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

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ABSTRACT

It is commonly assumed that when markets are characterized by network effects, this universally affects all competing products. In reality, however, firms often have agency in terms of whether or not to incorporate social features that have the potential to generate network effects. When this is the case, markets are characterized by partial network effects—some products have network effects, whereas others compete on the basis of a standalone value proposition. In this study, we focus on the differences in demand uncertainty between network products and standalone products competing in such a market. We develop theory predicting how a product's social features interact with other known drivers of demand uncertainty to impact diffusion. We test our arguments in the global board games industry, where board games designed around the collection and trading of 'collectible components' compete against traditional board games. Results show that network products exhibit greater variance in diffusion and that their diffusion is disproportionately affected by the degree of product novelty and the intensity and type of competition. Our findings contribute to the literatures on network effects and the diffusion of innovations.

Keywords: *Network effects, demand uncertainty, diffusion of innovations, products, board games.*

INTRODUCTION

Network effects occur when the value of a product or service increases with the total number of users of the same product.[2] Prior literature has primarily focused on "markets characterized by network effects"—settings in which network effects universally apply to *all* market participants (Boudreau, Jeppesen, & Miric, 2022; Clements & Ohashi, 2005; Katz & Shapiro, 1992; Schilling, 2002; Zhu & Iansiti, 2012). However, we increasingly observe markets where network effects are partial: some products exhibit network effects, whereas others do not. Examples include ride-hailing services, where some services allow for carpooling whereas others strictly offer ride-hailing; fitness and health applications, where some applications encourage peer comparisons while others simply provide tracking functionality; and video games, where some products include online multiplayer modes while others exclusively offer single-player functionality. This variation in network effects is possible because, despite the prevailing assumption in the literature, firms very often have agency over whether to include social features in their products that have the potential to generate network effects (Dou, Niculescu, & Wu, 2013; Rietveld & Ploog, 2022; Zhu, Li, Valavi, & Iansiti, 2021).

Diffusion dynamics for products with social features (network products) differ from standalone products, given that network products' value proposition depends on the total number of users (Afuah, 2013; Schilling, 2003; Shankar & Bayus, 2003). It is well known, for instance, that network products tend to either diffuse widely and capture a large share of a market's addressable demand (so-called winner-takes-all/most dynamics) *or* that they fail to diffuse at all

[2] Much of the literature has used the terms "network effects" and "network externalities" interchangeably. A few articles in economics define network externalities as implying an impact on users that is not priced into a product or service, which can be either positive or negative (see for example Chou & Shy, 1990). We follow convention and use the term "network effects" to describe a change in a product's value as a function of its users (Katz & Shapiro, 1985; Schilling, 2002; Suarez, 2004). Firms can change the price of a product to generate or reflect network effects.

and get locked out of the market (e.g., Cennamo & Santalo, 2013; Schilling, 1998, 2002; Suarez, 2005). Network products' dependence on users imposes greater demand uncertainty. In the absence of a large user base, consumers may fail to perceive sufficient value, given variability in the eventual value created. To be successful, producers of network products must resolve this demand uncertainty to a greater extent than their standalone competitors. While strategies for how firms can increase their chances of widespread diffusion in markets with universal network effects are well-documented (Katz & Shapiro, 1994; McIntyre, Srinivasan, Afuah, Gawer, & Kretschmer, 2020; Schilling, 2003; Soh, 2010), we do not know when it is beneficial to implement social features in the first place, and whether strategies to stimulate the diffusion of network products are different from those of standalone products. Therefore, we ask: *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?*

To address these questions, we examine product diffusion dynamics in markets with partial network effects. Starting from the premise that consumers perceive greater uncertainty from network products given their strong reliance on attracting a large user base to create value, we develop theory that explains when network products are more or less likely to enjoy widespread diffusion. We draw from the diffusion of innovations literature to develop our arguments. We focus on three key drivers of demand uncertainty—product novelty, promoting early adoption, and competition from similar products—for two main reasons: First, these factors are well-known drivers of consumers' perceived uncertainty and, subsequently, of products' diffusion. Second, these factors are, at least in part, within the firm's control. We propose that the diffusion of network products is disproportionately influenced by factors that either amplify or alleviate consumers' perceived uncertainty. In essence, we argue that any factor that increases (reduces) demand uncertainty will correspondingly have a negative (positive) impact on the diffusion of network products, over and above the general impact these factors have on diffusion.

We test our hypotheses in the global board games industry by analyzing data from a unique sample of 19,432 products collected from *boardgamegeek.com*, the largest online archive of non-digital tabletop games. Board game designers can generate network effects by adding collectible components (e.g., tranding cards and miniatures) to their products. These collectible components encourage players to trade and upgrade their collections through social interactions such as competitions and gatherings. Popular examples of *collectible network games* include *Magic the Gathering* and *Warhammer 40k*. In contrast to standalone board games, where players only require a single copy of the game, with CNGs, all players need their own copy of the game in addition to a set of collectible components—referred to as a deck—to fully enjoy these products. Results show that the diffusion of network products exhibits greater variance than that of standalone products and that product strategies that increase consumers' perceived uncertainty are more detrimental to the diffusion of network products than standalone products.

We contribute by relaxing the common assumption that network effects are universal (Rietveld & Ploog, 2022; Zhu et al., 2021). Introducing the notion of markets with partial network effects allows us to illustrate how firms can design their products for network effects by adding social features, although doing so inflicts greater variability on their diffusion. We also offer novel insights on how non-network factors interact with a product's social features to impact diffusion. Last, we identify strategies for mitigating the negative impact of demand uncertainty on network products. For example, network products are comparatively more likely to attain widespread diffusion when paired with a less novel product design.

THEORY AND HYPOTHESES

Network Effects

Network effects occur when the value of a product or service to a user increases with the total number of other users or compatible offerings of the same product or service (Katz & Shapiro, 1985).[3] Examples of products with network effects include telephones, social media applications, video game consoles, and sharing economy platforms, among others. In all these examples, the standalone value of the product is somewhat limited, with a significant portion of the overall value created by these products coming from other users or the producers of complementary goods and services. Consequently, in the presence of network effects, competitive outcomes are often characterized by one or a few competing products capturing an outsized market share while others get locked out (Cennamo & Santalo, 2013; Eisenmann, Parker, & Van Alstyne, 2011; Schilling, 1998, 2002). Such winner-take-all or winner-take-most dynamics explain why strategies for competing in markets with network effects have often emphasized rapid user acquisition to avoid market exclusion (Boudreau, 2012; Schilling, 1998, 2002; Suarez, 2004).

In the presence of network effects, a product's value creation is conditional on the size of its user base (Banerjee, 1992; Shankar & Bayus, 2003). A social media application or a multiplayer video game increases in value when more consumers buy and use these products. When the number of users of a product or service is unknown, consumers often rely on their perceptions and expectations to create a projection of its anticipated user base (Katz & Shapiro, 1985, 1986; Schilling, 2002, 2003). Firms can implement myriad strategies to increase the actual

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[3] The literature distinguishes between direct network effects and indirect network effects (e.g., Parker & van Alstyne, 2005). This classification is especially pertinent in the context of two- or multisided platforms where both the presence of users on the same side of the platform (e.g., consumers) as well as that of users on the other side of the platform (e.g., complementors) can generate network effects. Here, we focus specifically on direct network effects, the value arising from consumers adopting the same product. Prior literature (e.g., Rietveld & Ploog, 2022; Zhu et al., 2021) has looked at partial network effects in the context of two-sided platforms.

or perceived size of a product's user base, including early market entry, penetration pricing and subsidization, extensive marketing, preannouncements, vaporware, and signaling commitment through vertical integration and related investments (Boudreau, 2021; Farrell & Saloner, 1986; Garud & Kumaraswamy, 1993; Katz & Shapiro, 1994; Soh, 2010). A problem with these strategies is that they are not sensitive to differences in the strength of network effects among market participants. Put differently, they are conditional on the assumption that all competing products are uniformly affected by network effects—i.e., that network effects are universal (Clements & Ohashi, 2005; Katz & Shapiro, 1986; Schilling, 2002; Zhu & Iansiti, 2012).

There is increasing realization, however, that network effects can indeed vary across market participants. Network strength describes the marginal value that an additional user contributes to a product and can vary as a function of a product's network structure, the users comprising a product's user base, a product's life cycle stage, and its features (Afuah, 2013; Cabral, Salant, & Woroch, 1999; Gretz & Basuroy, 2013; Shankar & Bayus, 2003; Suarez, 2005). Some recent studies have begun to explore how firms can increase their products' network strength through various design choices. Notably, firms can incorporate social features into their products to willingly increase their products' network strength at any level of adoption.

To illustrate, Dou et al. (2013) modeled the profits of firms that augment network strength by incorporating social media features into their products. They discovered an optimal point beyond which further (costly) increases in network strength are not commensurate with consumers' willingness to pay for these features. Zhu et al. (2021) investigated competitive dynamics between platforms with varying strengths of network effects due to platforms' level of network interconnectivity. They found that firms can set the level of network interconnectivity at a platform's inception but face difficulty altering it once the platform has become established. In another study, we have documented that the number of multiplayer features positively affects the likelihood of freemium video games becoming a hit, but only when the installed base of the platforms these video games are released on is sufficiently large (Rietveld & Ploog, 2022).

Network effects can lead to a product capturing a disproportionately large market share, which raises the question of why, in those situations where firms can choose to design for network effects, firms would refrain from adding social features. First, developing and implementing social features is often costly and typically comes at the expense of a product's standalone value. Second, by designing for network effects, the firm cedes control to external factors (i.e., consumers) to deliver on a product's value proposition. This increases the risks faced by both the firm and its customers (all other things being equal). We next develop the relationship between network effects and consumers' perceived uncertainty in more detail.

Demand Uncertainty of Network and Standalone Products

Demand uncertainty refers to the difficulty consumers perceive in accurately evaluating a product's benefits. Pre-adoption, demand uncertainty arises when consumers find it difficult to precisely predict the benefits a product will confer due to factors relating to complex or incomplete product information, a lack of quality signals, or high search costs from market crowding (Mishra, Konana, & Barua, 2007; Rindova & Petkova, 2007; Wijnberg & Gemser, 2000). Post-adoption, demand uncertainty stems from consumers experiencing difficulties in assessing the value realized from using a product, as is the case with many credence goods (Priem, Li, & Carr, 2012; Tripsas, 2008). The higher the demand uncertainty, the more difficult it is for consumers to accurately evaluate a product's benefits. Demand uncertainty impacts consumer behavior and, therefore, a product's success (Priem, 2007; Rindova & Petkova, 2007).

