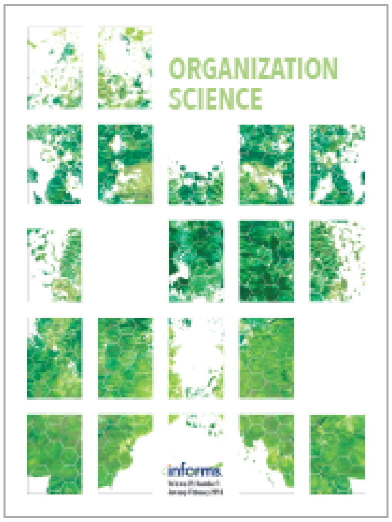

Organization Science

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To cite this article:
Carmelo Cennamo, Juan Santaló (2019) Generativity Tension and Value Creation in Platform Ecosystems. Organization Science 30(3):617-641. https://doi.org/10.1287/orsc.2018.1270

informs
http://pubsonline.informs.org/journal/orsc/

ORGANIZATION SCIENCE
Vol. 30, No. 3, May–June 2019, pp. 617–641
ISSN 1047-7039 (print), ISSN 1526-5455 (online)

Generativity Tension and Value Creation in Platform Ecosystems

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Received: August 17, 2017
Revised: June 6, 2018; October 10, 2018
Accepted: October 20, 2018
Published Online in Articles in Advance: May 20, 2019

https://doi.org/10.1287/orsc.2018.1270

Abstract. Platform-based technology ecosystems are new forms of organizing independent actors' innovations around a stable product system. This collective organization is proving superior to traditional, vertically integrated systems in many sectors because of greater "generativity"—the ecosystem's capacity to foster complementary innovation from autonomous, heterogeneous firms—which extends the usage scope and value of the platform to users. However, greater generativity can also lead to greater variance in the way ecosystem members' contributions satisfy users' needs, and it could potentially hinder the ecosystems' value creation. We draw on collective action theory to examine generativity's impact on user satisfaction and the mechanisms driving it. We argue that products enhancing user satisfaction contribute to a collective, shared asset, the platform system reputation, from which all participants benefit. Thus, generativity has both a positive (system reputation) and negative (free-riding) effect on the ecosystem members' incentives for developing products that enhance user satisfaction. We argue that the negative free-riding effect prevails as the platform system matures and competition with alternative platform systems increases. Using data from the video game industry, we find supportive evidence for the free-riding effect, which generates an average loss in total revenue for first-rate games of about $36.5 million and a drop of about 3.3% in the console's market share. By identifying the conditions that exacerbate free riding in platform ecosystems, our study contributes to the understanding of the evolutionary dynamics of platform ecosystems. It also highlights one feedback mechanism governing collective action in ecosystems and its implications for value creation.

Keywords: platform ecosystem • generativity • complement quality • free riding • complementarities • ecosystem governance

Platform-based technology ecosystems are emerging as powerful new ways of organizing interdependent innovation activities (Yoo et al. 2012, Jacobides et al. 2018) in various sectors, including the more traditional ones and the public sector (Van Alstyne et al. 2016, Visnjic et al. 2016). One of the key reasons for this organizing structure's increasing adoption rests on its ability to leverage the ecosystem of autonomous firms to free innovation through greater *generativity*: the overall system's capacity to produce new output "through unfiltered contributions from broad and varied audiences" (Zittrain 2008, p. 70). Platform systems can thus expand and evolve without hierarchical control from the system's creator (Faraj et al. 2011, Yoo et al. 2012, Wareham et al. 2014). While acting autonomously, firms serve a system-level objective through their complementary activities (e.g., fostering a given technology system, increasing the market for a given technology system). Consequently, these firms form a collective "meta-organization" (Gulati et al. 2012) for "open collaboration" (Faraj et al. 2011, Levine and Prietula 2014), more generally referred to as an "ecosystem"[1] (Jacobides et al. 2018, Adner 2017). A vantage point of such organization is firms' ability to modularize their complementary activities (Yoo et al. 2010) and specialize in a narrow set of activities, while coordinating to achieve system-level objectives (Jacobides et al. 2018). Yet, this characteristic challenges some of the tenets of traditional organizing logic, especially the capacity to coordinate interdependencies. If platforms must enhance participation of heterogeneous complementors to be generative (e.g., Zittrain 2006, Boudreau 2012, Parker et al. 2017) and if their contributions are largely "unfiltered" and uncoordinated (Zittrain 2008, p. 70), aligning interests and activities of ecosystem's members becomes a challenge. Tilson et al. (2010, p. 753) highlight the need for platform owners to manage this "paradox of change": cultivating flexibility to foster variation and change in the ecosystem through greater generativity while also guaranteeing stability (such that the ecosystem does not become fragmented). But how these generativity's tensions unfold through and affect the ecosystem's evolution remains poorly understood.

