost effect wherein consumers want to "get their money's worth" (Arkes & Blumer, 1985; Staw, 1976). Paying users will thus be more committed to fully experiencing all of a product's benefits (Bapna et al., 2018). Finally, users perceive comparatively greater benefits from paid products given that paid products' payment and use are conjoined—instead of temporally decoupled (Datta et al., 2015; Gourville and Soman, 1998). Combined, these differences suggest that use rates will be significantly higher for paid products than for freemium products. It also suggests that consumers will be less inclined to adopt paid products solely on the basis of social referral.

Taken together, these differences between paying users and freemium users suggest that paid products diffuse less quickly, but also that paying users are more engaged than freemium users. The strength of paid products' network effects therefore will depend less on the size of their user base than on the (larger) amount of time paying users spend consuming these products. That is, paid products' higher average use rates will render the platform's installed base size less of a contingent factor in creating value from social features:

> ***Hypothesis 2:*** *The interaction between platform installed base size and a product's social features on becoming a superstar is specific to freemium products; it will not apply to paid products.*

3.6 DATA SAMPLE AND MEASURE

I test my hypotheses in the context of Steam, the market-leading platform for digitally distributed PC games for the Windows, Mac, and Linux operating systems. Steam was created in 2003 by game publisher Valve as a platform initially for the maintenance and distribution of its internally developed PC games *Counterstrike* and *Half-Life 2*. Shortly after Steam was launched, however, Valve recognized an opportunity as the PC gaming industry underwent a resurgence and started developing tools to facilitate third-party game developers in offering their products on the platform. The first externally developed PC games on Steam were released in 2005, and the number of games has grown exponentially since. By 2016, Steam listed over 10,000 games—the vast majority of which (>99%) were released by external developers.

Developers that wish to release their games on Steam must design their software to be compatible with Steamworks, Valve's proprietary software development kit (SDK). In 2011, Valve added the in-game purchasing application programing interface (API) to Steamworks, allowing developers to forgo charging an upfront fee for their games and monetize in-game components. The introduction of this API enabled the freemium business model on Steam. Free-to-play games quickly followed and have been among the most successful games on the platform since. Examples of popular free-to-play games include *Dota 2* (Valve, 2013), *Paladins* (Hi-Rez Studios, 2016), and *Heroes and Generals* (Reto-Moto, 2016). These games have all been downloaded more than 10 million times and generate revenues from in-game purchases.

3.6.1 Data

Data were collected primarily from two sources. First, I collected game-level downloads data for every game released between 2005 and 2017 from Steam Spy, an online analytics service that uses Valve's web-based API. Every minute, Steam Spy culls from the API a random sample of user profiles and obtains lists of games these users own. Linking this information to the number of registered users, Steam Spy extrapolates ownership statistics for each game. Although Steam Spy provides estimates rather than exact downloads statistics, game developers were not allowed to publicly disclose these figures and the industry has largely relied on Steam Spy for accessing Steam performance data. Steam Spy's margin of error is less than 10%, and game developers regularly confirm the accuracy of Steam Spy's estimates for their games.[30] In addition to

[30] See, for example: https://www.pcgamesn.com/steam/steam-spy-accuracy-developers (accessed March, 2021) I note that since I collected our data, Valve implemented a number of important changes to its API (in April, 2018), and also updated its terms for developers (in November, 2018). As a result of these changes, developers may now disclose downloads data. Furthermore, citing GDPR legislation, Valve restricted its API functionality, which has significantly reduced the accuracy of Steam Spy's downloads estimates after November 2018.

downloads statistics, I also collected data on games' release dates, whether games are free-to-play or paid, and games' publishers. I further collected data on the number of registered Steam users for every year that I observe data in my sample.

My second data source is Valve's public web-based API. Using web scraping techniques, I requested game-level data on various aspects directly from Steam. These data include the type and number of social features embedded in a game (discussed below), a game's genre(s), the type of publisher and its prior experience on Steam, and several technical elements such as system requirements and usage statistics that I use for robustness checks.

The Steam Spy data also contain information on game quality as curated by Metacritic.com. Metacritic is a publicly accessible expert review database that collects, combines, weighs, and transforms expert review scores from over 180 online and offline publications (at the time of data collection). For each game, Metacritic publishes a so-called Metascore, which reflects a weighted average of all expert review scores, ranging from 0 to 100 (100 indicating a perfect score). Metacritic assigns different colors to its Metascores to distinguish between "good" Metascores (green; ranging from 75 to 100), "average" Metascores (orange; ranging from 50 to 74), and "bad" Metascores (red; scores below 50). Metascores are a good proxy for game quality given the aggregated and independent nature of these data.

3.6.2 Estimation Sample

I start my estimation sample by considering all games released on Steam from 2011 to 2016. I begin the sample in 2011 when Valve introduced the in-game purchasing API, and I end the sample in 2016 to allow all games at least one year to accumulate downloads. I exclude 142 observations that are non-game software (mostly software development tools), 119 observations for which I do not observe any information at the publisher level, and 514 observations that are compilations, demo versions, add-on packages released as standalone products, or games that were removed from Steam after my data collection period. My final sample for analysis includes 9,700 games, of which 771 games operate the freemium model.

Insert Table 3.1 about here.

Table 1 provides an overview for some of the key measures in my estimation sample. The distribution of downloads is heavily skewed as superstar games (defined below) generate on average 2.6 million cumulative downloads per game whereas non-superstar games generate 107 thousand downloads per game. The asymmetry in downloads between superstars and non-superstars has widened over time.[31] The share of free-to-play games also grew during my study time-period from 0.05 in 2011 to 0.10 in 2016. The share of superstars within the subsample of free-to-play games is 0.16. The number of social features per game (defined below) declined. In 2011, free-to-play games had an average of 1.58 social features, whereas in 2016 this had declined to 0.81 social features. I observe a similar trend for paid games. Further exploration of the data suggests that this decline is largely driven by a slight absolute decrease in games incorporating local multiplayer functionality and by an increase of low-quality games entering the platform without any social features. I control for these trends through my identification strategy and my various robustness checks. Steam's installed base grew exponentially from more than 38 million registered users in 2011 to nearly 223 million registered users in 2016.

[31] Downloads for superstar games in 2013 are distorted by the release of Valve's *Dota 2*, the all-time most downloaded (free-to-play) game on Steam with more than 112 million downloads.

3.6.3 Variable Definitions

Dependent variable. I follow prior studies on superstar products in platform markets by applying a performance-based cutoff to distinguish superstar products from non-superstar products (Binken & Stremersch, 2009; Cox, 2014; Ershov, 2020; Gretz et al., 2019; Lee, 2013; Sun, Rajiv, & Chu, 2016; Yin et al., 2014). In deciding on an appropriate cutoff value, however, the researcher faces at least three challenges. First, products face different levels of competition at different points in a platform's life. A product released at the start of a platform's life might face only a handful of relevant competitors, whereas a product released towards the end of a platform's life may face thousands (Boudreau, 2012). The same applies to a product's demand potential (i.e., the installed base): Users may be reluctant to adopt a new platform when it first launches, whereas once a platform establishes itself as the dominant design, it may command a large share of the overall consumer base in a market (Boudreau and Jeppesen, 2015). Second, the distribution of demand changes over time such that the gap between the top- and bottom-performing products widens as a platform matures (Rietveld et al., 2020; Rietveld & Eggers, 2018). Last, there often exists variation in the amount of time products can accumulate performance—especially when analyzing cross-sectional product-level data. This implies that a product's performance as observed by the researcher will be highly contextual.[32]

I aim to address these challenges by creating a standardized measure of a game's download performance based on the subsample of all games released in the same year as a focal game. I treat each year as a separate market and calculate a game's z-score such that:

[32] My review of the literature suggests that not all prior studies have fully considered these challenges (see Appendix 3A).

$$z_i = \frac{x_i - \overline{x}_t}{S_t}$$

where z_i represents game i's standardized performance as a function of the difference between its own cumulative downloads (x_i) and the mean cumulative downloads of those games released in the same year t as game i ($\overline{x}_t$), divided by the standard deviation of all games released in the same year t as game i (S_t). A game's z-score is contingent on a subset of games that were released around the same time and thus face similar conditions in terms of installed base size and competition dynamics. Nevertheless, because z-scores are standardized, I can meaningfully compare the z-score of a game released in 2016 to one released in 2011.

Next, I determine a game's status as a superstar by applying the following cutoff:

$$Superstar_i = \begin{cases} 1, & z_i \geq 1 \\ 0, & z_i < 1 \end{cases}$$

where the variable *superstar* takes the value of 1 if game i has a z-score (z_i) equal to or greater than 1, and 0 otherwise. It should be noted that games' downloads are not normally distributed and that a z-score of 1 does not correspond with the standard normal cumulative density function (see Appendix 3B). Rather, 3.58% of all games are coded superstars (n=347). This proportion is consistent with prior work on superstar products in platform markets (e.g., Gretz et al., 2019; Lee, 2013; Sun et al., 2016). Furthermore, research on breakthrough innovations and blockbuster products such as patents and drugs either found or applied similar thresholds to denote outlier performance (e.g., Kaplan & Vakili, 2015; Kneeland et al., 2020). My measure for superstar products thus is generally representative, while also giving me sufficient power for statistical analysis. I assess the sensitivity of my results by estimating various alternative measures in the Robustness Tests section.

Independent variables. First, *social features* measures the extent that a game can be played by more than one player simultaneously. Some games on Steam are designed exclusively for single-player experiences whereas others provide multiplayer functionality. Among multiplayer games, three further distinctions are worth mentioning. First, the potential pool of players for any multiplayer game depends on the type of connectivity a game offers, which can be either local—between players using the same computer or those connected via a local area network (LAN)—or online. Second, games differ in whether multiplayer functionality is meant to be cooperative, competitive, or a combination of the two. Finally, while most multiplayer games can only be played by players on the same operating system, some can be played across operating systems, and sometimes even on different platforms altogether (e.g., PlayStation 3, Xbox 360). These three dimensions of multiplayer functionality are independent of one another; developers can vary each dimension as they see fit.

I collected data on whether a game includes any of the following social features at launch: local cooperative play, online cooperative play, local competitive play, online competitive play, and cross-platform multiplayer. Table 2 provides distributions from my sample, broken out by free-to-play and paid games. While all features are equally present across both subsamples, free-to-play games, on average, have a higher number of multiplayer modes. I measure a game's social features by counting the number of multiplayer modes it offers.[33] The

[33] I abstain from weighting the different multiplayer modes since I do not observe the exact number of players a multiplayer mode can accommodate. Moreover, prior research on network structure found that users often exhibit local bias, suggesting that network effects are stronger when users have stronger ties to each other (Afuah, 2013; Lee, Lee, and Lee, 2006; Suarez, 2005). Players that play together locally likely will have stronger ties than players that play together in an online setting. Additionally, while local multiplayer on the same computer will involve a limited number of players, the same does not necessarily hold for local multiplayer via LANs, which Steam lumps into a single category. Finally, cooperative play is not by definition restricted to two players only, and can, in fact, include coordination between large groups of players in online settings.

assumption is that games offer greater network functionality when they provide more ways for users to play together via different multiplayer modes. My results are robust to various alternative measurements, including a dummy variable indicating whether a game has any social features as well as excluding local multiplayer from the count-based measure.

Insert Table 3.2 about here.