Network products exhibit greater demand uncertainty than standalone products due to their dependence on users to create value. A network product's value proposition comprises two parts (Cabral et al., 1999; Shankar & Bayus, 2003; Srinivasan, Lilien, & Rangaswamy, 2004): First, *standalone value* entails the benefits a consumer expects to derive from using the product in isolation—this value is independent of a product's sales or usage. While standalone products exclusively offer standalone value, network products can also provide some standalone value (e.g., a single-player campaign included in an online-multiplayer video game). Second, *network value* entails the benefits a consumer derives from other users adopting and using the same product. Network value has two components—(1) the total number of users that have adopted the product and (2) the extent of interactions facilitated by social features (Rietveld & Ploog, 2022; Shankar & Bayus, 2003). For example, the network value of an online multiplayer video game is affected by the design of the multiplayer campaign (e.g., how many players the game can accommodate, the extent of coordination or competition among players, etc.) and by the number of gamers playing the same game. Firms can manipulate a product's network value through the design of its social features and by promoting its diffusion. **Figure 1** illustrates the difference between standalone products (product A) and network products (product B).

Insert Figure 1 about here.

While network products have the potential to create substantially more value than standalone products—given that network value scales with diffusion—the actual outcome is uncertain because the value creation depends on enough consumers adopting the product for network effects to materialize. Subsequently, consumers cannot be sure whether a product will take off or find itself locked out of the market. This demand uncertainty is further amplified by the fact that, at the time of launch, a product's user base is zero. Especially shortly after a product's market launch, consumers will, therefore, struggle to accurately predict a network product's value creation due to the high degree of variability in its eventual diffusion. Given that the market-level consequences of this dynamic have been fairly well documented (Eisenmann et al., 2011; Schilling, 1998, 2002), we begin by offering the following baseline hypothesis:

Baseline hypothesis: *The diffusion of network products varies more widely than that of standalone products.*

Prior research argued that firms need to adjust their strategies when confronted by demand uncertainty (Atuahene-Gima & Li, 2004; Autio, Dahlander, & Frederiksen, 2013; Cohen, Lobel, & Perakis, 2016; Moeen, Agarwal, & Shah, 2020). The prevailing guidance for network products in this regard has been to attract as many users as quickly as possible (Schilling, 2002; Suarez, 2004). Owing to the assumption that all competing products are subject to the same network effect and that market outcomes are either "win" or "lose," the literature has largely ignored any qualitative differences between products and how these can interact with a product's social features to affect their success. Moreover, winner-take-all strategies such as early market entry and pricing subsidies are conditional on a firm's decision to produce a network product—the literature has not offered much guidance on when it might pay to implement social features in the first place. In this light, strategies for network products are likely to differ from standalone products, not least given their differences in demand uncertainty.

Therefore, below, we develop arguments around three key factors that are well-known determinants of consumers' perceived uncertainty and, by extension, influence a product's diffusion: product novelty, promoting early adoption, and competition (Moore, 1991; Rogers, 2003). A novel product design, for example, can help attract innovators and early adopters who tend to be novelty-seeking, but it amplifies demand uncertainty for late adopters who are famously risk-averse. Nevertheless, appealing to innovators and early adopters remains paramount, given that late adopters tend to look to early adopters for guidance regarding their own adoption decisions. Furthermore, competition intensity increases demand uncertainty as consumers face more options to choose from and engage with and it also limits the chances of any given product performing well in real terms. In developing our hypotheses, our overarching argument is that the diffusion of network products is disproportionately influenced by those factors that either amplify or alleviate consumers' perceived uncertainty for a product.

The Disproportionate Effect of Novelty on Network Products

A firm's ability to remain competitive often derives from its capacity to innovate (Adner & Kapoor, 2010; Christensen, Suárez, & Utterback, 1998). However, innovation is also associated with novel product designs, which can amplify demand uncertainty (Criscuolo, Dahlander, Grohsjean, & Salter, 2017; Taylor & Greve, 2006). Consumers may experience difficulties forming an adequate value assessment when a product and its features are more novel (Rindova & Petkova, 2007). Departure from familiar designs can disrupt a consumer's evaluation schemas and upend their ability to discern whether a product matches their preferences (Atuahene-Gima & Li, 2004; Priem, 2007). As a result, novel products tend to primarily appeal to a small subset of consumers—so-called innovators and early adopters—while later adopters apply a more cautious "wait-and-see" approach, awaiting the experiences of early adopters before making any decisions of their own (Payne, Frow, & Eggert, 2017; Rietveld & Eggers, 2018; Rogers, 2003).

This reluctance is particularly problematic for network products. Fast adoption by as many consumers as possible is crucial for network products as it expedites the generation of network effects, enhancing a product's value creation and boosting its appeal (Schilling, 2003;

Suarez, 2004). Hence, the wait-and-see approach induced by product novelty can impede widespread diffusion, slowing the rate at which network value is created. Standalone products are relatively insulated from this because their value proposition is designed around standalone value and, therefore, does not depend on fast and widespread diffusion to the same extent. As a result, standalone products can better withstand a slow uptick in initial diffusion without significantly limiting their value for consumers. Therefore, we hypothesize that while product novelty can negatively affect the diffusion of any product due to the inherent demand uncertainty it introduces, the effect is more pronounced for network products than standalone products:[4]

Hypothesis 1: *Novelty negatively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.*

The Disproportionate Effect of Promoting Early Adoption on Network Products

Innovators and early adopters can act as catalysts in a product's diffusion (Priem et al., 2012; Rogers, 2003; Xiong & Bharadwaj, 2014). Early adopters typically rely on their independent judgment and research when evaluating products, whereas late adopters are often driven by social influences and what early adopters have chosen before them. However, inhibiting factors such as product availability or launch timing can deter even the most ardent of early adopters, potentially causing a lasting negative impact on a product's wider diffusion. For example, Catalini and Tucker (2017) found that when early adopters are prevented from adopting first, their rate of disengagement with a product increases. This implies that early adopters' motivation is in part driven by their ability to adopt early and that any obstructions can negatively impact a

[4] We note that Hypothesis 1 and all subsequent hypotheses test against two null hypotheses. The first null hypothesis concerns a factor's main effect on a product's diffusion (e.g., novelty—which is well established in the literature) whereas the second null articulates a factor's disproportionate impact on network products compared to standalone products (our proposed contribution). Our hypotheses are supported only if both null hypotheses can be rejected.

product's wider diffusion. Firms can employ various tactics to promote early adoption, including offering pre-orders, facilitating early access, and launching crowdfunding campaigns.

Attracting early adopters plays a vital role in alleviating demand uncertainty, especially for network products (Eisenmann et al., 2011; Schilling, 2002; Suarez, 2004). Early adoption not only signals approval from a critical and well-informed subset of consumers, which lessens evaluative uncertainty for later adopters, but it also sets in motion the generation of network effects (Boudreau & Jeppesen, 2015; Lee & O'Connor, 2003). Frontloading a product's demand via, for example, pre-orders or a crowdfunding campaign can help to create the impression of a large user base. Frontloaded demand further signals product viability and the potential for extensive social interactions with others (Boudreau, 2021). This, in turn, expedites the creation of network value and instills self-fulfilling expectations among later adopters (Subramanian, Mitra, & Ransbotham, 2021). Hence, the benefits of promoting early adoption are particularly pronounced for network products. We thus posit the following hypothesis:

> ***Hypothesis 2:*** *Promoting early adoption positively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.*

The Disproportionate Effects of Competition on Network Products

Competition from similar products can negatively impact a product's demand uncertainty.[5] A proliferation of competing offerings can lead to the dispersion of consumers and their attention

[5] We acknowledge that competition can also have a market expansion effect resulting in demand spillovers. The exent of demand spillovers (and whether it mitigates the negative effects of crowding) depends on the context and the type of competition a product faces. For example, demand spillovers tend to be larger in nascent markets and two-sided platforms (e.g., Lee, Han, Park, & Oh, 2022; Mahajan, Sharma, & Buzzel, 1993). Moreover, demand spillovers also are stronger when market entry occurs by dissimilar (rather than similar) products (Boudreau, 2012; Cattani, Porac, & Thomas, 2017). In established markets and non-platform contexts—including our board games setting—the negative effects of attention dilution and consumer dispersion outweigh any demand spillover benefits.

(Porter, 1979; van den Steen, 2018). Such attention dilution is further compounded in those settings where an overabundance of available alternatives can result in choice paralysis (Schwartz, 2004), potentially dissuading consumers from selecting any offerings at all.

Competition intensity—the number of similar products entering the market around the same time as a focal product—is especially detrimental for network products, given their reliance on users to create value. Competition intensity disproportionally obstructs the diffusion of network products in two ways. First, competition intensity distributes consumers across a larger number of available products, decreasing the user base size of any given product. A smaller initial user base can thwart the further diffusion of network products in the absence of network effects (Schilling, 2002; Shankar & Bayus, 2003). Second, consumers may anticipate a slower rate of user base growth when competition intensity is high. Such dampened expectations can add to consumers' perceived uncertainty and reduce their likelihood of adoption (Boudreau, 2021; Katz & Shapiro, 1985; Schilling, 2003). Standalone products are comparatively shielded from these additional adverse effects of competition intensity. We therefore argue that:

Hypothesis 3a: *Competition intensity negatively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.*

Competition varies not only by intensity but also by type (Barney, 1986). For instance, the presence of a successful hit product can change a market's competitive dynamics. Due to their outsized popularity, hit products often dominate consumers' attention, making it harder for competing products to gain a foothold in the market (Gretz, Malshe, Bauer, & Basuroy, 2019; Yin, Davis, & Muzyrya, 2014). This is particularly problematic for network products that require large user bases comprised of engaged users (Rietveld & Ploog, 2022). Competition from hit products increases consumers' perceived uncertainty and can result in market lockout for network products—especially if the hit competitor also benefits from network effects (Schilling, 1998). Therefore, the type of competition—embodied here by a hit product—can differentially impact the diffusion of network products relative to standalone products. Hence, we argue that:

Hypothesis 3b: *Competition from a hit product negatively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.*

In sum, we have argued that network products exhibit significant demand uncertainty. Furthermore, other factors that augment or mitigate consumers' perceived uncertainty disproportionately affect diffusion dynamics for such products. We identified three such factors that—to some degree—are within the firm's control: product novelty, promoting early adoption, and competition intensity and type. Product novelty is a function of a firm's design choices, and firms can promote early adoption as part of their product-launch strategy. While firms may not be able to directly influence a market's competitiveness, they can opt to launch their products at a time when competition is more or less intense—or when there are no competing hit products—on the basis of market research. Consequently, these factors can guide firms in deciding whether or not to implement social features and determine the optimal launch timing for their products.

DATA AND METHODS

The Board Games Industry

We test our predictions in the global board games industry. The board games industry encompasses all economic activity within the realm of non-digital tabletop games, including dice and card games. Examples of well-known board games include *Monopoly*, *Settlers of Catan*, and *Ticket to Ride*. The global board games industry was estimated to be worth between $15 and $26 billion in 2021 and has experienced continuous growth over the past decade for two main reasons. First, the supply of board games has surged recently due to crowdfunding platforms such as Kickstarter and Indigogo. Prior to the rise of crowdfunding platforms, board game designers would need to negotiate deals with large publishers such as *Asmodee*, *Hasbro,* and *Ravensburger* to fund and commercialize their products. With the advent of crowdfunding, self-publishing has become a viable route to market. Second, the rise of "digital fatigue" has steered many consumers to non-digital forms of entertainment, which has boosted the visibility of independent game stores and local board game cafes (e.g., the *Dice Saloon* in Brighton, UK).