This research gap is unfortunate because, when spurred by heterogeneous complementors, changes in generativity continuously reshape the platform system's user value and, thus, complementors' value and motivation to participate in the ecosystem. By increasing the variety of complements available for a platform, greater generativity extends the platform technology system's possible uses, which can enhance the value for final users (Zammuto et al. 2007, Yoo et al. 2010). However, with generativity leading to new unintended uses of the technology may come also unintended consequences as per the ecosystem's evolutionary trajectory, with an increase in the variance of how this extended technology's "affordances" satisfy the final user (Zammuto et al. 2007, p. 750). Greater generativity, then, can lead to increased fragmentation within the system (Wareham et al. 2014, Tiwana 2015), which can be detrimental for user satisfaction and the technology system's overall market performance.

We address this gap by examining how this inherent generativity's tension unfolds over time and affects user satisfaction. Such analysis offers the possibility to explore the unstructured coordination mechanisms taking place in ecosystems based on the feedback each complementor receives from others' participation and contributions. We build on collective action theory (Olson 1967, Ostrom 2003) and related literature to advance a technology system evolutionary perspective on when generativity enhances or hinders user satisfaction (and the value created) in an ecosystem. Acting as a collective entity (e.g., Faraj et al. 2011), ecosystem members feed on each other's contribution while competing at the individual level to capture the greater part of the jointly created value. These interactions create both positive and negative feedback on ecosystem members' innovation activity. Whether generativity enhances value creation depends on how the collective responds to such tensions (Faraj et al. 2011). As we argue later in more detail, generativity creates tension between a positive *reputation spillover effect*, which provides more collective resources for complementors, and a negative *free-rider effect*, which reduces the benefits from joint contribution to the collective and lowers complementors' incentives to make platform-specific investments that enhance user satisfaction.

Complementors autonomously decide the levels of development effort and investment in the complements' features that may enhance user satisfaction, which, beyond benefiting their own products, will also contribute to a shared asset—the platform's overall system reputation (Roger and Vasconcelos 2014)—which guides individual users' discrete adoption decisions. Not all complements are created equal. Some complements are more valuable to end users and have a disproportionate effect on platform sales (Binken and Stremersch 2009) and platform competition (Cennamo 2018). By enhancing the system reputation and overall platform value to users, first-rate complements will also have a positive effect on demand for other complements produced for the platform. In fact, users can only discern the prospective value of a complement imperfectly ex ante; thus, they base their purchasing decisions partly on how well they expect the average platform complement to satisfy their preferences. Because of this positive spillover effect from the system's reputation, greater generativity can increase complementors' expected returns from investing in products for the platform that enhance user satisfaction. However, because all complement providers benefit from the positive reputational and market-demand spillovers, they may have incentives to free ride (Gupta, Jain, and Sawhney 1999, Yalcin et al. 2013) and underinvest in user satisfaction to capture the residual demand generated by first-rate complements. We articulate that determining which effect is more important depends on the evolutionary stage of the technology system (i.e., platform maturity) and the extent to which complementors can operate across competing technology systems (i.e., cross-platform competition). As platform maturity reaches later stages, the free-riding effect strengthens, whereas the spillover effect fades. Likewise, as competition among rival platform systems intensifies, complementors seek to participate in multiple ecosystems and thereby reduce their "collective identification" with one ecosystem (Wareham et al. 2014, p. 1199); thus, platform competition heightens the negative effect of free riding at late stages of platform maturity. This effect leads to complements of lower user satisfaction and hampers value creation. These free-riding problems pose a critical yet underexplored organizational challenge for ecosystems and their platform sponsors, who must cultivate greater generativity through members' greater participation while preserving providers' incentives for valuable contributions.

In the context of video game platform systems, using a data set on 4,145 new video game titles launched on nine different console platforms over the period 1995–2008, we find supportive evidence for our hypotheses. Generativity (operationalized as the variety of newly launched game titles in a given console-game genre) affects game titles' user satisfaction (as assed by end users' evaluation ratings) negatively as the console matures, and this effect is greater when competition with other console systems intensifies. In line with our underlying theoretical mechanism of free-riding problems' increasing acuteness, we find that greater generativity reflects greater variance in user satisfaction ensuing from more releases of low-rated complements, lower innovation development effort, and lower marketing investments at late stages. This free-rider effect harms the value generated in the ecosystem. We find that an increase of one standard deviation in the proportion of low-rated (to high-rated) games in a given quarter generates a loss in total revenue for high-rated games [those scoring high in user satisfaction rating (USR)] of about $36.5 million and is associated with a 3.3% drop in the platform's market share for that quarter.