Second, since I observe data from one platform only, I exploit temporal variation in genre popularity to construct a measure of installed base size at the genre-year level. Specifically, for each year in my data I calculate a genre's market share by dividing the sum of downloads for all games released in a genre by the sum of downloads for all games released that year. I then multiply these market shares by the number of yearly new Steam adopters (in millions) to arrive at a measure of *genre installed base*. Thus, for each year in my data, I observe the number of new platform adopters per genre based on a genre's relative popularity. Since there is extensive research showing that the number of (superstar) products positively impacts the diffusion of the platform itself (e.g., Binken and Stremersch, 2009; Clements and Ohashi, 2005), I lag my measure by one year to avoid issues of reverse causality.

I chose to calculate *genre installed base* using yearly new platform adoption and yearly genre market shares (as opposed to cumulative statistics) for two main reasons. First, there exists significant variation in terms of which genres are popular at different times (also see: Ozalp & Kretschmer, 2019). Second, cumulative installed base measures tend to overstate a product's demand potential given that users adopt most products shortly after joining a platform (Nair, Chintagunta, & Dube, 2004; Tellis et al., 2009). That said, my results are fully robust to using a measure that is based on cumulative statistics as well as to using measures based on platform-wide new adoption and Steam's cumulative installed base.

For H1 to be supported, I expect the interaction between *social features* and *genre installed base* to be positive for the subsample of free-to-play games. For H2 to be supported, I expect the interaction between *social features* and *genre installed base* to have a stronger positive effect on free-to-play games than paid games, for which I expect no effect.

Control variables. I include several control variables at the platform, publisher, and game levels. Though the overall effect of competitive crowding in multisided platforms is ambiguous given the positive spillover effect of product variety on platform diffusion (Parker and Van Alstyne, 2005), it is well-established that entry by similar products can have a negative effect on the performance of a focal product (Boudreau, 2012)—especially when rivals enter the platform around the same time (Rietveld and Eggers, 2018). I therefore control for competitive crowding by including the variable *genre competition*. For each game i, *genre competition* counts the number of newly released games within the same genre(s) as game i, from 30 days before to 30 days after the game's release, divided by the number of genres game i lists on Steam. I apply this timeframe because games typically have very short lifecycles and generate the bulk of their downloads and revenues shortly after release (Nair, 2007). This measure can be interpreted as the mean competition a game faces across all genres it competes in; I expect it to have a negative effect on the probability of becoming a superstar.

I include two measures to account for heterogeneous capabilities and resources at the publisher level. First, I control for publisher type by including the variable *indie publisher*. The industry broadly distinguishes between two types of publishers. Independent—or *indie*—

publishers are smaller in size, focus their development efforts on creative and innovative output, and tend to have less (financial) resources. Incumbent publishers, on the other hand, are larger, focus on exploiting established intellectual properties, and are typically flush with resources, financial and otherwise (also see: Benner & Waldfogel, 2016). The variable *indie publisher* takes the value of 1 for games by indie publishers and 0 for games by incumbent publishers. Second, I control for publishers' prior experience on Steam. Not all publishers embraced Steam when it was first launched, whereas others are Steam specialists. The variable *past releases publisher* counts the number of games a publisher launched on Steam over a rolling window of five years dating back from a focal game's release. I chose a rolling window rather than publishers' cumulative experience because prior experience may become obsolete due to the dynamic and evolving nature of the platform. I log-transform the measure to account for the skew in my data. I expect *indie publisher* to have a negative effect on the probability of becoming a superstar and *past releases publisher* to have a positive effect.

Finally, I control for several game-level factors. First, I control for game quality by including Metacritic's Metascore in my models. I distinguish between games with good Metascores, games with average Metascores, and games with bad Metascores. I include Metacritic's review classification as a vector of dummies and omit as the base category games with bad Metascores and games with missing review scores, the latter of which typically denotes very poor quality. I thus expect both included dummies to have a positive effect on the probability of becoming a superstar. Second, I control for a game's listed genres given that players often have heterogeneous preferences for different types of games. On Steam, games can list one or more of the following genres: *Action, Adventure, Casual, Massively Multiplayer,* *Racing, Role Playing Game (RPG), Simulation, Sports*, and *Strategy*. I include all of these as dummy variables in my models. Third, I control for seasonality by including 11 calendar month-of-release fixed effects and exclude *January* as the base category. Finally, I control for macro-level and platform-level trends (e.g., changing consumer preferences, increasing technological requirements, updates, etc.) by including year-of-release dummies.

3.7 METHODS

Since I rely on archival data for my study and cannot take advantage of some quasi-exogenous shock, I am confronted with a potential endogeneity problem: The existence of unobserved factors that are correlated with the *free-to-play* variable and with my outcome variable of being a *superstar*. Structural differences between developers of free-to-play games and developers of paid games may bias my results (Rietveld, 2018; Tidhar and Eisenhardt, 2020). Moreover, shrewd developers may refrain from releasing free-to-play games with social features when Steam's installed base is small, while being more inclined to do so when the installed base is large, anticipating a larger demand potential. Though I cannot fully rule out these potential concerns, I take several precautionary steps to account for the choice of business model as well as for the potentially endogenous timing of game launches.

I control for the choice of business model by fitting a treatment effects model in which both the treatment and the outcome are binary, also known as a recursive bivariate probit model (Greene, 2018). This model is akin to the Heckman two-step control function, such that:

$$\text{Outcome equation: } y_i = x_i\beta + w_i\delta + \varepsilon_i,$$

$$\text{Treatment equation: } w_i^* = z_i\gamma + u_i, w_i = 1 \text{ if } w_i^* > 0, \text{ and } w_i = 0 \text{ otherwise}$$

$$Prob(w_i = 1|z_i) = \Phi(z_i\gamma)$$

and

$$Prob(w_i = 0|z_i) = 1 - \Phi(z_i\gamma)$$

where x_i is a vector of exogenous variables determining a binary outcome y_i (i.e., *superstar*), and w_i is an endogenous dummy variable indicating the treatment condition (i.e., *fee-to-play*). Contrary to the Heckman two-step control function model, however, the outcome y_i is observed for both $w_i = 1$ (i.e., *free-to-play*) and $w_i = 0$ (i.e., *paid*). This allows me to conduct a Chow test on the interactions between *social features* and *genre installed base* to assess their equality (and test H2). Notably, there need not be an exclusion restriction for recursive bivariate probit models to be identified—granted the exogenous variables provide sufficient variation.[34]

I include several covariates in my treatment equation. Since I expect some genres to be a better fit for the freemium business model than others, I include the vector of genre dummies. I additionally include the *indie publisher* and *past releases publisher* variables to control for variation at the publisher level. At the platform level, I control for *genre installed base* at the time of a game's release. I further include a variable that counts the number of *past freemium superstars* measured over a rolling window of three years before a game's release up to one year before a game's release, to reflect a typical video game development cycle. I expect that, at the time a game goes into production, publishers will be guided by the extant success of the freemium model on Steam in deciding whether their games should be free-to-play or paid.

[34] Formal proofs for why exclusion restrictions are not strictly required in recursive bivariate probit models are beyond the scope of this paper. The general intuition is that the identification of such models relies on the nonlinearity of the function and variation in the derivatives of the probability that y_i = 1 with respect to the covariates in x_i and z_i. The treatment correction hazard (λ_i) is linearly independent of x_i, even if $z_i = 1$; all that is required is that there is variation in x_i and in z_i (William Greene, personal communication, March 2019).

Finally, I add year-of-release dummies to account for platform-level time trends. First-stage results are reported in **Appendix 3C**.

The treatment effects model accounts for the non-random assignment of games into the free-to-play and paid conditions. The treatment correction hazard (λ_i), which is included in the outcome equation, balances against differences in genre and year of release, the type of publisher, the size of the installed base, and the success of the freemium business model.

I take an additional step to reduce imbalance in the empirical distribution of my covariates (x_i) by applying a coarsened exact matching (CEM) algorithm (Iacus, King, and Porro, 2012). Based on a set of matching covariates, CEM prunes observations so that the remaining data have a better balance between the treatment and the control conditions. For each free-to-play game i, the algorithm finds at least one paid game that is similar on the following covariates: *social features*, *genre installed base*, *indie publisher*, *past releases publisher*, and *genre*. Thus, for each free-to-play game, the algorithm finds at least one same-genre paid game with an equivalent number of social features that is released around the same time by a comparable publisher. After pruning 4,641 observations, the imbalance (L_1) in my estimation sample reduces from 0.66 to 0.06. The CEM algorithm assigns weights based on the number of control group observations for each treated observation, which I use in my models to further improve the quality of my inferences (Blackwell, Iacus, King and Porro, 2009).

In sum, while my results are correlational, I attempt to mitigate endogeneity concerns that are both structural (i.e., choice of business model) and time varying (i.e., release timing of games on Steam) by fitting a treatment effects model on a matched and rebalanced sample.

3.8 RESULTS

3.8.1 Main Results

Table 3.3 lists descriptive statistics and pairwise correlations for my covariates. My main results are reported in Table 3.4. Model 1 includes control variables only. Model 2 adds independent variables (*social features* and *genre installed base*). Model 3 adds the interaction between *social features* and *genre installed base*, testing H1. Model 4 controls for the non-random (treatment) assignment into *free-to-play*. Model 5 prunes and rebalances the sample by applying the CEM algorithm. Model 6 estimates the fully-specified model on the matched subsample of *paid* games. Model 7 tests H2 by comparing regression coefficients across both models.

Insert Table 3.3 about here.

Insert Table 3.4 about here.

Results lend support to my hypotheses. Consistent with H1, the interaction between *social features* and *installed base* in Model 5 is positive and significant (β = 0.102, p = 0.000). This suggests that free-to-play games with many social features have a better chance of becoming a superstar when the platform's installed base is large. Given that the interpretation of interaction effects in non-linear models is complicated, I obtain the marginal effects on *superstar* at different values of *social features* and *genre installed base* (Hoetker, 2007; Zelner, 2009). Figure 3.1 depicts the margins slopes for games with five social features and games without any social features at different values of the installed base. The figure shows that when the installed base is large, free-to-play games with many social features have a 49 percentage points higher probability of becoming a superstar than free-to-play games without any social features, whereas when the platform's installed base is small, free-to-play games with many social features have a 26 percentage points lower probability of becoming a superstar.

Insert Figure 3.1 about here.

To test H2, I take the coefficient on the interaction between *social features* and *genre installed base* for the subsample of free-to-play games and compare it to the same coefficient for the subsample of paid games. To do so, I conduct a Chow test to assess the equality of coefficients (Chow, 1960). The interaction between *social features* and *genre installed base* for the subsample of paid games is positive but not statistically significant ($\beta = 0.021$, $p = 0.226$). Moreover, the Chi-square test statistic is significant ($\chi^2 = 6.32$, $p = 0.012$), confirming that the coefficients on the interaction effects are statistically different across both subsamples. The right-hand margins plot in Figure 1 further illustrates the absence of an interaction effect for paid games. Notably, free-to-play games with many social features that are released on a platform with a large installed base are 37 percentage points more likely to become a superstar than paid games with many social features released on a platform with a similar installed base.

To interpret my control variables I estimate a model on the matched and rebalanced subsample of free-to-play games that does not include any interactions or variable transformations (Wiersema & Bowen, 2009). I find that one additional social feature is associated with a 4.36 percentage points increase in the probability of becoming a superstar ($p = 0.001$). *Genre installed base* has no significant effect on becoming a superstar. One hundred additional same-genre games (i.e., *genre competition*) reduces the probability of becoming a superstar by 7.79 percentage points ($p = 0.018$). Publisher type (i.e., *indie publisher*) has no effect on becoming a superstar. Adding ten games to a publisher's past releases is associated with a 3.75 percentage points higher probability of becoming a superstar (p = 0.081). Free-to-play games with good Metascores have a 29 percentage points higher probability of becoming a superstar than games with bad or missing Metascores (p = 0.082). *Action* games are 13 percentage points more likely to become a superstar than any of the other genres (p = 0.086).