The board games industry is an opportune setting for our study. First, board game designers can add social features in the form of collectible components for players to trade and collect. Collectible components can take the shape of cards (e.g., *Pokémon* cards), miniatures (e.g., *Warhammer 40k* miniatures), or dice (e.g., *Marvel Dice Masters* dice). *Magic the Gathering* is a prime example of a game with collectible components or a *collectible network game* (CNG). Released in 1993, *Magic the Gathering* is a card game centered on competitive, one-on-one matches in which players use individually crafted 60-card decks. More than 20,000 unique *Magic the Gathering* cards, which vary in rarity and power level, affect players' gameplay abilities. A key element of playing *Magic the Gathering* is trading cards with other players to gradually level up one's "deck" for competitive use. Trading is facilitated through conventions and tournaments. Thus, besides the value from playing the game, *Magic the Gathering* players also derive value from trading cards and competing against other players, which becomes more valuable when more players own the game. Other popular CNGs include *Yugioh!*, *Heroclix,* and *Warhammer 40k*. Players of these and other CNGs often spend large amounts of money, energy, and time to improve their collections through social interactions.

Second, collectible components are intertwined with a board game's physical materials and rules of play. Therefore, they are key to a board game's product design, and designers must decide whether to add them before commercial release. Notably, they cannot reverse this decision later. In contrast, producers of many digital products can alter their designs by adding social features after release. While interesting, a setting where firms can change their products' social features is problematic for researchers trying to study them because a firm's decision to add social features after a product's release will likely be informed by its prior diffusion.

Third, unlike other settings (e.g., social media applications), not all board games are designed to have network effects. Instead, board games with collectible components compete against standalone board games, and both types of products can be easily identified.[6]

Data Collection

We collected our data from *boardgamegeek.com* in September 2020. *Boardgamegeek.com* launched in 2000 as a forum for its more than two million users to keep track of their board game collections, rate, talk about, and arrange meetings to play board games and trade collectible components. With over 180,000 board game listings, it is the most comprehensive online archive of board games. We collected rich board-game level data, including title, year of release, genre, publisher, gameplay mechanics, whether a board game launched a crowdfunding campaign, and whether it has collectible components. We further collected data on the number of times a board game was rated and how many users own it. We also collected country-of-origin data for the 5,926 publishers in our sample. Finally, we collected data from *Kaggle.com* (a machine learning

[6] We acknowledge that virtually all board games contain a social element. However, the term *standalone game* is appropriate for those board games that are not categorized as *collectible network games* because only one game set is required to play these kind of games. For example, when a group of friends wishes to play *Monopoly*, they only require one copy of the game. However, when the same group wishes to play *Magic the Gathering*, each friend needs to have purchased the base game as well as a variety of collectible trading cards to be able to play.

and data science community) on the number of Kickstarter backers and funding rates for those board games in our estimation sample that launched a crowdfunding campaign.

Estimation Sample

We consider all board games released between 2011 and 2017 (inclusive). We begin our sample in 2011 because the board games industry experienced a major shift with the introduction of Kickstarter in 2009. Considering a typical board game's development cycle of two years, all board games launched from 2011 onwards had the possibility to get crowdfunded. We end the sample in 2017 for two main reasons. First, *boardgamegeek.com* users provide most information by suggesting edits to board games' listings on the website. Administrators then check these suggestions and either reject or approve the proposed changes. Therefore, product data on *boardgamegeek.com* become more accurate over time. By restricting the sample to board games released in 2017, we ensure that each game in our sample has at least two years for updated information. Second, our sample timeframe allows each game to accumulate users for at least two years, accounting for approximately 50% of a typical game's cumulative ownership (see **Figure 2,** upper-left quadrant). This avoids any potential bias from right-truncated data.

From these 34,334 board games, we excluded all expansions, any unreleased board games, board games that *boardgamegeek.com* flagged as being out of scope (e.g., *Rock, Paper, Scissors*), board games not published in English, and those that failed to acquire a single comment, which hints at fundamental issues with either the board game or its listing on the website. After applying these restrictions, our estimation sample has 19,432 observations, of which 225 board games have collectible components. In supplemental analyses, we apply coarsened exact matching to address potential concerns relating to sample imbalance.

Insert Figure 2 about here

Figure 2 depicts ownership statistics broken out by board games with and without collectible components. *Cumulative owners* measures the number of *boardgamegeek.com* users who indicate ownership of a game.[7] We note three interesting observations. First, board games with and without collectible components follow similar ownership accumulation trajectories. The upper-left quadrant in **Figure 2** shows that, on average, both types of board games accumulate approximately 62% of their lifetime owners within the first three years of release. Second, CNGs display greater variance in cumulative ownership than standalone board games. The upper-right quadrant in **Figure 2** depicts the mean ownership as well as the 5-to-95th percentile range of owners two years after release. On average, standalone board games have 124 owners on *boardgamegeek.com*, with the 95th percentile being 451. CNGs attain 275 owners on average, with the 95th percentile being 1,243. Third, the bottom graphs in **Figure 2** depict the average and the standard deviation of board game ownership over time, showing that the standard deviation of ownership for CNGs increases more markedly than that of standalone board games. These visualizations illustrate that collectible network games generally behave as we would expect network products to and provide model-free evidence supporting our baseline hypothesis.

[7] We interpret ownership statistics on *boardgamegeek.com* as indicative of the wider market for board games. Actual sales numbers for the products in our sample are likely to be much higher than what is recorded in our data, given that not all consumers who play board games track their collections online. There are also likely some discrepancies between users on *boardgamegeek.com* and the broader consumer demographic that comprises the overall market for board games. For example, it is plausible that innovators and early adopters—so called "board game geeks"—are overrepresented on the website. This may bias the estimates for our main effects, including the coefficient on *collectible components* (e.g., we expect avid players to have stronger preferences for CNGs than the typical consumer). However, we note that our substantive interest is in the interaction effects of novelty, early adoption, and competition and how these effects vary between CNGs and standalone board games, respectively. Here we believe that any bias will be much less of an issue and that we can take our point estimates at face value.

Measures

Dependent variable. Our hypotheses pertain to the diffusion of board games. Obtaining sales data for individual board games is not feasible, as publishers keep this information closely guarded. Therefore, we use ownership data from *boardgamegeek.com* to measure diffusion. Users on *boardgamegeek.com* can indicate which board games they own, and these indications are time-stamped. In our sample, a typical *boardgamegeek.com* user owns 12 different board games; approximately 71% of all *boardgamegeek.com* users own more than one board game and 29% own at least one CNG. Our dependent variable counts the number of *owners* two years after a board game's release. We chose two years as our cut-off point for two reasons. First, if games with collectible components do not attract any owners two years after release, they likely never will (i.e., they experience lockout).[8] Second, by ending the estimation sample in 2017, we ensure we can track each game's ownership over (at least) two years. We take the natural logarithm to account for skewness. To test our baseline hypothesis, we look at the variance of *owners*.

Independent variables. First, *collectible components* is a dummy variable that takes the value of 1 if a board game has any collectible components (i.e., it is a CNG) and 0 otherwise. Some notable examples of CNGs in our estimation sample include *Android Netrunner*, *Star Wars X-Wings*, and *The Lord of the Rings Trading Card Game*. Within the subsample of 225 CNGs, most board games include trading cards (199), while the other 26 either come with miniatures (19) or collectible dice (7). The underlying mechanics of requiring a set of collectible components to engage in competitive gameplay are the same across these three types of

[8] To illustrate this point, we divided all CNGs into those games with above and below median ownership counts two years after their release and then examined the slope of ownership increase from two to four years after release. We find that, on average, CNGs with below median owners only obtain about one additional owner per year. In contrast, CNGs with above-median ownership counts obtain an additional 211 owners per year. We additionally looked at all board games that did not attract a single owner within six months of release. Of all standalone games, 12% had no owners whereas 17% of all CNGs had no owners six months after release. These statistics are consistent with the notion of lockout and that CNGs face greater risk of suffering lockout than standalone board games.

collectible components. We also did not want to divide our data further into separate sub-categories of CNGs to maintain sufficient statistical power for estimation.

Second, we measure *novelty* by assessing a board game's gameplay mechanics relative to prior board games in the same genre. *Boardgamegeek.com* lists 182 distinct gameplay mechanics ranging from "dice rolling" to "force commitment" and "variable set up".[9] To create our novelty measure, we start by assigning each game a value of either 1 or 0 per mechanic, depending on whether it lists the respective mechanic. We then concatenate these 182 binary codes into a single vector. Next, we calculate the market average vector for each game by considering all board games released five years prior that share at least one genre with the focal game. We then measure a board game's novelty by calculating the cosine distance between its gameplay vector and the board game-specific market average. Consequently, a higher value of *novelty* corresponds with a more novel product design. Prior studies (e.g., Haans, 2019; Zhao, Ishihara, Jennings, & Lounsbury, 2018) have used similar techniques to measure product novelty. Some examples of novel games in our sample include *Tapple* (combining *matching*, *memory*, and *player elimination*), *Santorini* (combining *grid movement*, *map reduction race*, *three dimensional movement*, and *variable player powers*), and *Letters from Whitechapel* (combining *hidden movement*, *point-to-point movement*, *secret unit deployment*, and *team-based game*).

Third, to measure a board game's promotion of early adoption, we constructed the variable *Kickstarter success*, which takes the value of 1 when a board game was funded via a successful Kickstarter campaign and 0 otherwise. Designers can propose a Kickstarter project and state the minimum amount required to realize the project, called a funding goal. Kickstarter

[9] See https://boardgamegeek.com/browse/boardgamemechanic for a full list of mechanics (last accessed 26/04/24).

backers can then pledge funds. A project is successfully funded only if it reaches its funding goal within the time set for the campaign. Kickstarter can be an enabler of early adoption for board games. It allows designers to showcase their board games before release, and fans can support their development by providing feedback and pledging funds. Backers of a successfully funded project receive a copy of the product once finished. Industry experts and board game designers agree that one of Kickstarter's biggest advantages is reaching an audience of early adopters.[10] There is no statistically significant difference between the share of CNGs (8% of observations) and the share of standalone games (9%) that launch with a Kickstarter campaign; neither is there a significant difference between the share of self-published board games (10%) and that of board games published by an external publisher (9%) with a Kickstarter campaign.