Our study offers different contributions to the literature on ecosystems. Previous studies (e.g., Tilson et al. 2010, Yoo et al. 2010, Yoo 2012, Anderson et al. 2014, Wareham et al. 2014) have identified generativity as a key property of this new collective organization and highlighted the technology aspects, such as its layered, modular architectural design, and the governance rules for complementors' participation that make a platform system generative. We extend this research by advancing a collective action perspective that allows us to examine how increasing the variance of an ecosystem's innovative output affects the user value of such output and the overall system. Although it has been proposed that ecosystems can follow emerging patterns of self-organizing from the feedback of generativity and that tensions can arise from generativity and shape the evolution of the ecosystem (e.g., Henfridsson and Bygstad 2013, Yoo et al. 2012, Tilson et al. 2010, Tiwana et al. 2010), the exact way in which the tensions and feedback mechanisms of generativity operate and affect members' contributions remains underexplored. Yet, this aspect is key in understanding the distinct nature of coordination and organizing logic in ecosystems compared with other organizing forms (e.g., markets, hierarchies, alliances). We advance knowledge in this area by uncovering the asymmetric effect of generativity and the underlying factors affecting its positive and negative feedback. More generally, research has advanced that alignment in ecosystems (Adner 2017) can emerge from specific complementarities among members' activities (Jacobides et al. 2018). We show how complementors differ in the way they respond to generativity and, accordingly, how these complementarities may change over time. This approach contrasts with the implicit view in the economic literature that network effects apply uniformly across platform participants, and that the value from participating in the ecosystem increases with greater participation (e.g., Clements and Ohashi 2005, Armstrong 2006). It suggests that different strategies might be needed at different evolutionary stages to align ecosystem members' activities such that complementarities can be positive and reinforcing.

Our study also suggests that it is hard for the ecosystem orchestrator to eliminate the negative free-riding effect and balance out the generativity tension. Whereas some analysis has been conducted on selection and other incentive mechanisms to attract providers and users (e.g., Grewal et al. 2010) and stimulate desired variance of generativity (Wareham et al. 2014), we show how incentives of participants whose activities are aligned can change with increasing participation, which implies that solving the ex ante selection problem (i.e., ecosystem membership) is not sufficient; ex post regulation of collective action is needed to minimize moral hazard problems. The ecosystem orchestrator would then need to adopt dynamic, adaptive governance systems to keep sustaining generativity and value creation. We discuss some of the mechanisms that might be effective in this task, disciplining providers' contributions without constraining generativity.

Theoretical Background: Platform Ecosystems as New Organizing Forms

Platform ecosystems have been discussed in the literature as complex ecologies of firms with individual and collective, intertwined interests, whose evolution follows some emergent self-organizing patterns based on complementarities and coevolution of participants' activities and capabilities (as the ecosystem evolves; e.g., Yoo et al. 2010, 2012; Gulati et al. 2012; Henfridsson and Bygstad 2013; Wareham et al. 2014; Adner 2017; Jacobides et al. 2018). The literature on platform economics generally describes platform systems as two-sided markets (between end users and complement providers), with the distinct sides characterized by the presence of positive complementarities (or indirect network effects; Gupta et al. 1999, Caillaud and Jullien 2003, Armstrong 2006, Rochet and Tirole 2006). Network effects are reinforcing, so more participation on each side creates more value, with complementor's activities coordinating via market-based feedback mechanisms. The majority of studies have thus focused on the initial conditions affecting platform adoption on each side (such as membership rules, pricing, etc.). However, we know little about how ecosystems evolve. The way in which feedback from participants' interdependent activities affects individual choices, and thus the collective's self-organizing, is a dimension largely underexplored (e.g., Yoo 2012, Yoo et al. 2012, Henfridsson and Bygstad 2013).