3.8.2 Robustness Tests and Mechanism Checks

I took several steps to mitigate potential endogeneity concerns: First, I constructed a novel measure for superstar products that accounts for supply- and demand-side variation as well as for time trends by standardizing performance for products released in different circumstances. Second, to control for structural differences between free-to-play and paid games I first estimated an endogenous treatment effects model before estimating the equation of interest. Third, I pruned and rebalanced the estimation sample via CEM to further reduce imbalance in my data. My hypotheses remain fully supported after these steps. Nevertheless, I conduct several additional robustness checks to further rule out potential alternative explanations.[35]

First, one might argue that variation in installed base size cannot be fully separated from other potentially relevant time-varying factors. Consequently, the argument goes, what determines which games become superstars likely changes over time. I run an additional set of tests to check for this further. First, because fluctuations in the average number of social features may affect the relative value of incorporating these features, I control for either the average number of social features per game at the genre-year level or the share of games with any social features. Second, to account for time-varying demand heterogeneity, I include the median number of games owned by different user cohorts based on the year of joining Steam. Consistent

[35] Fully tabulated results from these robustness checks are reported in Appendix 3C.

with Rietveld and Eggers (2018), I note that the median number of games owned decreases over time. Third, I add games' system requirements in the form of random-access memory and hard-disk space (measured in gigabytes) to account for increasing technological demands, which could affect the type of games players download (Ghose & Han, 2014). In all these alternative specifications my arguments remain supported.

Second, I construct three alternative measures for determining whether a game is a superstar. First, instead of basing a game's z-score on the subsample of all games released in the same year, I create a more granular measure at the level of a game's genre(s). Computing separate z-scores for each genre a game competes in, I denote a game as a superstar when the statistical average of these genre-based z-scores is equal to or greater than 1. Second, to rule out the possibility that my findings are specific to my z-score based performance measure, I estimate my results using measures that indicate whether a game is among the top 5% most downloaded games in a year or genre. Results are consistent with my reported main results.

Third, I run several supplementary analyses for my social features variable. The first alternative measure operationalization takes the value of 1 if a game has any social features and 0 if a game has no social features. The second measure pools online and local multiplayer modes, restricting the count to three. The third drops local multiplayer functionality from the count, focusing exclusively on the various online multiplayer modes. The fourth takes the log-transformation of the number of social features to account for the skewness in the data. Furthermore, I add control variables indicating whether games include leaderboards and achievements as examples of social features that do not materially alter a game's value proposition. Results from all these specifications are fully consistent with my main results.

Fourth, I similarly run several supplementary analyses for my installed base measure. First, instead of operationalizing the genre installed base measure using yearly statistics, I recreate the measure using cumulative data (from the start of the platform up to a focal year). Second, instead of using a genre-specific measure, I estimate platform-wide measures. Relatedly, I create a measure of the platform's yearly growth rate and control for platform age (in months). Year-of-release fixed effects are absorbed in these robustness checks, and multicollinearity is an issue in some of the models. That said, my arguments remain supported.

Fifth, one of the mechanisms driving H2 is consumers spending less time on freemium products than paid products. To generate network effects, freemium products therefore require a disproportionally larger user base (i.e., to offset lower engagement rates). To check for this, I estimate results on the log of games' median playing time, or the median number of minutes per user playing a game, as dependent variable. Results from a linear regression with endogenous treatment effects suggests that free-to-play games indeed have disproportionately lower use rates (β = -4.769; p = 0.000; also see: Rietveld, 2018). In fact, I note that the median playing time for free-to-play games in my estimation sample is 54 minutes while it is 270 minutes for paid games. Exponentiating the regression coefficient tells me that free-to-play games have a 99 percentage points lower median playing time (per user) than paid games. These findings on playing time are consistent with the suggested mechanisms for my results.

Finally, I estimate the fully-specified model on the pooled sample of free-to-play and paid games and test the three-way interaction between *free-to-play*, *social features*, and *genre installed base*. My findings are fully robust; the three-way interaction effect is positive and statistically significant (β = 0.069, p = 0.030). I additionally find support for my hypotheses using a rare events logit estimator (King and Zeng, 2001). I conclude that my results are robust to various alternative model specifications and measurement operationalizations.

3.9 DISCUSSION AND CONCLUSION

Recognizing the need for widespread diffusion and the potentially mixed effects of incorporating social features into freemium products, I asked: *How and when do social product features affect the likelihood of a freemium product becoming a superstar?* To answer this question, I analyzed a sample of 9,700 digital PC games launched on Steam between 2011 and 2016. Results from an endogenous treatment effects model estimated on a matched and rebalanced sample show that, when the platform's installed base is large, free-to-play games with many social features have a 49 percentage points higher probability of becoming a superstar than free-to-play games without any social features. Conversely, when the platform's installed base is small, free-to-play games with many social features have a 26 percentage points lower probability of becoming a superstar. Furthermore, I find that the contingent effect of incorporating social features is specific to free-to-play games; the effect does not apply to paid games. My study makes several contributions and holds implications for future research on network effects, freemium strategies, and superstar products in platform markets.

First, my study contributes to the literature on network effects. By relaxing the common assumption in the strategy literature that network effects are a market-level construct, I explored how firms can increase the strength of network effects through their product design choices. By incorporating multiplayer modes into freemium games, the publishers in my sample added network functionality to products' standalone functionality, thereby increasing their chances of attaining market-leading performance. The notion that firms can alter the strength of their products' network effects has previously been examined in the fields of marketing and information systems (e.g., Aral and Walker, 2011; Dou et al., 2013), but remains largely unexplored in strategic management (for an exception, see: McIntyre & Subramaniam, 2009). This lack of attention is surprising given the myriad implications *tractable network effects* can have on such issues as market entry timing, product innovation management, and competitive dynamics. Allowing for product-level variation in the strength of network effects, for example, may shed new light on how new entrants can successfully compete with dominant incumbents or when winner-take-all dynamics are likely to occur.

However, designing products around network effects is no panacea. The efficacy of this strategy importantly depends on external factors, including a product's demand potential. My results suggest that firms can increase the chances of their products becoming a superstar if they incorporate social features when demand potential is large, whereas they decrease the chances of their products becoming a superstar when demand potential is constrained. This finding is consistent with Srinivasan, Lilien, and Rangaswamy (2004), who found that network effects have a negative impact on the survival rate of pioneering products—those products that are first to enter a nascent market when demand is still limited. I conclude that there exist contingencies as to when firms should rely more on network functionality versus standalone functionality for their products' value proposition (Cabral et al., 1999; Lee and O'Connor, 2003). Future research should explore how other factors, such as demand heterogeneity or competitive dynamics, impact the efficacy of incorporating social product features.

Second, I contribute to our understanding of how and when the freemium business model works (Kumar, 2014). There exist qualitative differences between freemium and paid products—

including usage patterns and diffusion dynamics—that have implications for firms operating the freemium business model. On the one hand, freemium products diffuse more quickly and more widely than paid products, due to their lower barriers to adoption and stronger word-of-mouth dynamics (Bond et al., 2019; Lin et al., 2019). On the other hand, freemium consumers have a lower willingness-to-pay and they are less engaged than paying consumers (Bapna et al., 2018; Rietveld, 2018). Given that the strength of any product's network effects is a function of the product's network functionality *and* its active user base (Shankar and Bayus, 2003), incorporating social features will therefore only benefit those freemium products that manage to attract a disproportionately large user base. Thus, while prior literature has addressed *why* firms should adopt a freemium business model in the presence of network effects (Cheng and Liu, 2012; Shi et al, 2019), I add by documenting *how* firms operating the freemium business model can design their products to optimally benefit from network effects.

Third, I contribute a novel measure for operationalizing superstars in platform settings. Many digital platforms are characterized by markedly skewed demand distributions (e.g., Benner and Waldfogel, 2020). When this is the case, there exists a strong demarcation between superstar products and (less successful) products that reside in the long tail of these platforms (Brynjolfsson et al., 2010; Elberse, 2008). What exactly constitutes a superstar, however, is a moving target. Considering platforms' two-sidedness and products' embedded nature within these markets, the size of the market for such products—both on the demand side and on the supply side—is subject to constant variation. As a result, applying a fixed threshold based on a product's downloads or its sales ranking may yield inconsistent results. To account for this, I proposed a measure based on a product's standardized performance relative to similar products released around the same time on the platform. I hope my z-score-based measure for superstar products will benefit scholars conducting research in similar settings.

My study also has some limitations that must be acknowledged. Most notably, I only have data on one platform. While this enabled me to develop a deep understanding of games on Steam, as well as to construct measures and conduct analyses that are highly contextual, I cannot unequivocally ascertain that my results are caused by variation in Steam's installed base. Neither can I assure the generalizability of my findings to other digital platforms or social features. I encourage colleagues to duplicate and extend my findings in related settings such as mobile app stores. The share of freemium products on Apple's App Store and Google's Play Store, for example, is much higher. Developers on these platforms also often operate hybrid business models, where income is generated from both consumers and advertisers (Casadesus-Masanell & Zhu, 2010, 2013). Non-gaming apps further incorporate different kinds of social features such as ride-sharing functionality and virtual collaborative tools.

How do my findings replicate to these different platforms and social features? A study by Boudreau et al. (2020) documents dynamics similar to mine in the context of Apple's App Store: An increase in market-level network effects benefitted freemium market leaders more than paid market leaders. Thus, in line with my arguments, they document that network effects are more beneficial to freemium than paid superstars. Their study differs, however, in its focus on market-level network effects, and it does not explore the antecedents of market leadership.

A potential boundary condition of my work is the extent that a platform's life cycle is finite. Platforms tied to a specialized technology product, such as a video game console or a smartphone, are often replaced by a next-generation platform after some time (e.g.,Kretschmer &

Claussen, 2016). Consumers may be tempted to abandon a focal platform in lieu of a next-generation platform (e.g., Kim & Srinivasan, 2009), causing a contraction of the installed base—and with it products' demand potential. Thus, in the presence of generational breaks, a platform's installed base size positively impacts the inclusion of social product features *to the point that consumers won't anticipate the introduction of a next-generation platform*.

I also believe it will be important to gain better understanding about the life cycle dynamics of freemium products. At what point do freemium superstars fail to retain and engage their users, why? These questions are pertinent given that consumers seem to lose interest in these products virtually overnight—as witnessed by *H1Z1*, a freemium superstar game on Steam that was abruptly dethroned by *PlayerUnknown's Battleground,* another freemium game in the same genre (also see: Lee, Zhang, & Wedel, 2021). Similarly, it should be interesting to investigate the effects of different social features. For example, in my data, I observed a decline in the number of games incorporating local multiplayer modes. While this trend can be explained by increased connectivity and targeting larger user bases via online multiplayer, firms may exercise some caution. Prior research found that users often exhibit local bias, meaning that network effects are stronger when users have stronger ties to each other (Afuah, 2013; Lee et al., 2006; Suarez, 2005). Local multiplayer functionality may therefore not accommodate the same scale of connectedness, but they will likely result in stronger engagement, which could offset the smaller user base. More work is needed on the tradeoff between user base growth and engagement dynamics for network effects (also see: Claussen, Kretschmer, and Mayrhofer, 2013). Finally, scholars may want to study value capture strategies for freemium products. Little is known still about the effective design of freemium price menus (for exceptions, see: Meng, Hao,

& Tan, 2021; Tidhar and Eisenhardt, 2020). This is a complex issue at the intersection of product design and consumer psychology. Archival data is unlikely to generate conclusive evidence, which may be better studied using experiments or machine learning techniques.