Fourth, the variable *competition intensity* counts the number of board games released within the same genre as the focal game from three months before to three months after its release, divided by the count of genres in case it competes in more than one genre.[11] As such, *competition intensity* captures the mean competition a board game faces across its genres within a six-month rolling window of its launch. Competition from similar products tends to have a stronger negative impact on sales and engagement than competition from dissimilar products, which can have a demand spillover effect (Boudreau, 2012; Cattani, Porac, & Thomas, 2017).[12]

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[10] See for example https://www.launchboom.com/blog/5-reasons-why-crowdfunding-is-the-best-way-to-launch-your-new-product/, https://orangenebula.com/the-outpost/understanding-crowdfunding-unsettled-kickstarter-reflections-part-two/, and https://stonemaiergames.com/top-10-reasons-to-launch-a-product-via-crowdfunding/ (last accessed 26/04/24).

[11] *Boardgamegeek.com* lists a total of eleven genres: *strategy, abstract strategy, war, customizable, thematic, party, family, children, cards, dice*, and *miniatures*. We code games that are not categorized within any of these genres as *no genre* (n = 2,186), giving us a total of twelve genre categories. The board games in our estimation sample compete in 1.29 genres on average (standalone board games = 1.29 genres; CNGs = 1.44 genres).

[12] Supplemental analyses reported in the **Online Appendix** show this is true also in our context.

We chose the six-month timeframe because most board games' sales and marketing campaigns are heavily concentrated on the months immediately leading up to and following release.

Last, the dummy variable *hit competition* takes the value of 1 when a board game competes against a game with an ownership share of 15% or more (calculated excluding the focal game) released within the same six-month rolling window used in our *competition* variable and 0 otherwise. Hit products generally hold widespread appeal. Therefore, instead of restricting this measure at the genre level, we consider all board games released in the same period. Well-known examples of hit board games in our sample include *Gloomhaven* (16.68% market share), *Terraforming Mars* (15.43%), and *Mansion of Madness* (15.02%). Consistent with studies on blockbuster products (e.g., Binken & Stremersch, 2009; Kneeland, Schilling, & Aharonson, 2020; Yin et al., 2014), 6.9% of all board games (n=1,338) compete against a hit game.

Control variables. We include several control variables at the game, publisher, and market levels. At the publisher level, we include the dummy variable *self-published,* which takes the value of 1 if a board game is self-published and 0 if it is published by one of the major publishers (e.g., *Hasbro*, *Ravensburger*). We expect *self-published* to be negatively associated with diffusion, given that these board games tend to be commercialized by firms with fewer resources. We also include the variable *publisher experience,* which counts the number of prior board games released by a board game's publisher over a five-year rolling window. We take the natural logarithm to account for skewness. We expect a positive effect of *publisher experience* on owners. We further include the logarithm of *team size,* which counts the number of designers and artists credited on a board game. We expect *team size* to positively affect a board game's owners since larger teams can be a proxy for firm resources and are positively correlated with marketing expenditures, access to distribution, and geographical reach (Mollick, 2012).

Finally, we include several fixed effects. First, we control for the publisher's country of origin as this can affect both a publisher's access to resources and consumer perceptions of products (Bilkey & Nes, 1982). Second, we include board-game genre dummies to account for heterogeneous consumer preferences (Boudreau, 2012; Hsu, Roberts, & Swaminathan, 2012). Third, we include month-of-release fixed effects to control for seasonality. Last, year-of-release fixed effects control for macroeconomic trends and account for the growing stock of evergreen games (e.g., *Monopoly*) that might have a lingering impact on competition and performance.

Methods

First, to test the baseline hypothesis that the diffusion of network products varies more widely than that of standalone products, we conducted two tests—Levene's test (Gastwirth, Gel, & Miao, 2009; Levene, 1960) and a heteroskedastic linear regression (Harvey, 1976). While Levene's test is a convenient way to assess the equality of variances across subsamples, it does not allow for control variables. For this reason, we also run a linear heteroscedasticity regression that allows us to estimate the variance in *owners* as a function of *collectible components*.

Second, board games with collectible components might be systematically different from standalone board games. For example, firms might decide to design a CNG if they anticipate widespread diffusion. For our main hypotheses tests, we thus face a potential endogeneity concern in the absence of a naturally occurring experiment or exogenous shock. We attempt to account for this by estimating a treatment model in which the endogenous variable is binary (*collectible components*) and the outcome variable is continuous—called a linear endogenous treatment regression model (Greene, 2012; Wooldridge, 2010).[13] The endogenous treatment effect model includes two equations—one for the outcome (1) and one for the treatment (2):

$$(1)\ y_i = x_i\beta + \delta t_i + \epsilon_i$$

Where y_i is the outcome variable (i.e., *owners*), x_i is a vector of independent variables, δ is the potential bias of the OLS estimation for the treatment effect, t_i is the endogenous treatment effect (i.e., *collectible components*), and ϵ_i is the error term. The endogenous treatment equation is:

$$(2)\ t_i = 1, if\ w_i\gamma + \mu_i > 0, and\ t_i = 0 \text{ otherwise}$$

where w_i is a vector of independent variables that model the treatment assignment (*collectible components*), and μ_i is the error term. Both error terms ϵ_i and μ_i are normally distributed with a mean of zero and have the covariance matrix $\begin{Bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{Bmatrix}$. The covariates x_i and w_i are exogenous.

We include several covariates in the treatment equation. Foremostly, *MtG events* counts the logged number of official *Magic the Gathering* social events in the same country as the board game's publisher two years before the launch of the focal board game (the average time it takes to develop a board game). The intuition is that seeing the success that *Magic the Gathering*—the world's most popular CNG—has in attracting consumers to tournaments and conventions in the home market of a publisher will have a positive impact on its decision to develop or commission a board game with collectible components, but no effect on the diffusion of the focal game

[13] An instrumental variable regression is appropriate only when the endogenous variable is continuous as it operates under the assumption of linearity for the two-stage least square estimates to be identified (Greene, 2012; Wooldridge, 2010). The endogenous treatment effects model, also known as an endogenous binary variable model, is an extension of the instrumental variable regression for nonlinear models—it is specifically designed for situations where the endogenous variable is binary (Heckman, 1977). An exclusion restriction is not required (Greene, 2012).

itself.[14] We further include genre dummies as some genres are better suited for collectible components than others. We also include several firm-level variables, such as *self-published, publisher experience*, *team size,* and country of origin dummies. Finally, we include year-of-release dummies to account for macroeconomic factors that may affect the popularity of CNGs. The outcome equation controls for the non-random assignment of a board game launching as a CNG (instead of a standalone game) by adding the residuals from the treatment equation.

RESULTS

Descriptive Statistics, Baseline Hypothesis, and First-Stage Results

Table 1 lists descriptive statistics and pairwise correlations of the untransformed covariates. None of the pairwise correlations between variables raises concerns about multicollinearity.

The baseline hypothesis is supported across both Levene's test and the heteroskedastic linear regression: The variance of *owners* for CNGs is 3.10 times larger than that for standalone board games, and this difference is statistically significant (p = 0.00). Furthermore, the heteroskedasticity regression confirms that *collectible components* is associated with an increase in variance after controlling for the effects of all other predictor variables on variance.[15]

Model 0 in **Table 2** reports results from the first-stage treatment equation. As predicted, *MtG events* has a positive effect on the likelihood of a board game launching with collectible components ($\beta = 1.10$, $p = 0.01$). A doubling in the number of *Magic the Gathering* events in a publisher's home country increases the likelihood of releasing a collectible network game by one percentage point—a near doubling in the baseline rate of CNGs in our estimation sample. The other variables—*self-published* ($\beta =$ -0.89, $p = 0.07$), *publisher experience* ($\beta =$ -0.07, $p =$

[14] We offer three key reasons for this: First, the variable measures events related to a different board game released by a different firm. Second, the events take place two years before the release of the focal board game. Third, whereas the measure looks at social events in a specific country, our outcome variable tracks ownership globally.
[15] We report these results in-text because the tests produce single test statistics of interest and no tabulated results.

0.01), and *team size* ($\beta = 0.10$, $p = 0.10$)—also have significant effects. Board games in the *family* genre are least likely to have collectible components, whereas those that require some degree of *customization* in play are most likely to have collectible components.

Main Results

Models 1-6 in **Table 2** present results from our endogenous treatment effects. Model 1 includes all independent variables. While we do not offer any predictions about the main effect of *collectible components*—given the uncertain outcomes of launching a product with social features (per our baseline hypothesis)—we find a negative and significant effect ($\beta =$ -0.75, $p =$ 0.07) such that CNGs are associated with a 52.88% decrease in ownership two years after a board game's release compared to standalone board games. Models 2-5 report the stepwise inclusion of the interaction effects testing our main hypotheses. We focus on Model 6, the fully specified model including all interactions, for the interpretation of our main results.

Insert Tables 1 and 2 about here

We note support for Hypothesis 1, which states that product novelty negatively affects product diffusion and that this effect is more pronounced for network products than standalone products. The main effect of *novelty* is negative and significant ($\beta =$ -0.35, $p = 0.00$). Moreover, the interaction effect between *collectible components* and *novelty* is also negative and significant ($\beta =$ -0.60, $p = 0.09$). A 25% increase in product novelty (equal to one standard deviation from the mean) is associated with a 15.34% decrease in owners two years after a board game's release for collectible network games, but only a 7.33% decrease for standalone board games.

We do not find support for Hypothesis 2, which states that early adoption positively affects a product's diffusion and that this effect is more pronounced for network products than standalone products. While the main effect of *Kickstarter success* is positive and significant ($\beta =$ 0.89, $p = 0.00$), the interaction between *collectible components* and *Kickstarter success* is negative and significant ($\beta =$ -1.17, $p = 0.00$). A successful Kickstarter campaign is associated with a 24.76% decrease in *owners* of collectible network games but a more than doubling in owners of standalone games. Thus, the interaction points in the opposite direction of our hypothesis. We conjecture that this counterintuitive result may be driven by a failure to appeal to and expeditiously attract late adopters. We further expand on our conjecture in the discussion.

We find support for Hypothesis 3a, which states that competition intensity negatively affects product diffusion and that this effect is more pronounced for network products than standalone products. The main effect of *competition intensity* is negative and significant ($\beta =$ -0.0011, $p = 0.00$). The interaction between *collectible components* and *competition intensity* is also negative and significant ($\beta =$ -0.0014, $p = 0.01$). Each additional 150 same-genre games released within six months of a focal game's release is associated with a 15.50% decrease in owners for collectible network games, but only a 9.65% decrease for standalone games.

Finally, we also note support for Hypothesis 3b, which states that competition from a hit product negatively affects diffusion and that this effect is more pronounced for network products than standalone products. The main effect of *hit competition* is negative and significant ($\beta =$ -0.08, $p = 0.07$). Moreover, the interaction between *collectible components* and *hit competition* is also negative and significant ($\beta =$ -0.81, $p = 0.02$). Competition from a hit game is associated with a 58.85% reduction in owners for collectible network games, but only a 7.48% reduction in owners for standalone games. **Figure 3** visualizes the interaction effects for all hypotheses.