It has been proposed that a key feature of the platform ecosystem is its ability to maintain its own evolution inertia through *generativity* at the collective level (e.g., Yoo et al. 2010, Yoo 2012), or the "capacity to produce unprompted change driven by large, varied, and uncoordinated audiences" (Zittrain 2006, p. 1980). Evidence of such dynamics is found in sectors such as video games (Corts and Lederman 2009), software enterprise systems (Wareham et al. 2014), online communities (Faraj et al. 2011), smartphone apps (Boudreau 2012), and many others. Generativity allows more value to be created through the ecosystem organizing logic than in traditional organizations (e.g., Yoo et al. 2010) by extending the technology's affordances to its users (Majchrzak and Markus 2012, Zammuto et al. 2007), and thus the potential consumption benefits they can derive from it.[2] Accordingly, through their participation in the ecosystem, complementors constantly reshape the platform's user value through the variety of complements they create, and in doing so also affect the value for other complementors to participate in the ecosystem.

Early literature holds the underlying assumption that the greater a platform's generativity and complement variety are, the greater the value created for platform users will be. However, user preferences are not homogenous, and neither are they complements when it comes to addressing consumer utility. In fact, it is precisely the capacity to draw on a diffused, heterogeneous pool of specialized and autonomous firms that renders this new form of organizing complementary activities more effective to address the heterogeneous needs of a broad set of users (Yoo et al. 2010, 2012; Parker et al. 2017). Not all complements are created equal;[3] some offer more value to users, whereas others may have very limited value (e.g., Cennamo 2018). The benefits users derive from using the platform vary in scope and intensity. By enlarging the platform's scope through the different types of complements, generativity affects its potential value *of use*; more users with diverse preferences and consumption needs can be attracted to the technology system. However, the users' realized benefits from using specific platform–complement combinations will vary according to how well each complement addresses consumer utility, that is, the platform's value *in use*. Thus, generativity influences platform value through *variance in types* of complements, and thus the possibilities of use of the platform, and *variance in degree* of complements' utility to users, and thus the consumption benefits from using the platform with the focal complement. Taken together, these two effects of generativity affect value creation by inducing sales of the platform and sales of its complements. We know little about how generativity affects user satisfaction, so we have yet to see how it affects platform usage. Recent research has highlighted the possible organizational and evolutionary tensions associated with generativity—for example, the tension between stability and flexibility, as well as that between centralized control and individual autonomy (Zittrain 2006, Tilson et al. 2010, Yoo 2012, Yoo et al. 2012, Henfridsson and Bygstad 2013, Wareham et al. 2014). With unprompted change in the ecosystem from unfiltered heterogeneous complementors propelling generativity comes also the potential risk of the system's fragmentation (Tiwana 2015) due to the system creator's lack of control over the output of the ecosystem's participants (Wareham et al. 2014). This may undermine the overall value created.

Compared with more traditional interfirm collaboration contexts, such as alliances, platform ecosystems differ in the nature and structure of agents' collaboration (Yoo et al. 2012) that affect their opportunistic behavior, and hence the opportunities for joint value creation (Jacobides et al. 2018). Relationships[4] between the platform owner and complement providers are established on the basis of noncontractible product complementarity (Jacobides et al. 2018). Complementors are not direct partners with each other; even though they may pursue a joint value-creation objective while supporting the same technology system (i.e., expanding the platform's market of end users), they do not sign collaboration agreements among themselves (e.g., Venkatraman and Lee 2004, Gulati et al. 2012). In this sense, they are only indirectly collaborating by deciding autonomously to support the same system. As in any relationship involving complementarity, and thus varying degrees of asset specificity, transaction hazards exist within the platform–provider relationship that may limit platform-specific investments, and thus joint value creation.[5] Also, the platform ecosystem hub tends to avoid one-to-one contracting and screening mechanisms, instead adopting collaboration arrangements on a self-selection basis (Wareham et al. 2014) to avoid constraining participants' innovation initiative, and to favor the rapid growth of the ecosystem by fostering generativity therein (Yoo et al. 2010). Thus, the platform ecosystem hub lacks hierarchical authority and direct control over complement providers' output (Gulati et al. 2012). Although this enhances system generativity, it also increases the risk of greater variance in members' output and fragmentation of the ecosystem (Tiwana 2015) and the risk of participants free riding on others' investments (e.g., Gupta et al. 1999). Once we consider these aspects and account for the fact that the level of user satisfaction of complementors' innovation is neither given nor contractible ex ante, the value-creation effect of greater generativity cannot be taken for granted. Below, we articulate the positive and negative consequences of generativity for user satisfaction, and we discuss *when* and *why* one can prevail.