The freemium business model has become the leading business model on many digital platforms. Some of the most popular products today are commercialized with a freemium model. These products often incorporate social features such as multiplayer functionality in games, virtual collaboration tools in productivity software, and carpooling in ride-hailing applications. Social features add network functionality to a product's standalone functionality, and they can increase the strength of network effects. Incorporating social features, however, is a double-edged sword: On the one hand, when a freemium product's demand potential is constrained, network effects won't materialize and users may feel they are missing out. On the other hand, when a freemium product's demand potential is large, social product features can set in motion a virtuous cycle of more adoption, more usage, and more in-app purchases.

Table 3.1 Game and Platform Statistics by Year

Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**All**
Games released	256	332	462	1,609	2,661	4,380	9,700
Free-to-play games	12	21	28	81	190	439	771
Share of superstars in							
Free-to-play	0.25	0.19	0.18	0.36	0.22	0.09	0.16
Paid	0.07	0.05	0.00	0.04	0.02	0.02	0.03
Mean downloads							
Superstars	4,598,066	5,859,613	31,996,919	1,735,460	1,633,832	1,470,115	2,633,332
Non-superstars	366,269	403,848	472,266	94,787	56,840	38,543	106,677
Mean number of social features							
Free-to-play	1.58	1.43	1.46	1.11	0.82	0.81	0.90
Paid	0.49	0.39	0.46	0.30	0.31	0.33	0.33
Platform statistics							
New platform users	10,708,000	13,747,000	25,579,000	36,915,000	47,682,000	60,317,000	32,491,333
Installed base	38,738,000	52,485,000	78,064,000	114,979,000	162,661,000	222,978,000	222,978,000

Notes. Based on estimation sample.

Table 3.2 Distribution of Social Features by Game Type

Social features (type)	Free-to-play games	Paid games	Net difference
Local cooperative play	115	628	7.88%
Online cooperative play	50	196	4.29%
Local competitive play	288	1,395	21.73%
Online competitive play	118	367	11.19%
Cross-platform multiplayer	120	391	11.19%
Social features (count)	**Free-to-play games**	**Paid games**	**Net difference**
0	428	7,328	-26.56%
1	122	730	7.65%
2	139	539	11.99%
3	50	202	4.22%
4	19	87	1.49%
5	13	43	1.20%

Notes. Based on estimation sample. Local play includes multiplayer functionality on the same PC as well as over multiple PCs connected to the same local network (LAN). Cross-platform multiplayer facilitates online multiplayer functionality between Steam accounts using different operating systems (i.e., Windows, Mac, and Linux), and sometimes between non-Steam platforms (e.g., video game consoles or other PC platforms).

Table 3.3 Descriptive Statistics and Pairwise Correlations

	Variable	Mean	St Dev	Min	Max	1	2	3	4	5	6
1	*Superstar*	0.04	0.19	0.00	1.00						
2	*Free-to-play*	0.08	0.27	0.00	1.00	0.19					
3	*Social features*	0.38	0.88	0.00	5.00	0.17	0.17				
4	*Genre installed base*$_{t\text{-}1}$	4.57	3.23	0.00	10.66	0.02	0.07	0.05			
5	*Genre competition*	159.90	100.59	1.00	456.00	-0.08	-0.11	-0.06	0.52		
6	*Indie publisher*	0.67	0.47	0.00	1.00	-0.10	-0.07	-0.03	0.26	0.21	
7	*ln(Past releases publisher)*	1.05	1.32	0.00	4.82	0.05	-0.13	-0.06	-0.12	-0.08	-0.37

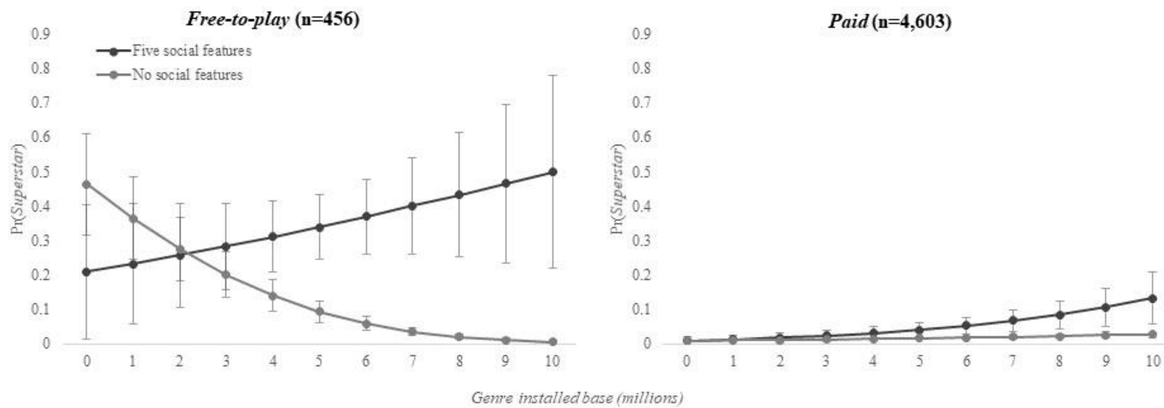
Notes. Based on estimation sample (n=9,700). Mean variance inflation factor (VIF) = 2.54.

Table 3.4 Regression Estimates of Games' Likelihood of Becoming a Superstar

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.21 [0.05]	0.07 [0.09]	0.06 [0.09]	-0.22 [0.15]	0.006 [0.13]	1.28
Genre installed base$_{t-1}$		0.002 [0.019]	-0.03 [0.03]	-0.08 [0.06]	-0.38 [0.13]	0.07 [0.04]	10.24
Social features x Genre installed base$_{t-1}$			0.02 [0.01]	0.03 [0.01]	0.10 [0.03]	0.02 [0.02]	6.32
Genre competition	-0.004 [0.001]	-0.004 [0.001]	-0.004 [0.001]	-0.004 [0.001]	-0.006 [0.002]	-0.001 [0.001]	3.40
Indie publisher	-0.24 [0.14]	-0.23 [0.14]	-0.23 [0.14]	0.11 [0.37]	1.70 [0.87]	-0.22 [0.32]	4.31
ln(Past releases publisher)	0.13 [0.07]	0.15 [0.07]	0.15 [0.07]	0.34 [0.21]	1.29 [0.51]	-0.16 [0.14]	7.59
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.04 [0.29]	-1.14 [0.31]	-0.99 [0.32]	0.47 [1.48]	5.95 [3.28]	-2.10 [0.70]	6.85
McFadden's *Pseudo* R^2	0.22	0.23	0.24	0.24			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of free-to-play games. Model 4 estimates an endogenous treatment effects model on the subsample of free-to-play games. First-stage results are reported in Appendix 3C. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of free-to-play and paid games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

Figure 3.1 Predicted Probability Plots Based on Subsample Analyses



Notes. Predicted probability plots for free-to-play and paid video games with many (5) and without any social features based on split-sample probit regressions reported in Models 5 and 6 in Table 4.

CONCLUSION

In this dissertation, I focused on network effects, which are fundamental drivers behind major technology companies' success. While network effects can drive firms' growth and market dominance, they also present unique challenges and opportunities for strategic management. Strategy research commonly advises that firms should adapt to the presence of network effects by implementing aggressive tactics such as price reductions, extensive marketing, or significant investments to build a large user base quickly (Boudreau, 2012; Eisenmann, Parker, & van Alstyne, 2006; Suarez, 2004). Instead of discussing strategies to cope with network effects, I focused on a firm's agency to actively shape network effects through product and platform design. *When should firms design their products for network effects in the first place, and what strategic actions contribute to or impede the success of firms operating in situations characterized by heterogeneous network effects?* By answering these questions, I open up new avenues for research, provide advice for strategic action, and emphasize factors traditionally overlooked in discussions of network effects. Specifically, I highlight the crucial role of match quality within digital platforms in sustaining network effects, the impact of non-network factors such as product novelty and market competition, and the importance of aligning network effects with the suitable business model and market demand potential. These considerations provide firms with strategic levers to compete in markets with heterogeneous network effects. By examining these dimensions, this dissertation enriches our understanding of network effects and illustrates the significant implications of strategic firm actions in shaping market outcomes.

Summary

I have explored the multifaceted impacts of heterogeneous network effects across various contexts, highlighting the critical role these effects play in shaping firm strategy. In the first chapter, I developed theory on the balance between openness and curation on multi-sided platforms. Due to user heterogeneity, open platforms lead to more transaction volume but require more intricate curation strategies. This work underscores the importance of adjusting curation strategies to the evolving needs of heterogeneous user bases. In the second chapter, I focused on the board games industry, a sector characterized by partial network effects where traditional and network products compete side-by-side. I demonstrated that the strategic incorporation of social features influences product diffusion due to their impact on the product's underlying demand uncertainty. In the third chapter, I examined the role of social features in the success of digital freemium games, revealing the double-edged nature of these features. While beneficial under certain conditions, their effectiveness varies depending on the size of the platform's installed base. **Figure C** summarizes the key takeaways from this dissertation following the two-sided market structure, and **Table C** contrasts the three studies in this dissertation. Both stand at the end of this Conclusion section.

Theoretical Contributions

My dissertation offers various theoretical contributions, which are more extensively mentioned in the individual chapters but can be synthesized into overarching contributions as follows:

Reconceptualization of network effects. The dissertation reconceptualizes network effects from being a market-level construct that universally affects all market participants to a product-level construct that, to some extent, lies within firm control. In doing so, I add nuance to an ongoing conversation within the literature on network effects and strategies in platform markets by introducing an element of strategic choice (e.g., Agarwal et al., 2023; Boudreau et al., 2022; Zhu et al., 2021). While we know a lot about adequate strategies to adapt to the presence of network effects (see Katz & Shapiro, 1994; Schilling, 2002, 2003; Soh, 2010; Suarez, 2004), my dissertation provides insights into when it makes sense to (not) induce network effects by implementing social features into products. Indeed, the second and third chapters explicitly hint at the risks of trying to induce network effects due to increased demand uncertainty and the necessity for a suitable business model and market conditions fit. The first chapter, albeit less explicit, also provides insights into the negative side of network effects by outlining the difficulty of sustaining network effects over time and hinting at the inertia strong network effects cause.

Impact of non-network factors on network effects. Most research on network effects identified and explored the number of users or network strength as the main contributors to the success of network effects (McIntyre & Srinivasan, 2017; Shankar & Bayus, 2003; Suarez, 2004; Zhu & Iansiti, 2012). However, my dissertation highlights the importance of non-network features such as platform curation, product novelty, or business model choice. Similar to the prior contribution, this is particularly interesting to scholars in strategic management since it opens up an additional set of variables impacting firm performance. Exploring these factors might also offer an explanation for findings in which network effects did not lead to winner-takes-most dynamics or failed to create value for platform sponsors despite a large user base (Farronato, Fong, & Fradkin, 2023; Lee, Lee, & Lee, 2006). On top of that, the generated insights are of great importance to innovation and marketing scholars interested in product diffusion and the interplay of network effects and product quality (Rogers, 2003; Stremersch et al., 2007; Tellis et al., 2009). My findings show that non-network features are essential to competitive market outcomes, even in the context of strong network effects.