Insert Figure 3 about here

We interpret our control variables by looking at the results from Model 1 (**Table 2**). Surprisingly, *self-published* is positively associated with *owners* ($\beta = 0.16$, $p = 0.06$), implying that self-published board games, on average, attract 17.35% more owners than board games released by an established publisher. Our industry contact offers a potential explanation: *boardgamegeek.com* attracts mostly enthusiast board game players who are more likely to play games from smaller, independent publishers. *Publisher experience* has a significant and positive effect on the ownership of board games ($\beta = 0.09$, $p = 0.00$). A doubling in the number of board games published by a board game's publisher in the past five years is associated with a 6.44% increase in the number of *owners*. Finally, publisher *team size* positively and significantly affects board game ownership ($\beta = 0.90$, $p = 0.00$). A 10% increase in the number of team members working on a board game is associated with an 8.96% increase in the number of *owners*.

Robustness Tests and Additional Analysis

While our endogenous treatment effects model accounts for the non-random assignment into *collectible components*, one additional concern might be the imbalance between covariates, especially considering the smaller subset of board games with *collectible components* in our sample (see **Appendix A** in the **Online Appendix**). To address this, we applied a coarsened exact matching (CEM) algorithm to our estimation sample (Iacus, King, & Porro, 2012). Based on observable covariates, the CEM algorithm prunes and rebalances the estimation sample by matching each board game with collectible components to at least one standalone game. To strike the right balance between retaining enough observations while also materially decreasing sample imbalance, we match on firm-level covariates: *self-published*, *publisher experience*, *publisher country of origin* dummies, as well as *year* and *calendar month* of release dummies. The algorithm retains 3,863 matched observations, of which 220 are CNGs. Compared with the unrestricted sample, the sample imbalance reduces from $L = 0.85$ to $L = 0.37$ (Blackwell, Iacus, King, & Porro, 2009). CEM also assigns weights based on the number of matched control observations for each treated observation (Blackwell et al., 2009). Models 7-12 in **Table 3** present results from the matched and weighted sample. Our main results remain unchanged.

Insert Table 3 about here

We also ran several additional robustness checks to assess the sensitivity of our findings. First, we estimated results by using alternative measurements for *owners*. Results are robust to estimating a negative binominal regression on the untransformed number of owners two years after release. They also remain fully robust when using 12 or 18-month (instead of 24-month) periods to track a board game's *owners.* Using the number of reviews posted for a board game 12, 18, and 24 months after release generates similar results. Results also remain robust to winsorizing the top 1% of all board games in both the main and the pruned samples.

Second, we created a categorical measure to capture a board game's varying degrees of dependence on network value. Standalone board games were assigned a value of 0, and CNGs were stratified further based on the collectible component acquisition strategy. CNGs with non-random component acquisition, meaning consumers could selectively purchase specific components (n=101), received a 1, whereas CNGs using a random component acquisition approach (n=124), such as booster packs, were assigned a value of 2. This distinction is based on the idea that randomized acquisition amplifies a game's trading requirements. Our findings remained mostly consistent. We further introduced a similar classification for those CNGs that allowed for solo play, which should increase their relative share of standalone value. Since only ten games allowed for solo play, we could not test hypothesis 3b in this specification. While we issue some caution due to limited power, all other results are directionally consistent.

Third, our results are fully robust to measuring board game *novelty* over the past three years rather than five. Fourth, our results are consistent with taking the logarithm of the number of *backers* a successful Kickstarter campaign had instead of the *Kickstarter success* dummy. Fifth, results are robust to using different rolling windows for measuring *competition intensity,* including 12 and 18 months. Results also remain unchanged when we include board game expansions in the competition consideration sets and when we control for the number of out-of-genre games entering the market. Finally, results are supported when we construct a continuous *hit competition* measure by taking the ownership share of a game's most successful competitor in a given year. Tabulated results for all robustness checks are reported in the **Online Appendix**.

DISCUSSION AND CONCLUSION

Departing from the common assumption that all competing products are subject to the same network effect, we studied markets with partial network effects. Unlike in markets with universal network effects, firms in markets with partial network effects can choose to implement social features in their products with the potential to generate network effects. While successful network products are known to capture a large share of the overall market, network products that fail to take off get locked out, thus increasing the risks for both the firm and its customers. Identifying demand uncertainty as a key mechanism affecting network products, we developed theory predicting how both positive and negative drivers of demand uncertainty differentially impact the diffusion of network products and standalone products competing in the same market. We tested our predictions in the global board games industry, analyzing a unique sample of 19,432 products from *boardgamegeek.com*. **Table 4** provides a summary of our main findings.

Insert Table 4 about here

We make at least two contributions to the literature. First, we contribute to the network effects literature by examining how factors unrelated to network value impact the diffusion of products with network effects. Prior research has largely focused on installed base size and network strength as key determinants of success for network products (Boudreau et al., 2022; Schilling, 2002; Suarez, 2004, 2005). We extend our understanding by documenting that in markets with partial network effects, non-network factors interact with a product's social features to affect a network product's diffusion. These insights are related to findings in marketing where scholars have engaged in a longstanding debate about the interplay between product quality and network effects (e.g., Gretz & Basuroy, 2013; McIntyre et al., 2020; Tellis, Yin, & Niraj, 2009). Moreover, our results suggest that including social features—often assumed to be wholly advantageous—is not unequivocally beneficial (Schilling, 2003). In fact, we only found support in our reported analyses for the disproportionately negative effects of pairing social features with a novel product design or launching network products in crowded markets. Our data did not support predictions regarding the disproportionately positive effect of attracting early adopters on network products. These insights provide practical guidance for managers in markets with partial network effects by highlighting the need to consider a broader range of factors in deciding whether and when to introduce a product with social features.

Second, we contribute to the diffusion of innovations literature by exploring demand uncertainty from the customer's perspective. Prior studies have primarily considered the implications of demand uncertainty from the firm's point of view (e.g., Autio et al., 2013; Atuahene-Gima & Li, 2004; Cohen et al., 2016; Moeen et al., 2020). Here, we have flipped the perspective by analyzing how demand uncertainty in the form of unrealized network value interacts with other known drivers of demand uncertainty, such as product novelty, competition intensity, and frontloading demand through early adopters. By focusing on how firms' decisions shape customers' perceived uncertainty, we can begin to unpack how firms can influence their products' demand uncertainty. In markets with partial network effects, we find that drivers of demand uncertainty have a disproportionately negative impact on network products. Network products need to quickly accumulate a large user base to realize their network value (Afuah, 2013; Eisenmann et al., 2011; Schilling, 2003; Shankar & Bayus, 2003). When customers perceive uncertainty about the (standalone) value of a product, this can significantly impede the diffusion of network products, whereas standalone products can endure a slower diffusion without significant loss of perceived value. Practically, our findings thus suggest that firms should carefully consider how product-market decisions (e.g., social features, novelty of a product's design, timing of release) interact to affect customers' perceived uncertainty.

Our data did not support predictions about the positive effects of promoting early adoption on network product diffusion. In fact, we rather found that launching a board game with collectible components via a successful Kickstarter campaign dampens diffusion. On the one hand, a crowdfunding campaign primarily caters to early adopters who derive value from being the first to adopt and engage with the product development process (Rogers, 2003). On the other hand, firms might inadvertently alienate more mainstream customers if they design their products mainly with early adopters' needs in mind. For example, if early adopters receive perks and benefits not given to late adopters, or when there exists a substantial time gap between the release of a product to early adopters and the mainstream, a firm risks driving a "chasm" between these adopter subgroups that could thwart diffusion among late adopters (Moore, 1991).

In our sample, a board game's commercial release occurred, on average, 159 days after the successful conclusion of its crowdfunding campaign, potentially not only leading to a decline in initial consumer enthusiasm and engagement but also prolonging a period in which the network cannot grow. We conjecture that this chasm disproportionately affected board games with social features that rely on attracting a large user base quickly. We invite future research to test our conceptual arguments in settings with different means to promote a product's early adoption.

Our study has several limitations. First, we relied on archival data in a highly contextualized setting. We invite future research to replicate our findings using different data samples from other industries including digital product markets. Second, we did not directly measure demand uncertainty in the context of the board games industry, nor did we register variation in consumers' perceived uncertainty based on whether they are early or late adopters. Instead, we relied on known drivers of demand uncertainty that have been documented in the diffusion of innovations literature, which we applied to our board games setting through the use of contextualized measures. Future research might consider alternative research designs, such as laboratory experiments or demand-uncertainty questionnaires, to capture consumers' perceived uncertainty regarding specific products more precisely. Third, besides crowdfunding, various other ways exist for firms to frontload their products' demand, including the release of beta versions, crowdsourcing, influencer partnerships, and pre-orders, which we did not consider here. Future research may benefit from studying these and other options for a more holistic understanding of how promoting early adoption can impact the diffusion of network products.

Regarding the boundary conditions and generalizability of our study, several aspects are noteworthy. First, while we label the network effects in our setting *partial network effects*, the term *heterogeneous network effects* might be more appropriate in other settings for two reasons.

First, firms can sometimes design social features in a more granular fashion, meaning that one can observe continuous or intermediate levels of network strength in the same product market. Video games, for example, can come with different types of multiplayer functionality, such as local cooperative play and online massive multiplayer modes (Rietveld & Ploog, 2022). Second, in some settings, firms can adjust their network strength over time by implementing new or dropping old social features from their products. For instance, ride-hailing services such as Uber are known to introduce carpooling functionality (i.e., Uber Pool) only after gaining a foothold in a local market. Furthermore, we focused exclusively on direct network effects, where the value of a product increases with its user base. Sometimes, however, firms can also have agency over indirect network effects. For example, multi-sided platform firms can decide how much they want their complementor functionality to be interoperable with other platforms (Zhu et al., 2021). What distinguishes these examples from our context is that they are all digital. Digital connectivity facilitates firms in releasing different versions of the same product and making changes to their products after release. We thus consider our analog board game setting a conservative context for studying the implications of selectively inducing network effects.

We encourage future research to study settings where products' social features are even more versatile, such as (1) contexts with truly heterogeneous network effects, (2) settings where firms introduce network value after their products have been on the market for some time, and (3) heterogeneous network effects in the context of two- or multi-sided platform markets. Moreover, we invite scholars to study the dynamics of user engagement for network products. While widespread diffusion is a prerequisite for generating network effects, it is user engagement that sustains them. How can firms strike the right balance between attracting new users and ensuring existing users remain engaged? Additionally, we believe researchers will benefit from developing more conceptual work on network effects (for instance, see: Karhu, Heiskala, Ritala, & Thomas, 2024). For example, some social features affect a product's core functionality—such as online multiplayer modes in video games—whereas others fall outside a product's key functionality—such as online leaderboards in fitness apps. While social features that are core to a product's functionality are likely to lead to stronger network effects, they are also more costly to develop and implement, as well as stronger potential drivers of a product's demand uncertainty.

We examined product diffusion dynamics in markets with partial network effects. Our investigation in the board games industry—a context where network products and standalone products compete side by side—suggests that network value is no guarantee for widespread diffusion. Instead, the inherent variability in the value created by network products instills a larger degree of uncertainty in consumers in comparison to their standalone counterparts, all else being equal. Moreover, network products are disproportionately affected in their diffusion by other drivers of demand uncertainty, such as a novel product design or launching in a highly competitive market. Our findings challenge the common narrative of network effects as a universal catalyst for market dominance and emphasize the need for managers to carefully consider the interaction between a product's network value and its other value drivers.