Generativity Tension and the Implications for User Satisfaction

The Positive Effect of Generativity on User Satisfaction: The Reputation Spillover Effect

The quality[6] of individual complements exerts a positive externality on the sales of other complements belonging to the same platform, inasmuch as end users transfer some of the goodwill that they associate with the quality of one complement to the expected average quality of others and, thus, the expected user satisfaction. User satisfaction increases the value of the platform system and its market irrespective of its source, benefiting all providers in terms of a larger target market (Gupta et al. 1999). In other words, average user satisfaction forms a key part of a platform's system reputation, that is, the aggregate of all its end users' perceptions (Roger and Vasconcelos 2014). System reputation thus represents a common-pool resource type of collective good (Ostrom 2003) that all ecosystem participants contribute to and can exploit. Because of this positive interdependence, complementors can enhance their private benefits (i.e., greater complement sales) while contributing to the collective good. Thus, based on the expectation that other complementors will participate in the ecosystem and contribute to the collective good, many will have incentives to contribute products that enhance user satisfaction, and accordingly their expected sales (e.g., Monge et al. 1998, von Hippel and von Krogh 2003, Yalcin et al. 2013, Parker et al. 2017). Greater generativity reinforces a complementor's positive expectations about the prospects of the platform's user value and the incentives of other complementors' participation in the ecosystem. Hence, the ex ante expected returns from investing in complements that enhance user satisfaction of the focal platform increase with greater generativity. We refer to this positive impact of generativity as the spillover effect.

The extent to which individual complement sales can reap the system reputation spillover benefits largely depends on whether greater complementor participation in the platform ecosystem increases both the value of the platform to its users and the potential market demand for complements. With greater generativity, both can be expected to increase. Generativity enhances a platform's scope and value to users through greater technological affordances (i.e., the possible different uses and functionalities the platform affords; Zammuto et al. 2007, Yoo et al. 2010, Majchrzak and Markus 2012, Yoo 2012), and thus helps expand the market of users (Armstrong 2006, Hagiu 2009). In this sense, generativity can help propel indirect network effects in terms of platform usage (Rochet and Tirole 2006), that is, the benefits that users derive from using the platform. The iPhone and its iOS platform, for example, function as a navigation system when used in conjunction with maps and navigation apps, and they serve as a photo and video tool when used in conjunction with photo- and video-editing apps. These affordances evolve as complementors provide new ways to use the platform through their diverse complements and identify new needs for affordances (e.g., Zammuto et al. 2007, Faraj et al. 2011). With the platform evolving by affording new possibilities of use to customers through novel, diverse complements, it continuously offers new value propositions and reasons for using the platform more and "consuming" it with these complements. The higher the degree of satisfaction that users derive from each platform–complement usage is, the greater these benefits will be (Cennamo 2018). To the extent that the diverse complements consistently meet consumers' needs and quality requirements, the benefits of using the platform and its complements will increase as a result of increasing generativity. In extending both the value *of use* and *in use* of the platform, generativity can reinforce complementors' positive expectations about platform value and the reputation spillover on complement sales.[7] In other words, all else equal, the expected returns from investing in complements that enhance user satisfaction for a platform increase with the usage value of that platform to users, which is expected to increase with greater generativity. Also, because platform affordances increase with generativity, complements of diverse types will not compete directly for user demand (e.g., Corts and Lederman 2009, Boudreau 2012) and can thus benefit more from the reputation spillover from consumption of other first-rate complements of diverse types.[8]

Because of these positive spillover effects, generativity can lead to self-reinforcing feedback loops of collective action in ecosystems that may lead the system to self-organize and evolve despite members acting in their plain autonomy and individual interests and despite the absence of structured coordination mechanisms or hierarchical control of such activities by the ecosystem hub (e.g., Yoo 2012, Yoo et al. 2012, Jacobides et al. 2018). This logic is consistent with recent developments in collective action theory (see, e.g., Ostrom 2003) suggesting that the individual incentives to contribute to the collective good change according to the different types of interdependence of contributors' activity. As first advanced in Marwell and Oliver (1993, p. 63), when collective action also has "positive interdependence. . .each contribution makes the next one more worthwhile and, thus, more likely." Because of the positive spillover effects, generativity can have a virtuous, reinforcing effect on complementors' incentives to increase the capacity of their complements to satisfy platform users, which will further augment the platform system reputation and usage value to users, and, in turn, further reinforce complementors' incentives to contribute first-rate complements.