Strategic challenges when trying to achieve and sustain winner-takes-most status. While network effects are notorious for leading to winner-takes-all or winner-takes-most outcomes (Cennamo & Santalo, 2013; Eisenmann et al., 2006), my dissertation adds to this conversation by outlining the nuances in trying to achieve and, in the case of multi-sided platforms, the intricate strategies necessary to keep such a status. Importantly, simply providing the means of social interaction is no guarantee for network effects to materialize. And even if firms (platforms) succeed in seeding the market efficiently for network effects to kick in, they need to carefully adjust their strategy to keep an increasingly heterogeneous user base engaged over time. Consequently, I contribute by identifying boundary conditions that help kickstart network effects and strategies to sustain them over time.

Collectively, these contributions offer a framework for understanding network effects as a dynamic and partly controllable aspect of modern economies. They emphasize the strategic choices available to firms and the considerations involved in designing and managing products and platforms in a way that strategically leverages network effects for competitive advantage.

Practical Implications

This dissertation also provides several practical implications for managers and platform sponsors operating under heterogeneous network effects. It offers actionable advice on how strategic choices related to platform design, product features, and market timing can influence the success of network products and platforms. First, for platform sponsors, emphasizing match quality can help maintain user engagement and satisfaction, which are crucial for sustaining network effects over time. Platforms can enhance match quality through both manual and algorithmic curation strategies. Manual curation is particularly effective in the early stages of a platform when the user base is smaller and more homogenous. It allows platform sponsors to steer user behavior toward strategic goals and foster a shared purpose among users. However, as the platform grows and the user base becomes more diverse, I argue algorithmic curation becomes more suitable due to its scalability and ability to manage complex interactions despite offering less control over user alignment with strategic goals.

Second, for managing product launches in markets with heterogeneous network effects, this dissertation offers guidance on the timing and nature of product introductions. My findings advise against combining social features with novel product designs or launching network products in overly crowded markets. Such strategies increase consumer perceived uncertainty and can hinder product diffusion. Consequently, firms should avoid pairing social features with a novel product design. Moreover, they should strategically choose launch timings when the market is less crowded to mitigate the adverse effect of competition and maximize the potential for network effects to materialize.

Third, for firms aiming to launch digital hit products, my dissertation emphasizes the need to carefully consider the business model, product features, and market condition fit. It highlights the challenges of introducing network offerings in markets with limited demand potential. While social features can help propel products to a hit status, they actually impete their likelihood for success without a large potential user base. Overall, my dissertation results show that standalone products represent a less risky alternative to network products regardless of the setting.

In summary, the practical implications of this dissertation advise platform managers and product developers on how to strategically leverage network effects by actively managing product and platform design and market entry. These insights are valuable for sustaining competitive advantage and achieving long-term success, particularly in markets with heterogeneous network effects.

Future research

While this dissertation advances our understanding of network effects, it also highlights potential future research opportunities in this scholarly conversation. A first possibility for management research would be to explore different types of network effects and ways to add network value to products' standalone value. For example, some social features are part of a product's core functionality—such as an online multiplayer mode in a video game—while others are not—such as an online leaderboard on the iOS game center for the same video game (Boudreau et al., 2022). It is not intuitive which type of social feature is more beneficial in which situation and how the two types interact.

Second, we know very little about the user types that decide to adopt network over standalone products. This is important since network products require more active users to deliver their full value potential (Shankar & Bayus, 2003). Network products, such as multiplayer video games and board games with collectible components, generally require much more commitment (time and money) than standalone products.[36] Consequently, they seem to speak to super users, of whom, in comparison to light users, much less exist. This inherent appeal to super users directly conflicts with the necessity of network products to achieve a critical mass quickly. Therefore, exploring ways in which firms can ensure that super users do not just consider adopting their products will be essential to understanding how to generate a sustainable competitive advantage with heterogeneous network effects.

Third, we would benefit from tracking and determining the optimal adjustment of network strength over time. Based on the results of this dissertation, it seems that a valid strategy for firms would be to launch a high-quality standalone product and add social features after it has attracted a sizeable user base. Doing so would combine the best of both worlds by decreasing the initial demand uncertainty and harvesting the benefits of network effects later. Currently, we only have anecdotal evidence for the success of such a strategy, but considering the importance of network effects, it will be beneficial to explore these dynamics empirically.

Finally, it is essential to understand how smaller firms can leverage network effects to successfully dethrone dominant incumbents who exploit their installed base advantage to gain monopoly-like market positions (Suarez & Kirtley, 2012). Anecdotal evidence, such as TikTok dethroning Facebook and the freemium video game H1Z1 being dethroned by PUBG, show that it is, in principle, possible to compete successfully with seemingly locked-in market leaders. This dissertation provides a first step for identifying the necessary conditions for dethroning that might help to even the playing field in an increasingly unfair digital economy. However, future

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[36] See https://rareloot.medium.com/the-problem-with-multiplayer-games-5cb013a6842 and https://spikeybits.com/warhammer-40k/warhammer-is-it-really-an-expensive-hobby/ last accessed 30/04/24

research might provide more exploration of how regulators can avoid prolonged, monopoly-like positions of dominance.

This dissertation represents a single yet significant contribution to the ongoing scholarly endeavor to decode the complexities of network effects. While it addresses specific aspects of heterogeneous network effects and the strategic agency firms can exert over them, it is by no means exhaustive. I hope this work will serve as a valuable stepping stone for further research, inspiring continued exploration into the nuanced interplay of network dynamics across various platforms and markets. May it prove helpful in advancing academic understanding and informing practical strategies for firms navigating these pervasive and influential forces.

Figure C Key Takeaways

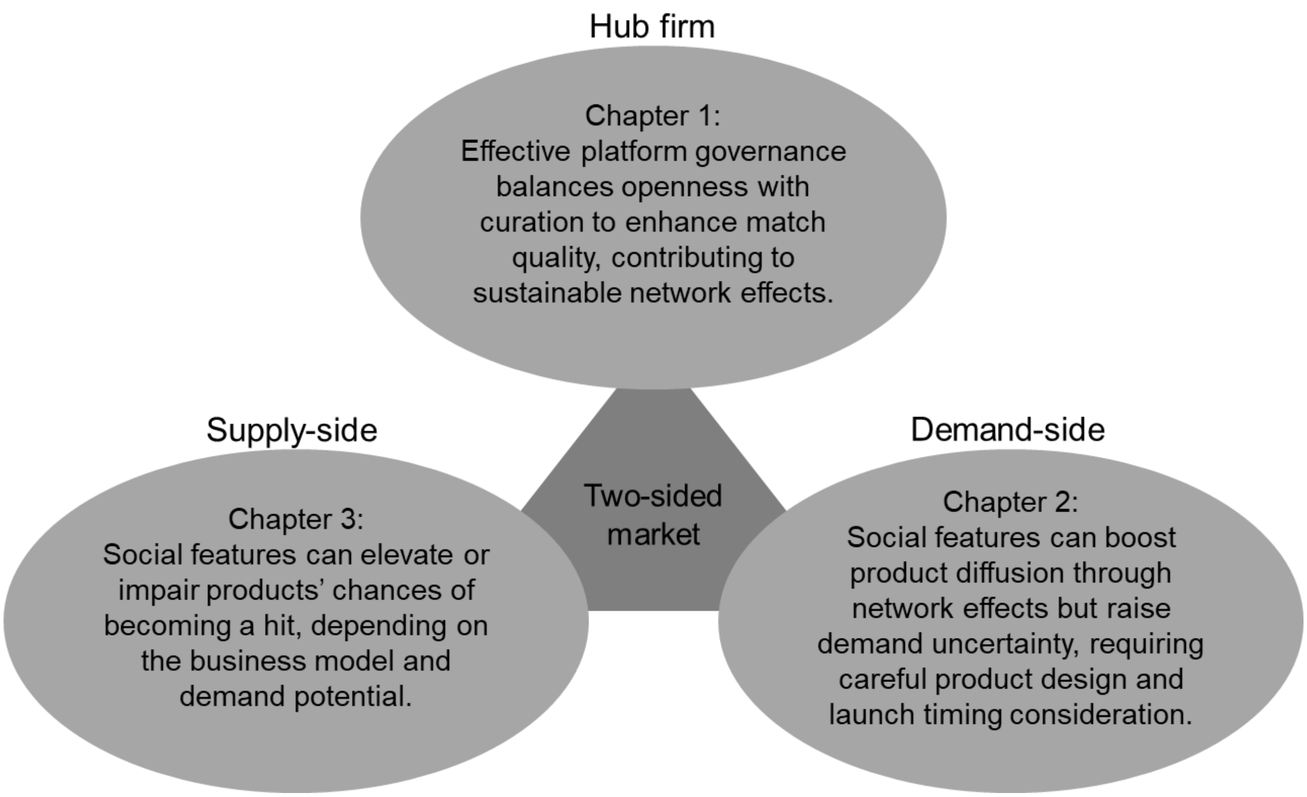

Table C Contrasting the Studies of this Dissertation

Chapter	Title	Research Question	(Empirical) Context	Key Take Away
1	Match Quality in Multi-Sided Platforms: Balancing Openness and Curation	*How should platforms balance openness and curation to ensure high match quality, and how does this relation evolve over time?*	Digital multi-sided platforms (Conceptual work)	Effective platform governance balances openness with strategic curation to enhance user interaction and match quality, which contribute to the sustainability of network effects.
2	Rolling the Dice: Resolving Demand Uncertainty in Markets with Partial Network Effects	*How does demand uncertainty differentially impact the diffusion of network products versus standalone products that compete in the same market? And, how do strategies to resolve consumers' perceived uncertainty affect the diffusion of network products compared to standalone products?*	Board games industry	Social features can boost product diffusion through network effects but simultaneously raise demand uncertainty, requiring careful product design and launch timing consideration.
3	On Top of the Game? The Double-Edged Sword of Incorporating Social Features into Freemium Products	*How and when do social product features affect the likelihood of a freemium product becoming a superstar?*	PC video games on Steam	Social features can elevate or impair digital products' chances of becoming a hit, depending on market demand potential and business model alignment.