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TABLES AND FIGURES

Table 1 Descriptive statistics and pairwise correlations

Variable		Mean	St Dev	Min	Max	1	2	3	4	5	6	7	8	9
1	*Owners*	125.77	687.62	0	27776									
2	*Collectible components*	0.01	0.11	0	1	0.02								
3	*Novelty*	0.65	0.25	0	1	-0.05	-0.03							
4	*Kickstarter success*	0.07	0.25	0	1	0.06	0.00	-0.04						
5	*Competition*	316.24	163.06	27	766	-0.11	0.03	0.04	0.04					
6	*Hit competition*	0.07	0.25	0	1	0.00	0.00	0.00	0.00	-0.07				
7	*Self-published*	0.17	0.38	0	1	-0.07	-0.01	0.01	-0.01	0.02	0.00			
8	*Publisher experience*	24.86	51.33	0	339	-0.02	-0.02	0.02	-0.09	0.00	0.01	-0.20		
9	*Team size*	2.20	2.28	1	103	0.17	0.05	-0.08	0.08	-0.02	0.00	-0.08	-0.03	
10	*MtG events*	81.07	97.57	0	361	0.04	0.02	-0.06	0.11	0.02	0.03	-0.37	0.20	0.04

Notes. Based on estimation sample (n=19,432). Mean variance inflation factor (VIF) = 4.27.

Table 2 Main regression results

	Collectible components	*ln(Owners)*					
Variable	**0**	**1**	**2**	**3**	**4**	**5**	**6**
Collectible components		-0.75†	-0.35	-0.73†	-0.27	-0.68†	0.11
		[0.42]	[0.46]	[0.41]	[0.48]	[0.41]	[0.50]
Collectible components x Novelty			-0.82*				-0.60†
			[0.35]				[0.36]
Collectible components x Kickstarter success				-1.19*			-1.17**
				[0.40]			[0.39]
Collectible components x Competition intensity					-0.0015**		-0.0014**
					[0.0005]		[0.0005]
Collectible components x Hit competition						-0.76*	-0.81*
						[0.32]	[0.34]
Novelty		-0.35**	-0.34**	-0.35**	-0.35**	-0.35**	-0.35**
		[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Kickstarter success		0.88**	0.88**	0.89**	0.88**	0.88**	0.89**
		[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Competition intensity		-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hit competition		-0.09*	-0.09*	-0.09*	-0.09*	-0.08†	-0.08†
		[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Self-published	-0.07*	0.16†	0.16†	0.16†	0.15†	0.15†	0.15†
	[0.03]	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]
ln(Publisher experience)	0.09**	0.09**	0.09**	0.09**	0.09**	0.09**	0.09**
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
ln(Team size)	0.10	0.90**	0.90**	0.90**	0.90**	0.90**	0.90**
	[0.06]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
ln(MtG events)	1.10**						
	[0.41]						
Year of release dummies (6)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of release dummies (11)	No	Yes	Yes	Yes	Yes	Yes	Yes
Board game genre dummies (12)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Publisher country dummies (77)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous treatment correction	N/A	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.26**	2.10**	2.09**	2.10**	2.08**	2.09**	2.07**
	[0.40]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]
Observations	19,432	19,432	19,432	19,432	19,432	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †p < 0.1;*p < 0.05; **p < 0.01.

Table 3 Results re-estimated on a pruned, rebalanced, and weighted sample

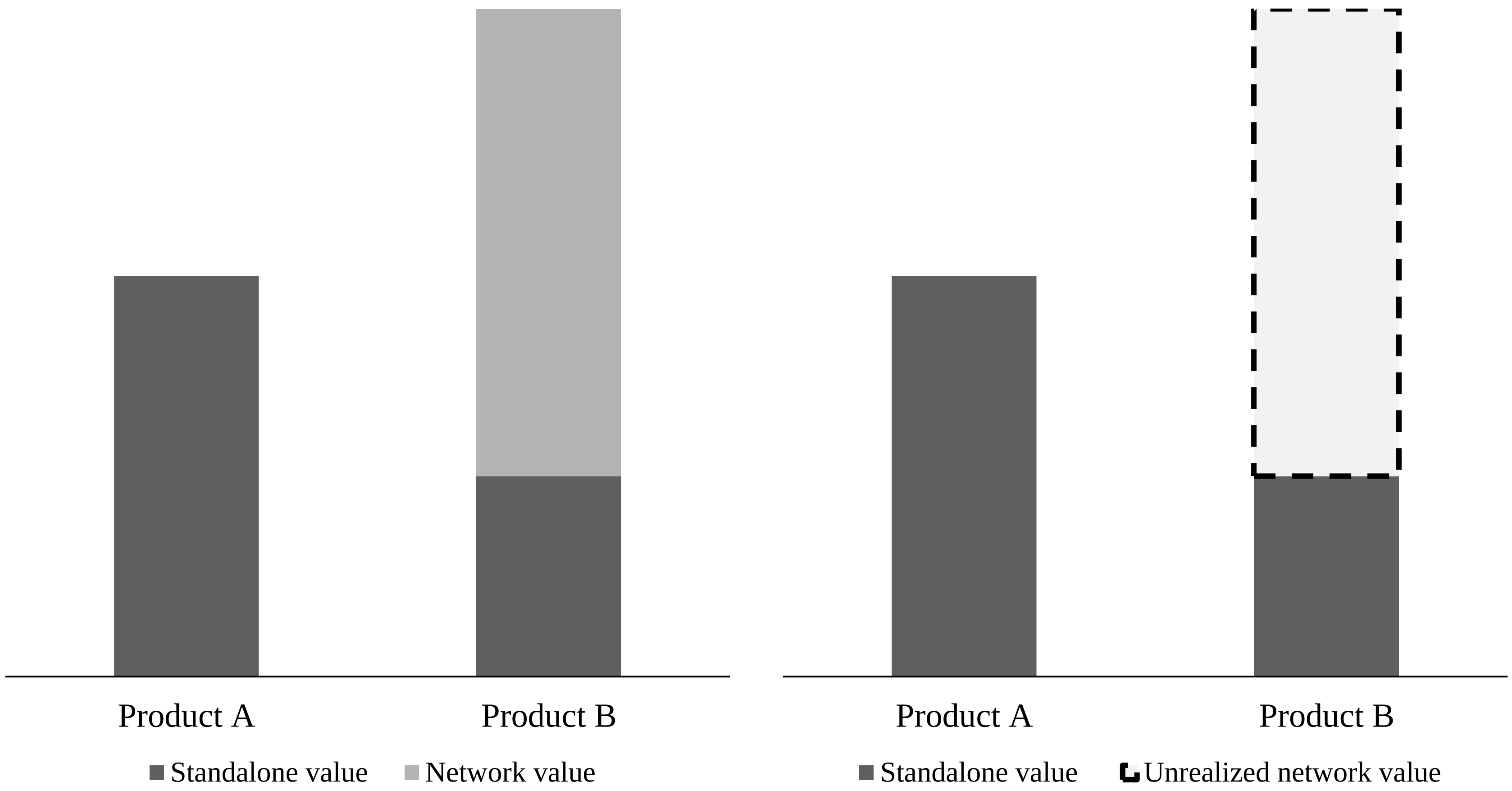
	ln(Owners)					
Variable	**7**	**8**	**9**	**10**	**11**	**12**
Collectible components	-2.29**	-2.13**	-2.32**	-1.98**	-2.22**	-1.81*
	[0.67]	[0.68]	[0.68]	[0.72]	[0.68]	[0.73]
Collectible components x Novelty		-0.83*				-0.71†
		[0.40]				[0.40]
Collectible components x Kickstarter success			-0.96*			-0.96*
			[0.46]			[0.44]
Collectible components x Competition intensity				-0.0010†		-0.0010†
				[0.0006]		[0.0005]
Collectible components x Hit competition					-0.61†	-0.61†
					[0.38]	[0.38]
Novelty	-0.32*	-0.27†	-0.32*	-0.32*	-0.32*	-0.30†
	[0.13]	[0.14]	[0.13]	[0.14]	[0.13]	[0.14]
Kickstarter success	0.78**	0.78**	0.84**	0.78**	0.78**	0.83**
	[0.10]	[0.10]	[0.11]	[0.10]	[0.10]	[0.11]
Competition intensity	-0.001*	-0.001*	-0.001*	-0.001†	-0.001*	-0.001†
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hit competition	-0.01	-0.01	-0.01	-0.01	-0.05	-0.05
	[0.14]	[0.15]	[0.15]	[0.15]	[0.15]	[0.15]
Self-published	0.21	0.20	0.22	0.20	0.20	0.19
	[0.15]	[0.15]	[0.15]	[0.15]	[0.15]	[0.15]
ln(Publisher experience)	0.21**	0.21**	0.21**	0.21**	0.21**	0.21**
	[0.02]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
ln(Team size)	0.82**	0.82**	0.83**	0.82**	0.82**	0.82**
	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
Year of release dummies (6)	Yes	Yes	Yes	Yes	Yes	Yes
Month of release dummies (11)	Yes	Yes	Yes	Yes	Yes	Yes
Board game genre dummies (12)	Yes	Yes	Yes	Yes	Yes	Yes
Publisher country dummies (77)	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous treatment correction	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.99**	0.96**	0.99**	1.00**	0.99**	0.98**
	[0.32]	[0.33]	[0.32]	[0.32]	[0.33]	[0.32]
Observations	3,863	3,863	3,863	3,863	3,863	3,863

Notes. Heteroskedasticity robust standard errors in parentheses. Sample weights were applied to account for differences in the number of standalone board games for each board game with collectible components.
†p < 0.1; *p < 0.05; **p < 0.01