Hypothesis 1a. *Greater generativity enhances user satisfaction by inducing positive system reputation spillover effects through reinforcing feedback loops of complementors' interdependent activities.*

The Negative Effect of Generativity on User Satisfaction: The Free-Riding Effect

If members can enjoy the benefits of a shared asset to which they do not contribute, like platform system reputation, issues of free riding can arise: as the size of the collective increases, incentives to contribute diminish, and individual contribution levels decline (Olson 1965, Monge et al. 1998). Free-riding problems like these have been documented in several contexts, including sellers' behavior in the eBay marketplace (Hui et al. 2016) or complementary goods and open-source software development (e.g., von Hippel and von Krogh 2003, Baldwin and Clarck 2006, Kumar et al. 2011). Drawing on these studies' insights, we claim that a similar problem is also present in platform systems. When complementors' investments in user satisfaction generate spillovers for other platform participants, the individual complementor cannot fully capture the returns from its investment, which will also benefit other competing complementors' products. This spillover creates moral hazard problems ensuing from incentives to free ride on others' demand-creation efforts (Gupta et al. 1999) and, consequently, a value-creation problem (Yalcin et al. 2013). Central to free-riding problems is the presence of information asymmetry about the agent's innovative effort and the underlying true value of its product output. Because of this innovation asymmetry, the platform owner (and other ecosystem members) cannot perfectly monitor the agent's innovative activity, and end users can discern the value of the complement only imperfectly ex ante. In the context of franchising, for instance, Michael (2000) has shown how this information asymmetry may induce some franchisees to free ride on the franchise's reputation and underinvest in quality to lower production costs while transferring the reputational costs of this lower quality to the franchisor's umbrella brand. This free-riding behavior can be more acute in cases of experiential and media products such as games, apps, movies, and the like, where consumers can only imperfectly evaluate product quality and the expected consumption benefits ex ante (Kirmani and Rao 2000) and must rely on some average expectations instead (Roger and Vasconcelos 2014).

In platform ecosystems like our research context, where information asymmetry is present both for users and the ecosystem hub, users' purchasing decisions are partly based on expectations of how well the average platform complement will satisfy their preferences. Because the benefits of higher platform system reputation stemming from average user satisfaction are distributed among all providers, whereas providers' efforts and output contributions to the system reputation can be assessed only imperfectly, incentives to free ride can increase. For instance, complementors may reduce their marketing investments in promoting the complement features that make it valuable for the given platform, so users may become less aware of certain complement benefits in the wake of increased generativity. Although lowering marketing investments *can* reduce sales of the complement, the complementor would still expect to make significant sales as long as the individual complement benefits from the overall platform reputation driven by the collective effort in marketing made by other complementors.

Generativity can amplify these problems. Because generativity originates from "unfiltered contributions from broad and varied audiences" (Zittrain 2008, p. 70), increases in generativity will also increase the underlying heterogeneity of motivations and cognitions of ecosystem contributors. Variance in the utility of their contributions can increase as a result of their diverse construal of meanings, values, and objectives of the ecosystem, which will affect their perception of what is valuable to users. On one hand, by enlarging the variety of complements and the range of platform affordances, generativity can significantly increase the ex ante information asymmetry users experience when assessing the prospective value of a given platform–complement combination. Because these are novel combinations, users have no basis to assess their prospective consumption benefits other than relying on some heuristics and average expectations. On the other hand, the increased generativity may come from more heterogeneous complementors that can have different perspectives on the ecosystem's shared objective and the way to satisfy users, thus holding different expectations about the right level of user satisfaction. Alignment can be more difficult to achieve; generativity will increase variance in user satisfaction from individual complements.

This increased variance of generativity can reinforce the free-riding problems. Some complementors may free ride on others' value-enhancing efforts just to exploit the system reputation (and other common resources) and explore in new ambivalent directions, or they may simply contribute complements of average quality to capture some residual market demand generated in the ecosystem by first-rate complements. Accordingly, as generativity increases, the underlying distribution of the platform system's capacity to satisfy consumers' preferences and increase their consumption utility can also change and lead to increases in the variance of user satisfaction. As generativity increases, greater divergence in the capacity of the diverse complements to enhance the system reputation can negatively affect the expectations of complementors to benefit from others' contributions. This can create negative feedback loops at the ecosystem level, such that a greater portion of complementors may believe that they provide the collective with more benefits than those they obtain from others' contributions to the collective good. As variance in users' satisfaction increases with greater generativity, the incentives of the individual complementor to contribute to the collective good will decrease on average. As a result, user satisfaction associated with an individual platform–complement combination may degrade. We call this the free-rider effect of generativity on user satisfaction.[9]