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APPENDIX

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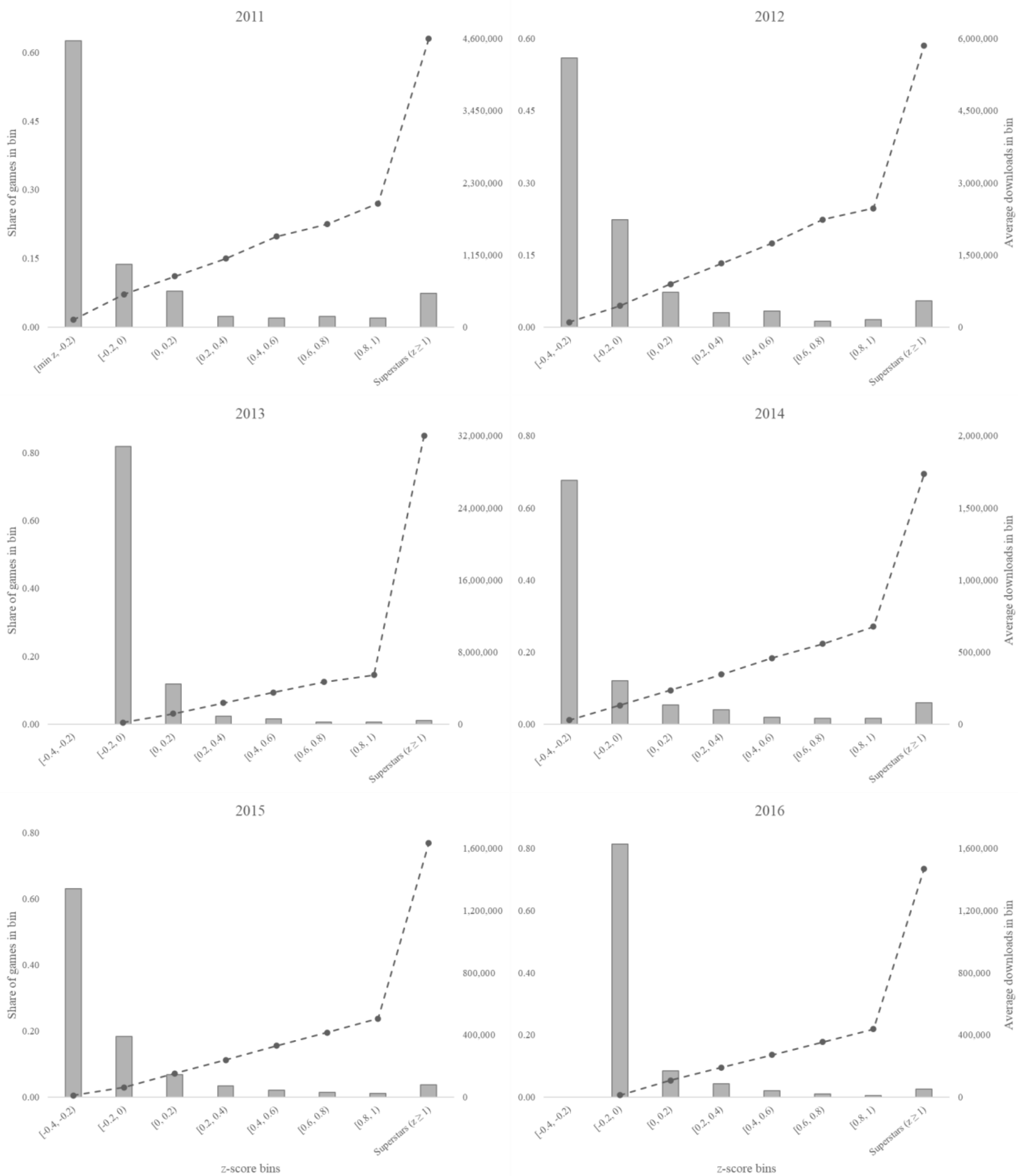
Appendix 3A –Studies on Superstar Products in Platform Markets

Study	Research question	Empirical context	*Superstar* operationalization	*Superstar* as	Includes all products	Accounts for supply-side market size*	Accounts for demand-side market size*	Accounts for time to accumulate performance*
Binken and Stremersch, 2009	*What are the returns of* ***software superstars*** *on hardware sales?*	US home console video games (1993-2004)	Video game's Metascore (aggregated expert review rating) is greater than or equal to 90/100 (Top 1.5%) - *binary*	Predictor	Yes	No	n/a	n/a
Lee, 2013	*What is the impact of exclusive* ***hit software*** *on hardware sales and consumer welfare?*	US home console video games (2000-2005)	Fixed threshold of 1 million units sold (Top 3.5%) - *binary*	Predictor	Yes	No	No	No
Sun, Rajiv, and Chu, 2016	*How do breadth and depth of software availability affect hardware adoption?*	US home console video games (1995-2000)	Video game's average rating (across IGN, GameRankings, and GameSpot) is greater than or equal to 9/10 (Top 3.2%) - *binary*	Predictor	Yes	No	n/a	n/a
Gretz, Malshe, Bauer, and Basuroy, 2019	*How does* ***superstar software*** *affect hardware sales across different stages of the product life cycle?*	US home console video games (1995-2007)	Video game's Metascore (aggregated expert review rating) of greater than or equal to 90/100 (Top 3.5%) - *binary*	Predictor	Yes	No	n/a	n/a
Ershov, 2020	*How does* ***superstar*** *entry affect market structure, prices and product quality in software markets?*	Games on the Google Play Store (2012-2013)	Game placing top spot in weekly category ranking within two weeks of launching onto market (Top 0.03%) - *binary*	Predictor	Yes	No	Yes	Yes
Cox, 2014	*What makes a* ***blockbuster*** *video game?*	US home console video games (September, 2011)	Fixed thresholds of 2 million (Top 1%), 1 million (Top 4%), and 500 thousand (Top 11%) units sold; log-transformation of cumulative units sold – *binary & continuous*	Outcome	No	No	No	Yes
Yin, Davis, and Muzyrya, 2014	*How does the development of* ***killer apps*** *vary by market and app characteristics?*	Apps on the iOS App Store (2009-2011)	App ranking in the Top 300 grossing chart (Top 1%) - *binary*	Outcome	Yes	No	Yes	No
This study	*How and when do social product features affect the likelihood of a freemium product becoming a* ***superstar****?*	Games on Steam (2011-2016)	Standardized downloads based on games released in same year. Z-score ≥ 1 (Top 3.6%) - *binary*	Outcome	Yes	Yes	Yes	Yes

Notes. * either by way of measurement or by way of controlling for this in the econometric model.

Appendix 3B – Distributions of Games and Downloads by Year



Notes. Based on estimation sample. Bars represent the distribution of z-scores based on all games released in the same year. Dots represent average cumulative downloads of games in bin (connected by trendlines). Z-score values fall within the range of -0.48 and 38.42 and have a mean value of 0. Downloads fall within the range of 864 and 112,516,563 and have a mean value of 177,932.

Appendix 3C – Robustness Checks

Controlling for time-varying factors

Alternative specifications outcome measure

Alternative specifications social features measure

Alternative specifications installed base measure

Alternative model estimations

3C1 Controlling for the Average Number of Social Features at Genre-Year Level

	Superstar						
	Free-to-play					Paid	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.20	0.04	0.04	-0.23	0.13	2.57
		[0.05]	[0.09]	[0.09]	[0.16]	[0.16]	
Genre installed base$_{t-1}$		0.0003	-0.04	-0.08	-0.38	0.10	11.41
		[0.02]	[0.03]	[0.06]	[0.13]	[0.05]	
Social features x Genre installed base$_{t-1}$			0.03	0.03	0.10	0.01	7.46
			[0.01]	[0.01]	[0.03]	[0.02]	
Avg social features in genre	0.17	0.05	0.14	0.11	0.02	-0.97	4.07
	[0.13]	[0.14]	[0.14]	[0.15]	[0.31]	[0.38]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	-0.001	3.53
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.22	-0.23	-0.21	0.08	1.69	-0.36	4.80
	[0.13]	[0.14]	[0.14]	[0.37]	[0.86]	[0.36]	
ln(Past releases publisher)	0.13	0.15	0.14	0.31	1.28	-0.17	7.81
	[0.07]	[0.07]	[0.07]	[0.21]	[0.50]	[0.15]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.13	-1.16	-1.01	0.25	5.90	-2.46	6.36
	[0.30]	[0.31]	[0.32]	[1.50]	[3.27]	[0.54]	
McFadden's *Pseudo* R^2	0.22	0.23	0.24	0.24			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C2 Controlling for Share of Games with Social Features at Genre-Year Level

	Superstar						
	Free-to-play					Paid	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.20	0.05	0.05	-0.21	0.12	2.10
		[0.05]	[0.09]	[0.09]	[0.16]	[0.16]	
Genre installed base$_{t-1}$		0.001	-0.04	-0.08	-0.39	0.10	11.83
		[0.020]	[0.03]	[0.06]	[0.13]	[0.05]	
Social features x Genre installed base$_{t-1}$			0.03	0.03	0.10	0.01	6.96
			[0.01]	[0.01]	[0.03]	[0.02]	
Share of social features in genre	0.27	0.05	0.21	0.15	-0.23	-1.49	1.68
	[0.29]	[0.31]	[0.32]	[0.32]	[0.72]	[0.65]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	-0.002	3.36
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.22	-0.23	-0.22	0.09	1.76	-0.36	5.16
	[0.13]	[0.14]	[0.14]	[0.37]	[0.86]	[0.35]	
ln(Past releases publisher)	0.13	0.15	0.14	0.33	1.33	-0.17	8.32
	[0.07]	[0.07]	[0.07]	[0.21]	[0.50]	[0.15]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.11	-1.15	-1.00	0.34	6.24	-2.51	6.92
	[0.30]	[0.31]	[0.32]	[1.50]	[3.28]	[0.53]	
McFadden's *Pseudo R^2*	0.22	0.23	0.24	0.24			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C3 Controlling for Demand Heterogeneity[37]

	Superstar						
	Free-to-play					Paid	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.19	0.01	0.01	-0.26	-0.04	1.33
		[0.05]	[0.09]	[0.09]	[0.15]	[0.12]	
Genre installed base$_{t-1}$		0.03	-0.01	-0.01	-0.20	0.06	5.94
		[0.02]	[0.03]	[0.05]	[0.10]	[0.04]	
Social features x Genre installed base$_{t-1}$			0.03	0.03	0.11	0.03	5.83
			[0.01]	[0.01]	[0.03]	[0.02]	
Median games per user cohort	0.68	1.08	1.04	1.02	1.42	0.86	0.11
	[0.72]	[0.73]	[0.73]	[0.75]	[1.21]	[1.11]	
Genre competition	-0.003	-0.004	-0.004	-0.004	-0.006	-0.001	5.87
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.15	-0.15	-0.15	-0.20	0.53	-0.16	0.88
	[0.13]	[0.13]	[0.13]	[0.30]	[0.66]	[0.32]	
ln(Past releases publisher)	0.14	0.15	0.14	0.12	0.57	-0.15	3.13
	[0.07]	[0.07]	[0.07]	[0.17]	[0.38]	[0.14]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.37	-1.81	-1.58	-1.76	0.51	-2.96	1.97
	[0.51]	[0.54]	[0.54]	[1.15]	[2.30]	[0.91]	
McFadden's *Pseudo* R^2	0.17	0.19	0.20	0.20			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

[37] Year of release dummies are absorbed in this specification.

3C4 Controlling for System Requirements

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.19	0.03	0.02	-0.31	-0.08	1.26
		[0.06]	[0.09]	[0.09]	[0.17]	[0.12]	
Genre installed base$_{t-1}$		-0.008	-0.05	-0.10	-0.43	0.04	9.67
		[0.021]	[0.03]	[0.06]	[0.15]	[0.04]	
Social features x Genre installed base$_{t-1}$			0.03	0.03	0.12	0.03	6.47
			[0.01]	[0.01]	[0.03]	[0.02]	
Storage (HD) requirement	0.06	0.05	0.05	0.06	0.06	0.07	0.11
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	
Memory (RAM) requirement	-0.08	-0.07	-0.07	-0.07	-0.19	-0.05	3.57
	[0.03]	[0.03]	[0.03]	[0.03]	[0.06]	[0.04]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.007	-0.002	2.96
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.09	-0.09	-0.08	0.23	1.86	0.16	3.12
	[0.15]	[0.15]	[0.15]	[0.41]	[0.92]	[0.29]	
ln(Past releases publisher)	0.13	0.14	0.14	0.32	1.36	-0.16	7.39
	[0.08]	[0.08]	[0.08]	[0.23]	[0.54]	[0.13]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.02	-1.07	-0.89	0.45	7.11	-2.88	7.63
	[0.33]	[0.36]	[0.37]	[1.63]	[3.58]	[0.50]	
McFadden's *Pseudo* R^2	0.26	0.27	0.28	0.28			
Observations	694	694	694	694	408	3874	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C5 Replacing Superstar with Genre-Based Z-score