Table 4 Summary of main findings

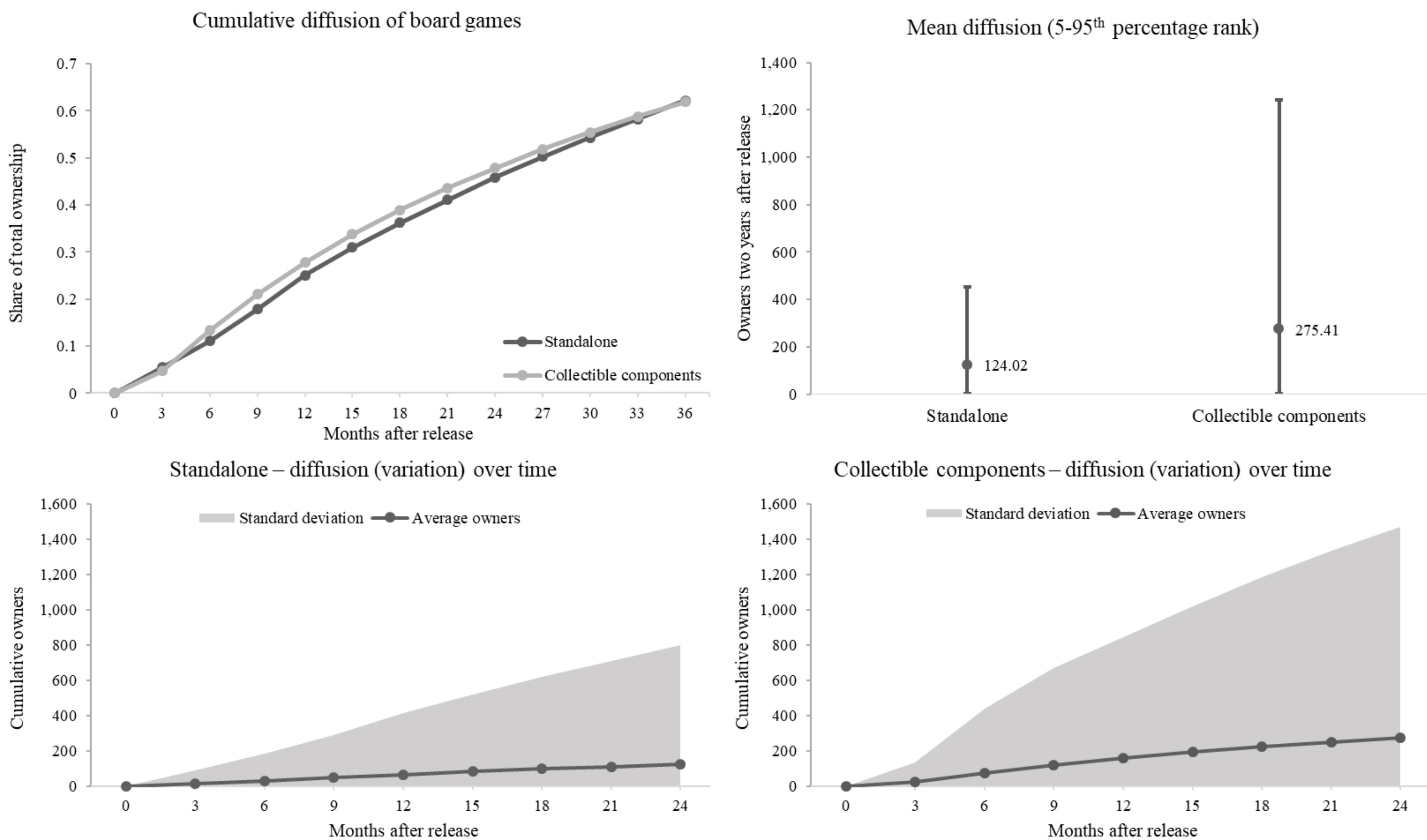
Hypothesis		Empirical finding	Supported
H_b	The diffusion of network products varies more widely than that of standalone products.	The variance in owners for board games with collectible components is 3.10 times larger than that for standalone board games.	**YES**
H_1	Novelty negatively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.	A 25% increase in product novelty decreases the number of owners for board games with collectible components by 15.34% and those of standalone board games by 7.33%.	**YES**
H_2	Promoting early adoption positively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.	A successful Kickstarter campaign decreases the number of owners for board games with collectible components by 24.76% while more than doubling those of standalone board games.	**NO**
H_{3a}	Competition intensity negatively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.	Each additional 150 board games released within six months surrounding the focal board game decreases the number of owners for board games with collectible components by 15.50% and those of standalone board games by 9.65%.	**YES**
H_{3b}	Competition from a hit product negatively affects a product's diffusion, and this effect is more pronounced for network products than standalone products.	The presence of a hit board game in the same six-month competition window decreases the number of owners for board games with collectible components by 58.58% and those of standalone board games by 7.48%.	**YES**

Figure 1 Value proposition of network products and standalone products



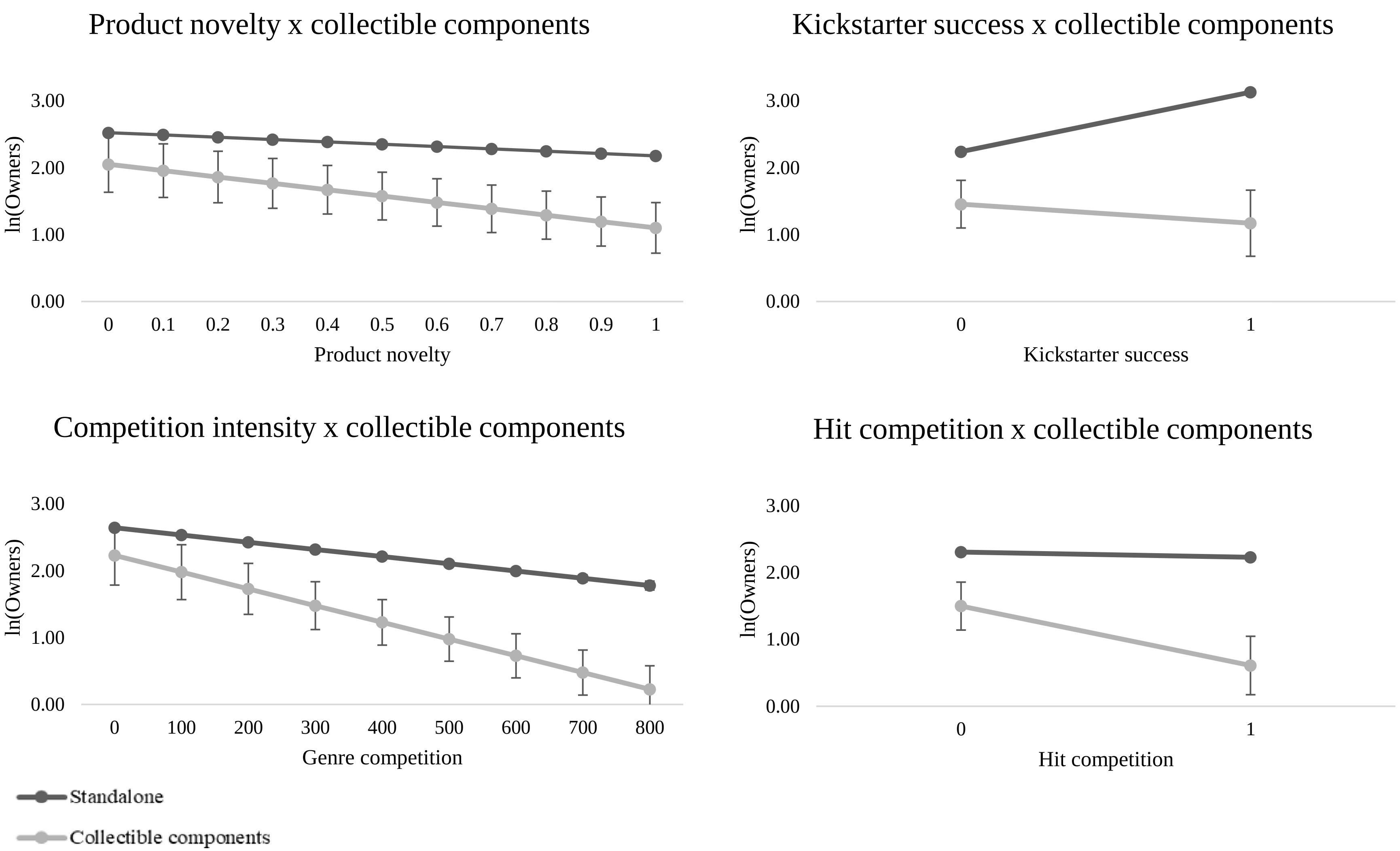
Note. The value proposition of a standalone product (Product A) comprises standalone value only—it does not covary with the number of product users. The value proposition of a network product (Product B) also includes network value—its value covaries, in part, with the number of users. In the absence of a large user base, Product B's network value remains unrealized.

Figure 2 Diffusion of standalone board games and collectible network games



Note. Based on estimation sample (n=19,432).

Figure 3 Interaction plots of predicted values



APPENDIX

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APPENDIX A Descriptive statistics for standalone and collectible network games

		Standalone (n = 19,207)				Collectible Components (n = 225)				t-test
Variable		**Mean (μ_1)**	**St Dev**	**Min**	**Max**	**Mean (μ_2)**	**St Dev**	**Min**	**Max**	**μ_1-μ_2**
1	*Owners*	124.02	679.28	0	27776	275.38	1195.96	0	12524	-151.36**
2	*Novelty*	0.65	0.25	0.06	1	0.57	0.25	0	1	0.08**
3	*Kickstarter success*	0.07	0.25	0	1	0.06	0.24	0	1	0.00
4	*Competition intensity*	315.79	162.64	27	766	355.94	193.20	40	738	-40.15**
5	*Hit competition*	0.07	0.25	0	1	0.08	0.27	0	1	-0.01
6	*Self-published*	0.17	0.38	0	1	0.12	0.33	0	1	0.05*
7	*Publisher experience*	24.96	51.45	0	339	16.29	38.99	0	311	8.67*
9	*Team size*	2.19	2.17	1	103	3.32	6.84	1	75	-1.14**
10	*MtG events*	80.84	97.49	0	361	100.23	102.49	0	346	-19.39**

Notes. Based on Estimation Sample. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$

APPENDIX B – Robustness Tests

Table of Contents:

Table B1 – Alternative DV (untransformed owners) with negative binominal estimator

	Owners (untransformed)		
Variable	**1**	**2**	**3**
Collectible components		-1.83*	-0.79
		[0.85]	[0.76]
Collectible components x Novelty			-1.88**
			[0.45]
Collectible components x Kickstarter success			-1.14**
			[0.40]
Collectible components x Competition			0.002**
			[0.001]
Collectible components x Hit competition			-1.04*
			[0.42]
Novelty		-0.42**	-0.40**
		[0.09]	[0.10]
Kickstarter success		0.73**	0.74**
		[0.07]	[0.07]
Competition		-0.002**	-0.002**
		[0.000]	[0.000]
Hit competition		0.11	0.11
		[0.10]	[0.10]
Self-published	0.48*	0.41†	0.40†
	[0.19]	[0.21]	[0.20]
Publisher experience	0.11**	0.13**	0.13**
	[0.2]	[0.02]	[0.02]
Team size	1.30**	1.25**	1.24**
	[0.04]	[0.04]	[0.04]
Year dummies (6)	Yes	Yes	Yes
Month dummies (11)	Yes	Yes	Yes
Genre dummies (12)	Yes	Yes	Yes
Country dummies (77)	Yes	Yes	Yes
Endogenous treatment correction	Yes	Yes	Yes
Constant	0.07	1.50**	1.48**
	[0.15]	[0.28]	[0.28]
Pseudo R^2	0.10	0.10	0.10
Observations	19,432	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. Models report step-wise results from a negative binominal regression on the number of owners of a board game two years after its release.