Hypothesis 1b. *Greater generativity lowers user satisfaction by engendering free-rider problems through negative feedback loops propagating from greater variance in the consumption utility of ecosystem members' contributions.*

When does generativity create positive interdependence, and when does it create free-riding frictions? We address this question by assessing how this tension unfolds at a given evolutionary stage of the ecosystem (e.g., Yoo et al. 2012) and in the given competitive context with rival ecosystems (e.g., Jacobides et al. 2018). Below, we advance that platform maturity critically affects the extent of the positive interdependence of complementors' activities and the underlying heterogeneity of complementors' shared objectives, henceforth, whether positive or negative feedback loops emerge as self-organizing patterns of ecosystem members' activities (e.g., Yoo et al. 2012, Henfridsson and Bygstad 2013, Rietveld and Eggers 2018). Instead, the intensity of cross-platform competition influences the extent to which a complementor cospecializes to a focal ecosystem and thus aligns to that ecosystem's objectives to create specific complementarities (Cennamo and Santalo 2013, Parker et al. 2017, Jacobides et al. 2018) or rather pursue individual interests across multiple ecosystems by identifying less with a focal ecosystem's collective and its objectives (Wareham et al. 2014).

Generativity Tension and Platform Maturity

Whether ecosystem members frame their participation as a positive-sum game depends on the extent to which their activities have positive, reinforcing interdependence (Jacobides et al. 2018), which also depends on the heterogeneity of their construal of the ecosystem's purpose and value and their role within it (Adner 2017). As argued above, when generativity leads to greater variety of complements of consistent user satisfaction, greater generativity can reinforce platform usage value, system reputation for users, and the expected benefits of complementors from participating in the ecosystem and investing in user satisfaction.[10] However, when generativity increases the ambivalence of user valuations and the variance in user satisfaction, free-riding incentives increase with greater generativity; the (negative) free-rider effect may prevail over the (positive) spillover effect. We posit here that early stages of platform maturity may reinforce the positive expectations of complementors about the individual benefits from greater generativity, and thus lead to the positive spillover effect. Instead, later stages of platform maturity increase the conditions for the free-rider effect; that is, greater variance in user valuations and information asymmetry.

Users' and complementors' expected benefits from greater generativity can differ according to platform maturity (e.g., Clements and Ohashi 2005, Hagiu 2009, Hagiu and Wright 2015, Rietveld and Eggers 2018). In the early stage of the platform evolution, a platform's system reputation and its value to users are yet to be established; the benefits from participating in such platform ecosystem for complementors are still uncertain. However, as generativity increases during this formation stage, platform value to users increases exponentially thanks to greater platform technological affordances that enhance platform usage benefits. Greater generativity can thus reinforce the typical momentum dynamic of new technology systems driving cascade effects in early adoption (e.g., Farrell and Saloner 1985, Binken and Stremersch 2009). Uncertainty, thus, progressively dissolves as generativity increases, making participation less risky and more rewarding, which will positively affect complementors' expected benefits of contributing to the ecosystem. Complementors self-select to contribute to the ecosystem at a given point in time (e.g., Wareham et al. 2014) according to their risk preferences (Rietveld and Eggers 2018) and commitment to the ecosystem (Jacobides et al. 2018). Because supporting the ecosystem at its early maturity stages is risky, complementors are more likely to expect generativity that reflects participation from other complementors that are equally interested in the fate of the ecosystem and committed to enhancing the system reputation while pursuing their individual interests. Accordingly, complementors are more likely to hold positive expectations about the impact of others' contributions to the overall system reputation and platform value; positive feedback loops are more likely to emerge and reinforce the positive spillover effect of greater generativity at this early stage.

Alignment and the positive interdependence of complementors' contributions can be reinforced with greater generativity at early stages also because of the greater consistency in user preferences as per what defines their consumption needs and benefits (e.g., Rietveld and Eggers 2018). It has been shown, for instance, that early adopters have a stronger preference for novelty and first-rate complements (Binken and Stremersch 2009, Cennamo 2018) and tend to search more for novel, diverse platform–complement combinations than later adopters (Rietveld and Eggers 2018). Thus, greater generativity in the early stages of a platform's maturity may come from a pool of complementors that, albeit heterogeneous as per their resources, competencies, and entrepreneurial visions, hold a more consistent understanding of the type of complements that can enhance platform value to end users and increase user utility. At the collective level, a greater sharing of what are valuable contributions can form the norm for the self-organizing of complementors' activities. As generativity increases at early maturity stages, the positive interdependence of complementors' activities becomes reinforced because of greater alignment and positive expectations of the individual benefits from greater participation. Free-riding incentives associated with generativity are present, but many will make value-adding contributions that happen to increase *also* the value of the shared asset (i.e., the system reputation) because they expect to benefit individually from their investments in user satisfaction (e.g., von Hippel and von Krogh 2003, Kumar et al. 2011, Levine and Prietula 2014).