	Genre Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.21	0.08	0.08	-0.06	0.11	0.78
		[0.05]	[0.09]	[0.09]	[0.15]	[0.10]	
Genre installed base$_{t-1}$		-0.003	-0.03	-0.03	-0.31	0.04	3.97
		[0.019]	[0.03]	[0.06]	[0.17]	[0.04]	
Social features x Genre installed base$_{t-1}$			0.02	0.02	0.09	0.01	8.05
			[0.01]	[0.01]	[0.03]	[0.02]	
Genre competition	-0.003	-0.002	-0.002	-0.002	-0.005	-0.001	4.18
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.16	-0.15	-0.14	-0.14	1.35	-0.1	1.53
	[0.13]	[0.13]	[0.13]	[0.34]	[1.06]	[0.28]	
ln(Past releases publisher)	0.08	0.10	0.09	0.09	1.06	0.04	2.75
	[0.07]	[0.07]	[0.07]	[0.19]	[0.61]	[0.09]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (3)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.65	-1.75	-1.55	-1.54	2.91	-2.54	1.90
	[0.38]	[0.38]	[0.39]	[1.39]	[3.93]	[0.46]	
McFadden's *Pseudo* R^2	0.15	0.17	0.18	0.18			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C6 Replacing Superstar with Top 5% Downloads in Year

	Top 5% in Year						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.25	0.11	0.10	-0.04	-0.07	0.03
		[0.05]	[0.08]	[0.08]	[0.15]	[0.12]	
Genre installed base$_{t-1}$		0.003	-0.03	-0.05	-0.26	0.04	6.07
		[0.018]	[0.03]	[0.05]	[0.12]	[0.04]	
Social features x Genre installed base$_{t-1}$			0.03	0.03	0.09	0.03	3.60
			[0.01]	[0.01]	[0.03]	[0.02]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	-0.001	5.44
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.14	-0.14	-0.13	-0.02	0.97	-0.03	1.62
	[0.12]	[0.12]	[0.12]	[0.31]	[0.74]	[0.27]	
ln(Past releases publisher)	0.12	0.14	0.14	0.21	0.63	-0.04	2.33
	[0.07]	[0.07]	[0.07]	[0.18]	[0.43]	[0.10]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (3)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-2.07	-2.20	-2.00	-1.49	0.11	-3.45	1.55
	[0.37]	[0.38]	[0.39]	[1.28]	[2.81]	[0.53]	
McFadden's *Pseudo* R^2	0.15	0.18	0.18	0.18			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C7 Replacing Superstar with Top 5% Downloads in Genre

	Top 5% in Genre						
	Free-to-play					Paid	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.15	-0.04	-0.04	-0.19	0.09	1.84
		[0.06]	[0.10]	[0.10]	[0.17]	[0.12]	
Genre installed base$_{t-1}$		-0.11	-0.16	-0.22	-0.13	0.01	1.19
		[0.02]	[0.03]	[0.08]	[0.12]	[0.06]	
Social features x Genre installed base$_{t-1}$			0.04	0.04	0.07	0.01	4.78
			[0.02]	[0.02]	[0.02]	[0.01]	
Genre competition	-0.003	-0.003	-0.002	-0.003	-0.004	-0.001	1.62
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	
Indie publisher	-0.07	-0.01	0.02	0.38	-0.01	-0.1	0.01
	[0.16]	[0.16]	[0.16]	[0.49]	[0.77]	[0.40]	
ln(Past releases publisher)	0.05	0.07	0.07	0.27	0.23	-0.08	0.43
	[0.08]	[0.08]	[0.08]	[0.29]	[0.45]	[0.15]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.15	-0.69	-0.50	0.94	0.04	-1.75	0.36
	[0.31]	[0.34]	[0.35]	[1.88]	[2.88]	[0.77]	
McFadden's *Pseudo* R^2	0.22	0.26	0.27	0.27			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C8 Replacing Social Features Measure with Binary Measure

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features (bin)		0.52	0.16	0.14	-0.55	0.31	3.95
		[0.16]	[0.26]	[0.26]	[0.35]	[0.26]	
Genre installed base$_{t-1}$		-0.01	-0.05	-0.09	-0.37	0.02	10.03
		[0.02]	[0.04]	[0.07]	[0.12]	[0.03]	
Social features (bin) x Genre installed base$_{t-1}$			0.07	0.07	0.23	0.06	4.12
			[0.04]	[0.04]	[0.07]	[0.04]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.004	-0.002	1.21
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	
Indie publisher	-0.24	-0.17	-0.13	0.19	1.39	0.01	3.22
	[0.14]	[0.14]	[0.14]	[0.39]	[0.74]	[0.21]	
ln(Past releases publisher)	0.13	0.13	0.13	0.32	1.04	-0.15	7.34
	[0.07]	[0.07]	[0.07]	[0.22]	[0.42]	[0.11]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.75	-1.15	-0.98	0.39	4.69	-2.93	7.45
	[0.58]	[0.30]	[0.32]	[1.53]	[2.75]	[0.44]	
McFadden's *Pseudo R^2*	0.22	0.23	0.23	0.24			
Observations	771	771	771	771	490	4,894	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C9 Replacing Social Features Measure with Pooled Local and Online Multiplayer

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features functions pooled		0.23	0.05	0.03	-0.29	0.09	2.08
		[0.07]	[0.12]	[0.12]	[0.17]	[0.20]	
Genre installed base$_{t-1}$		0.0003	-0.03	-0.09	-0.41	0.04	11.02
		[0.0194]	[0.03]	[0.06]	[0.13]	[0.04]	
Social features functions pooled x Genre installed base$_{t-1}$			0.03	0.03	0.13	0.03	6.84
			[0.02]	[0.02]	[0.03]	[0.02]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.004	-0.0004	2.81
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.0015]	
Indie publisher	-0.24	-0.22	-0.20	0.18	1.70	-0.20	4.97
	[0.14]	[0.13]	[0.14]	[0.38]	[0.80]	[0.28]	
ln(Past releases publisher)	0.13	0.15	0.15	0.37	1.28	-0.10	8.25
	[0.07]	[0.07]	[0.07]	[0.22]	[0.47]	[0.12]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.04	-1.13	-0.98	0.65	6.02	-3.02	8.55
	[0.29]	[0.31]	[0.32]	[1.51]	[3.04]	[0.52]	
McFadden's *Pseudo* R^2	0.22	0.23	0.23	0.24			
Observations	771	771	771	771	466	4,652	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C10 Dropping Local Multiplayer Measure from Social Features

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Online social features		0.30	0.11	0.08	0.02	0.60	1.58
		[0.08]	[0.14]	[0.14]	[0.33]	[0.32]	
Genre installed base$_{t-1}$		0.007	-0.01	-0.08	-0.34	0.09	6.23
		[0.019]	[0.02]	[0.06]	[0.17]	[0.04]	
Online social features x Genre installed base$_{t-1}$			0.03	0.04	0.13	-0.02	5.87
			[0.02]	[0.02]	[0.05]	[0.04]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	-0.004	1.04
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	
Indie publisher	-0.24	-0.27	-0.29	0.12	1.70	-0.28	3.27
	[0.14]	[0.14]	[0.14]	[0.36]	[1.08]	[0.22]	
ln(Past releases publisher)	0.13	0.14	0.14	0.38	1.40	0.09	4.29
	[0.07]	[0.07]	[0.07]	[0.21]	[0.63]	[0.09]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.04	-1.10	-0.98	0.78	5.97	-2.58	4.38
	[0.29]	[0.31]	[0.31]	[1.46]	[4.06]	[0.46]	
McFadden's *Pseudo* R^2	0.22	0.23	0.24	0.24			
Observations	771	771	771	771	467	4,980	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C11 Replacing Social Features Measure with Log-Transformation of Social Features

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
ln(Social features)		0.50	0.15	0.13	-0.52	0.09	2.09
		[0.13]	[0.21]	[0.21]	[0.32]	[0.28]	
Genre installed base$_{t-1}$		-0.001	-0.04	-0.10	-0.42	0.05	10.61
		[0.019]	[0.03]	[0.07]	[0.14]	[0.04]	
ln(Social features) x Genre installed base$_{t-1}$			0.06	0.07	0.25	0.05	7.35
			[0.03]	[0.03]	[0.06]	[0.04]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	-0.001	3.14
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.24	-0.20	-0.18	0.16	1.73	-0.16	4.26
	[0.14]	[0.14]	[0.14]	[0.38]	[0.86]	[0.32]	
ln(Past releases publisher)	0.13	0.15	0.14	0.34	1.26	-0.14	7.30
	[0.07]	[0.07]	[0.07]	[0.22]	[0.50]	[0.14]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.04	-1.17	-0.98	0.47	5.77	-2.77	6.93
	[0.29]	[0.31]	[0.32]	[1.52]	[3.21]	[0.49]	
McFadden's *Pseudo* R^2	0.22	0.24	0.24	0.24			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C12 Controlling for Leaderboards and Achievements

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.20	0.06	0.05	-0.23	0.007	1.37
		[0.05]	[0.09]	[0.09]	[0.15]	[0.127]	
Genre installed base$_{t-1}$		-0.002	-0.04	-0.09	-0.39	0.07	10.31
		[0.020]	[0.03]	[0.06]	[0.13]	[0.04]	
Social features x Genre installed base$_{t-1}$			0.03	0.03	0.10	0.02	6.54
			[0.01]	[0.01]	[0.03]	[0.02]	
Achievements	0.26	0.25	0.27	0.27	0.12	0.06	0.05
	[0.13]	[0.14]	[0.14]	[0.14]	[0.20]	[0.18]	
Leaderboard	0.11	0.08	0.07	0.09	-0.02	-0.07	0.01
	[0.21]	[0.22]	[0.22]	[0.22]	[0.30]	[0.23]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	-0.001	3.58
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.28	-0.28	-0.27	0.08	1.70	-0.23	4.32
	[0.14]	[0.14]	[0.14]	[0.38]	[0.87]	[0.32]	
ln(Past releases publisher)	0.12	0.14	0.14	0.34	1.30	-0.16	7.64
	[0.07]	[0.07]	[0.07]	[0.22]	[0.50]	[0.15]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.10	-1.17	-1.00	0.52	5.97	-2.74	6.90
	[0.29]	[0.31]	[0.32]	[1.51]	[3.28]	[0.49]	
McFadden's *Pseudo R^2*	0.22	0.24	0.25	0.25			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C13 Replacing Genre Installed Base Measure with Cumulative Genre Installed Base

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.21	0.05	0.05	-0.05	0.04	0.31
		[0.05]	[0.08]	[0.08]	[0.14]	[0.10]	
Genre cumulative installed base$_{t-1}$		-0.001	-0.01	-0.02	-0.05	0.01	13.33
		[0.005]	[0.01]	[0.01]	[0.01]	[0.01]	
Social features x Genre cumulative installed base$_{t-1}$			0.008	0.008	0.02	0.003	5.13
			[0.003]	[0.003]	[0.01]	[0.002]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	-0.001	4.21
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	
Indie publisher	-0.24	-0.23	-0.24	0.10	2.11	-0.08	4.22
	[0.14]	[0.14]	[0.14]	[0.43]	[1.02]	[0.32]	
ln(Past releases publisher)	0.13	0.15	0.14	0.37	1.77	-0.11	7.55
	[0.07]	[0.07]	[0.07]	[0.27]	[0.67]	[0.15]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-1.04	-1.11	-0.92	0.56	7.91	-2.94	7.73
	[0.29]	[0.31]	[0.31]	[1.71]	[3.85]	[0.65]	
McFadden's *Pseudo* R^2	0.22	0.23	0.25	0.25			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

3C14 Replacing Genre Installed Base Measure with New Platform-Level Adoption[38]

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.18	-0.08	-0.04	-0.38	0.40	3.66
		[0.05]	[0.17]	[0.18]	[0.32]	[0.25]	
New platform adoption$_{t-1}$		0.01	0.003	0.02	-0.03	0.02	3.26
		[0.01]	[0.009]	[0.01]	[0.02]	[0.01]	
Social features x New platform adoption$_{t-1}$			0.007	0.006	0.02	-0.006	5.61
			[0.004]	[0.004]	[0.01]	[0.006]	
Genre competition	-0.004	-0.005	-0.005	-0.005	-0.006	-0.001	5.37
	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	
Indie publisher	-0.15	-0.14	-0.15	-0.61	0.41	-0.21	0.74
	[0.13]	[0.13]	[0.13]	[0.34]	[0.64]	[0.35]	
ln(Past releases publisher)	0.14	0.16	0.15	-0.17	0.64	-0.14	2.95
	[0.07]	[0.07]	[0.07]	[0.23]	[0.43]	[0.15]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-0.97	-1.45	-1.06	-3.74	2.68	-2.83	2.75
	[0.28]	[0.41]	[0.48]	[1.88]	[3.25]	[0.71]	
McFadden's *Pseudo* R^2	0.17	0.19	0.19	0.20			
Observations	771	771	771	771	456	4,609	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

[38] Year of release dummies are absorbed in this specification.