Table B2 – Alternative DV (total reviews) and cut-offs

	ln(Owners)			*ln(Reviews)*			
Variable	**12 months**	**18 months**	**36 months**	**12 months**	**18 months**	**24 months**	**36 months**
Collectible components	0.24	0.14	0.34	0.22	0.10	0.06	0.25
	[0.44]	[0.48]	[0.51]	[0.44]	[0.48]	[0.50]	[0.50]
Collectible components x Novelty	-0.54†	-0.54	-0.80*	-0.61*	-0.66†	-0.72*	-0.87*
	[0.29]	[0.34]	[0.36]	[0.31]	[0.34]	[0.26]	[0.36]
Collectible components x Kickstarter success	-1.38**	-1.29**	-1.22**	-1.22**	-1.22**	-1.12**	-1.17**
	[0.35]	[0.37]	[0.39]	[0.32]	[0.35]	[0.38]	[0.38]
Collectible components x Competition intensity	-0.001*	-0.001**	-0.002**	-0.001*	-0.001*	-0.001**	-0.002**
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]
Collectible components x Hit competition	-0.75**	-0.82*	-0.98**	-0.45†	-0.53†	-0.53†	-0.70†
	[0.29]	[0.32]	[0.37]	[0.28]	[0.31]	[0.32]	[0.36]
Novelty	-0.30**	-0.33**	-0.36**	-0.28**	-0.31**	-0.33**	-0.34**
	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Kickstarter success	0.73**	0.85**	0.89**	0.75**	0.85**	0.89**	0.90**
	[0.04]	[0.04]	[0.05]	[0.05]	[0.04]	[0.04]	[0.05]
Competition intensity	-0.001**	-0.001**	-0.002**	-0.001**	-0.001**	-0.001**	-0.001**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Hit competition	-0.03	-0.06	-0.0001	-0.03	-0.07†	-0.10*	-0.01
	[0.04]	[0.04]	[0.0463]	[0.04]	[0.04]	[0.04]	[0.05]
Controls (3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummies (106)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endogenous treatment correction	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.90**	2.04**	2.29**	1.75**	1.90**	1.92**	2.14**
	[0.11]	[0.12]	[0.14]	[0.11]	[0.12]	[0.13]	[0.14]
Observations	19,432	19,432	16,216	19,432	19,432	19,432	16,216

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$.
The *36 months* models have less observations because the year 2017 is excluded since the data was collected in 2020.
Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B3 – Alternative DV (winsorized)

	ln(Owners)	
Variable	**1**	**2**
Collectible components	-0.83*	0.01
	[0.42]	[0.50]
Collectible components x Novelty		-0.60†
		[0.36]
Collectible components x Kickstarter success		-1.18**
		[0.40]
Collectible components x Competition intensity		-0.0014**
		[0.0005]
Collectible components x Hit competition		-0.80*
		[0.34]
Novelty	-0.35**	-0.35**
	[0.04]	[0.04]
Kickstarter success	0.90**	0.92**
	[0.04]	[0.04]
Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Hit competition	-0.10*	-0.09*
	[0.04]	[0.04]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	2.09**	2.07**
	[0.13]	[0.13]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. In both models, the DV is right winsorized at 1%. Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B4 – Alternative collectible components measure (random component acquisition)

	ln(Owners)	
Variable	**1**	**2**
Collectible components	0.30**	1.18*
	[0.11]	[0.53]
Random collectible components	0.22	1.20**
	[0.17]	[0.43]
Collectible components x Novelty		-0.69
		[0.61]
Random collectible components x Novelty		-0.55
		[0.44]
Collectible components x Kickstarter success		-0.94*
		[0.43]
Random collectible components x Kickstarter success		-1.79*
		[0.78]
Collectible components x Competition intensity		-0.0011
		[0.0007]
Random collectible components x Competition		-0.0015*
		[0.0007]
Collectible components x Hit competition		-0.80†
		[0.43]
Random collectible components x Hit competition		-0.85†
		[0.47]
Novelty	-0.35**	-0.35**
	[0.04]	[0.04]
Kickstarter success	0.88**	0.89**
	[0.04]	[0.04]
Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Hit competition	-0.09*	-0.08†
	[0.04]	[0.04]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	2.10**	2.07**
	[0.13]	[0.13]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. Models show the results broken out by CNGs with and without random component acquisition. Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B5 – Alternative collectible components measure (solo play)

	ln(Owners)	
Variable	**1**	**2**
Collectible components	0.27**	1.21*
	[0.07]	[0.33]
Solo collectible components	0.72	3.17*
	[0.51]	[1.34]
Collectible components x Novelty		-0.62†
		[0.36]
Solo collectible components x Novelty		-4.36*
		[2.06]
Collectible components x Kickstarter success		-0.99**
		[0.38]
Solo collectible components x Kickstarter success		-4.32**
		[0.49]
Collectible components x Competition intensity		-0.0014**
		[0.0005]
Solo collectible components x Competition intensity		0.003
		[0.003]
Collectible components x Hit competition		-0.78*
		[0.34]
Novelty	-0.35**	-0.35**
	[0.04]	[0.04]
Kickstarter success	0.88**	0.89**
	[0.04]	[0.04]
Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Hit competition	-0.09*	-0.08†
	[0.04]	[0.04]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	2.10**	2.04**
	[0.13]	[0.13]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. Models show the results broken out by CNGs with and without solo play option. Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B6 – Alternative novelty window (three years)

	ln(Owners)	
Variable	**1**	**2**
Collectible components	-0.37	0.09
	[0.46]	[0.50]
Collectible components x Novelty	-0.79*	-0.56†
	[0.35]	[0.35]
Collectible components x Kickstarter success		-1.17**
		[0.39]
Collectible components x Competition intensity		-0.0014**
		[0.0005]
Collectible components x Hit competition		-0.81*
		[0.34]
Novelty	-0.39**	-0.39**
	[0.04]	[0.04]
Kickstarter success	0.87**	0.89**
	[0.04]	[0.04]
Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Hit competition	-0.09*	-0.08*
	[0.04]	[0.04]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	2.12**	2.10**
	[0.13]	[0.13]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. The novelty measure compares a focal game's gameplay mechanics against the industry average mechanics of all games that share at least one genre with the focal game and have been released within three years before. Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B7 – Alternative early adoption measure (number of Kickstarter backers)

	ln(Owners)	
Variable	**1**	**2**
Collectible components	-0.73†	0.12
	[0.42]	[0.50]
Collectible components x Novelty		-0.61†
		[0.36]
Collectible components x ln(Backers)	-0.14*	-0.13*
	[0.07]	[0.06]
Collectible components x Competition intensity		-0.0014**
		[0.0005]
Collectible components x Hit competition		-0.82*
		[0.34]
Novelty	-0.35**	-0.34**
	[0.04]	[0.04]
Backers	0.13**	0.13**
	[0.01]	[0.01]
Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Hit competition	-0.09*	-0.07†
	[0.04]	[0.04]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	2.10**	2.08**
	[0.13]	[0.13]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B8 – Alternative competition windows (12 and 18 months)

	ln(Owners)	
Variable	**12 months competition**	**18 months competition**
Collectible components	-0.23	-0.24
	[0.57]	[0.56]
Collectible components x Novelty	-0.76**	-0.77**
	[0.35]	[0.35]
Collectible components x Kickstarter success	-1.26**	-1.25**
	[0.39]	[0.39]
Collectible components x Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Collectible components x Hit competition	-0.98**	-0.96**
	[0.38]	[0.38]
Novelty	-0.47**	-0.46**
	[0.04]	[0.04]
Kickstarter success	1.05**	1.05**
	[0.05]	[0.05]
Competition intensity	-0.0004**	-0.0002**
	[0.0001]	[0.000]
Hit competition	-0.05	-0.04
	[0.05]	[0.05]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	1.89**	1.71**
	[0.12]	[0.12]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. The first model takes a 12-month and the second model takes an 18-month rolling window for competition. Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B9 – Alternative competition measure (including expansions)

Variable	*ln(Owners)* 1	2
Collectible components	-0.54	-0.55
	[0.75]	[0.75]
Collectible components x Novelty	-0.71†	-0.75*
	[0.37]	[0.36]
Collectible components x Kickstarter success	-1.21**	-1.20**
	[0.40]	[0.40]
Collectible components x Competition with expansions	-0.001**	-0.001**
	[0.000]	[0.000]
Collectible components x Hit competition	-0.86*	-0.85*
	[0.34]	[0.34]
Novelty	-0.34**	-0.33**
	[0.04]	[0.04]
Kickstarter success	0.88**	0.88**
	[0.04]	[0.04]
Competition with expansions	-0.001**	-0.0003**
	[0.000]	[0.0001]
Hit competition	-0.09*	-0.07†
	[0.04]	[0.04]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	2.12**	1.78**
	[0.12]	[0.11]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. Model 1 takes a 6-month and Model 2 a 12-month rolling window for competition. Controls and dummies are the same as reported in the main Model in **Table 2**.

Table B10 – Additional competition intensity measure (including out of genre competition)

	ln(Owners)	
Variable	**1**	**2**
Collectible components	-0.75†	0.12
	[0.41]	[0.49]
Collectible components x Novelty		-0.62†
		[0.35]
Collectible components x Kickstarter success		1.19**
		[0.39]
Collectible components x Competition intensity		-0.0014**
		[0.0005]
Collectible components x Hit competition		-0.85*
		[0.34]
Novelty	-0.36**	-0.35**
	[0.04]	[0.04]
Kickstarter success	0.88**	0.90**
	[0.04]	[0.04]
Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Hit competition	-0.015	-0.002
	[0.04]	[0.04]
Out of genre competition	0.0002**	0.0002**
	[0.0000]	[0.0000]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	1.66**	1.63**
	[0.14]	[0.14]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. Controls and dummies are the same as reported in the main Model in **Table 2**

Table B11 – Alternative hit competition measure (market share of strongest competitor)

	ln(Owners)	
Variable	**1**	**2**
Collectible components	-0.17	0.70
	[0.54]	[0.29]
Collectible components x Novelty		-0.66†
		[0.36]
Collectible components x Kickstarter success		-1.16**
		[0.38]
Collectible components x Competition intensity		-0.001**
		[0.000]
Collectible components x Hit competition continuous	-10.47	-12.55**
	[7.14]	[7.13]
Novelty	-0.36**	-0.35**
	[0.04]	[0.04]
Kickstarter success	0.85**	0.87**
	[0.04]	[0.04]
Competition intensity	-0.001**	-0.001**
	[0.000]	[0.000]
Hit competition continuous	-15.17**	-15.14**
	[0.84]	[0.84]
Controls (3)	Yes	Yes
Dummies (106)	Yes	Yes
Endogenous treatment correction	Yes	Yes
Constant	2.73**	2.71**
	[0.12]	[0.12]
Observations	19,432	19,432

Notes. Heteroskedasticity robust standard errors in parentheses. †$p < 0.1$; *$p < 0.05$; **$p < 0.01$. Controls and dummies are the same as reported in the main Model in **Table 2**.