3C15 Replacing Genre Installed Base Measure with Platform-Level Installed Base[39]

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.18	-0.09	-0.07	-0.42	0.44	4.86
		[0.05]	[0.16]	[0.17]	[0.30]	[0.25]	
Platform Installed Base$_{t-1}$		0.001	-0.002	0.001	-0.02	0.0003	4.49
		[0.002]	[0.003]	[0.004]	[0.01]	[0.0039]	
Social features x Platform Installed Base$_{t-1}$			0.002	0.002	0.005	-0.002	7.46
			[0.001]	[0.001]	[0.002]	[0.002]	
Genre competition	-0.004	-0.004	-0.004	-0.004	-0.006	0.00002	7.29
	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.00130]	
Indie publisher	-0.15	-0.14	-0.16	-0.42	0.99	-0.13	1.94
	[0.13]	[0.13]	[0.13]	[0.36]	[0.72]	[0.34]	
ln(Past releases publisher)	0.14	0.16	0.15	-0.03	1.06	-0.10	5.15
	[0.07]	[0.07]	[0.07]	[0.24]	[0.49]	[0.15]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-0.97	-1.15	-0.75	-2.28	6.13	-2.55	5.45
	[0.28]	[0.39]	[0.45]	[2.01]	[3.65]	[0.68]	
McFadden's *Pseudo* R^2	0.17	0.19	0.19	0.19			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

[39] Year of release dummies are absorbed in this specification.

3C16 Replacing Genre Installed Base Measure with Platform Installed Base Growth Rate[40]

	Superstar						
	Free-to-play					*Paid*	Test of 5 ≠ 6
Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Social features		0.20	-0.004	-0.02	-0.38	0.5	5.19
		[0.05]	[0.18]	[0.18]	[0.28]	[0.3]	
Installed base growth rate$_{t-1}$		-0.007	-0.007	-0.007	-0.006	-0.007	0.04
		[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	
Social features x Installed base growth rate$_{t-1}$			0.0004	0.0005	0.0013	-0.0007	7.55
			[0.0003]	[0.0004]	[0.0005]	[0.0005]	
Platform age	0.01	0.08	0.08	0.07	0.05	0.07	0.34
	[0.01]	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	
Genre competition	-0.005	-0.004	-0.004	-0.004	-0.005	0.0001	6.22
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.0012]	
Indie publisher	-0.14	-0.20	-0.21	-0.14	-0.12	0.07	0.22
	[0.13]	[0.13]	[0.13]	[0.17]	[0.30]	[0.26]	
ln(Past releases publisher)	0.14	0.14	0.14	0.18	0.29	-0.03	2.34
	[0.07]	[0.07]	[0.07]	[0.09]	[0.18]	[0.11]	
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes	
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes	
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes	
Endogenous treatment correction	No	No	No	Yes	Yes	Yes	
Matched and rebalanced sample	No	No	No	No	Yes	Yes	
Constant	-2.57	-8.59	-7.97	-7.50	-4.65	-10.17	1.35
	[0.85]	[2.40]	[2.40]	[2.51]	[3.44]	[3.27]	
McFadden's *Pseudo R^2*	0.18	0.21	0.21	0.22			
Observations	771	771	771	771	456	4,603	

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively. The error terms in Models 5 and 6 are jointly estimated. Model 7 reports Chow test statistics estimating equality of coefficients between coefficients in Models 5 and 6.

[40] Year of release dummies are absorbed in this specification.

3C17 First-Stage Results

	Free-to-play
Variable	**1**
Past freemium superstars	0.007
	[0.002]
Genre installed base$_{t-1}$	0.08
	[0.01]
Indie publisher	-0.51
	[0.05]
Past releases publisher	-0.28
	[0.02]
Genre dummies	Yes
Year of release dummies	Yes
Constant	-1.42
	[0.15]
McFadden's *Pseudo* R^2	0.19
Observations	9,700

Notes. Heteroskedasticity robust standard errors in parentheses. Mean model VIF = 2.06.

3C18 Median Playing Time as Outcome Measure for Mechanism Check

	ln(Median Playing Time)				
Variable	**1**	**2**	**3**	**4**	**5**
Free-to-play		-1.41	-4.24	-1.41	-4.77
		[0.06]	[0.06]	[0.09]	[0.11]
Social features	0.10	0.14	0.13	0.16	0.16
	[0.02]	[0.02]	[0.02]	[0.06]	[0.06]
Genre installed base$_{t-1}$	-0.03	-0.01	0.02	-0.01	-0.01
	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Genre competition	0.0016	-0.0004	-0.0004	0.0001	-0.001
	[0.0004]	[0.0004]	[0.0004]	[0.0010]	[0.001]
Indie publisher	0.12	0.04	-0.16	0.11	0.15
	[0.04]	[0.04]	[0.04]	[0.10]	[0.10]
ln(Past releases publisher)	0.17	0.13	0.05	0.27	0.28
	[0.01]	[0.01]	[0.01]	[0.04]	[0.05]
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes
Endogenous treatment correction	No	No	Yes	No	Yes
Matched and rebalanced sample	No	No	No	Yes	Yes
Constant	3.75	4.20	4.56	4.05	4.47
	[0.11]	[0.11]	[0.11]	[0.24]	[0.24]
R^2	0.08	0.12		0.12	
Observations	9,700	9,700	9,700	5,059	5,059

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-2 report stepwise results from probit regressions on the pooled sample of all *free-to-play* and *paid* games. Model 3 estimates an endogenous treatment effects model. Model 4 prunes and rebalances the sample via coarsened exact matching. Model 5 estimates the endogenous treatment effects model on the matched and rebalanced sample.

3C19 Pooled Sample Results (Three-Way Interaction)

Variable	Superstar 1	2	3	4	5	6
Free-to-play		1.08	1.33	0.20	1.95	1.53
		[0.09]	[0.17]	[0.28]	[0.23]	[0.79]
Free-to-play x Social features			-0.22	-0.20	-0.22	-0.22
			[0.09]	[0.09]	[0.19]	[0.19]
Free-to-play x Genre installed base$_{t-1}$			-0.04	-0.03	-0.17	-0.17
			[0.03]	[0.03]	[0.05]	[0.05]
Social features x Genre installed base$_{t-1}$			-0.001	-0.001	0.02	0.02
			[0.008]	[0.007]	[0.02]	[0.02]
Free-to-play x Social features x Genre installed base$_{t-1}$			0.03	0.03	0.07	0.07
			[0.01]	[0.01]	[0.03]	[0.03]
Social features	0.26	0.24	0.26	0.24	0.04	0.04
	[0.02]	[0.03]	[0.05]	[0.05]	[0.13]	[0.13]
Genre installed base$_{t-1}$	0.04	0.01	0.01	0.03	0.05	0.05
	[0.01]	[0.01]	[0.02]	[0.02]	[0.03]	[0.03]
Genre competition	-0.006	-0.003	-0.003	-0.003	-0.002	-0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Indie publisher	-0.39	-0.32	-0.32	-0.42	-0.12	-0.12
	[0.06]	[0.06]	[0.06]	[0.06]	[0.17]	[0.17]
ln(Past releases publisher)	0.04	0.09	0.10	0.03	0.02	0.02
	[0.02]	[0.02]	[0.02]	[0.03]	[0.08]	[0.08]
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous treatment correction	No	No	No	Yes	No	Yes
Matched and rebalanced sample	No	No	No	No	Yes	Yes
Constant	-3.01	-3.17	-3.17	-2.87	-3.57	-3.49
	[0.19]	[0.20]	[0.21]	[0.23]	[0.47]	[0.53]
McFadden's *Pseudo* R^2	0.27	0.31	0.31		0.39	
Observations	9,700	9,700	9,700	9,700	5,059	5,059

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results from probit regressions on the pooled sample of all *free-to-play* and *paid* games. Model 4 estimates an endogenous treatment effects model. Model 5 prunes and rebalances the sample via coarsened exact matching. Model 6 estimates the endogenous treatment effects model on the pruned and rebalanced sample.

3C20 Rare Events Logit Estimator[41]

	Superstar					
	Free-to-play					*Paid*
Variable	**1**	**2**	**3**	**4**	**5**	**6**
Social features		0.35	0.16	0.17	-0.26	0.07
		[0.09]	[0.14]	[0.15]	[0.30]	[0.29]
Genre installed base$_{t-1}$		-0.001	-0.01	-0.02	-0.04	0.02
		[0.009]	[0.01]	[0.01]	[0.03]	[0.01]
Social features x Genre installed base$_{t-1}$			0.04	0.03	0.15	0.05
			[0.02]	[0.02]	[0.05]	[0.04]
Genre competition	-0.006	-0.006	-0.006	-0.006	-0.008	0.001
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.002]
Indie publisher	-0.45	-0.46	-0.45	-0.36	-0.13	-0.68
	[0.24]	[0.25]	[0.25]	[0.40]	[0.92]	[0.73]
ln(Past releases publisher)	0.19	0.23	0.22	0.27	0.48	-0.29
	[0.13]	[0.13]	[0.13]	[0.22]	[0.54]	[0.35]
Quality dummies (2)	Yes	Yes	Yes	Yes	Yes	Yes
Genre dummies (9)	Yes	Yes	Yes	Yes	Yes	Yes
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes
Year of release dummies (5)	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous treatment correction	No	No	No	Yes	Yes	Yes
Matched and rebalanced sample	No	No	No	No	Yes	Yes
Constant	-1.59	-1.73	-1.55	-1.21	-0.90	-5.58
	[0.49]	[0.54]	[0.54]	[1.40]	[3.84]	[1.25]
Observations	771	771	771	771	456	4,603

Notes. Heteroskedasticity robust standard errors in parentheses.
Models 1-3 report stepwise results on the subsample of *free-to-play* games. Model 4 estimates an endogenous treatment effects model on the subsample of *free-to-play* games. Models 5 and 6 estimate results on a pruned and rebalanced sample via coarsened exact matching, on the subsamples of *free-to-play* and *paid* games, respectively.

[41] Stata's rare events logit estimator (*relogit*) does not allow for the joint estimation of errors between subsamples. Therefore, we refrain from estimating Chow test results. Note that the interaction between *social features* and *genre installed base* is significant for the subsample of *free-to-play* games whereas it is not significant for *paid* games.