However, the balance shifts as the platform matures. As the number of platform users stabilizes and their growth rate flattens out (Clements and Ohashi 2005, Corts and Lederman 2009), greater generativity can have only a negligible impact on the platform's market expansion (Clements and Ohashi 2005, Cennamo 2018). Additionally, the platform usage's benefits of exploring novel technological affordances through increasing variety of complements can be marginal and decreasing at later stages. Mature platforms contain a mix of early and late adopters that vary largely in their preferences for the types of complements that satisfy their consumption needs (Rietveld and Eggers 2018); complementors face greater heterogeneity in end-user preferences. Early adopters tend to experiment more and prefer novelty, whereas later adopters tend to be more passive and enjoy a more stable set of complement types in their consumption decisions (e.g., Rietveld and Eggers 2018). Accordingly, at later stages, the novel platform–complement combinations resulting from greater generativity will be subject to greater valuation ambiguities by platform users; some will value them highly, whereas others will find them of low value. This divergence will widen the ex ante information asymmetry about the value of a given complement to users. Because of these issues due to greater heterogeneity of user preferences at later stages, greater generativity will reflect greater dispersion in the underlying valuation of novel complements while having a marginal, decreasing impact on enhancing market growth and system reputation. Thus, the positive spillover effect essentially vanishes, but the free-riding effect becomes more acute in mature stages. With greater imperfect information for end users, "as group size increases, noticeability of a member's contribution decreases, making free ride more probable" (Albanese and van Fleet 1985, p. 246).

The incentives of a greater pool of complementors can accordingly shift toward lower investments in activities like exploration of novel projects or promotional marketing campaigns that might enhance user satisfaction. With a mature, established ecosystem, a more heterogeneous pool of complementors may participate just to exploit the shared valued of the ecosystem (without further contributing to it). Because greater generativity is more likely to be propelled at later stages by greater heterogeneity in complementors' motivations, existing members who contributed early on to the ecosystem's formation, value, and reputation may respond to increases in generativity by reducing their level of investment in user satisfaction enhancement and decide to focus only on exploiting the established system reputation to capture residual market demand. Generativity will thus reflect greater heterogeneity in complementors' motivations and incentives at later stages, amplifying the negative free-rider effect relative to the positive spillover effect. Thus, we hypothesize the following.

Hypothesis 2. *As the platform progresses toward maturity, greater generativity will accentuate the free-rider effect, enhance variance in user satisfaction from platform usage, and lower user satisfaction.*

Generativity Tension and Platform Competition

The interplay of the spillover and free-rider effects may have different outcomes for complementors as a function of their cospecialization (Jacobides et al. 2018) or identification with the ecosystem (Wareham et al. 2014). When generativity reflects commitment of a large set of complementors to the ecosystem, the benefits from the positive interdependence of complementors' contributions will be far greater than the free-rider effect; many will invest in user satisfaction when generativity increases. However, the extent to which complementors commit to the focal ecosystem depends not just on the individual complementor's intrinsic motivations, but also on how important the focal platform is for the complementor (relative to competing platforms), which defines the level of identification of the complementor with the ecosystem. Studies point to providers' reputation and identification with the collective as important characteristics that influence the expected private benefits (such as higher wages for individual developers, market differentiation, and higher price points) they derive from their contributions to the shared asset (e.g., von Hippel and von Krogh 2003, Baldwin and Clarck 2006, Kumar et al. 2011).

As maintained in Wareham et al. (2014, p. 1198), in technology ecosystems, "individual complementors work toward their own benefit for financial compensation, career advancement, or other extrinsic motivations" while contributing to the greater collective benefits of the ecosystem. Consequently, in ecosystems, there is tension between collective identification, with the positive reputation externalities inducing members to direct their contributions toward the ecosystem's social goods, and individual identification, with financial motivations encouraging complementors to explore entrepreneurial opportunities and respond to market developments independently from the trajectory of ecosystem evolution. This tension is exacerbated if complementors participate in multiple ecosystems (e.g., Corts and Lederman 2009, Parker et al. 2017, Jacobides et al. 2018), particularly when rival platforms hold similar market power.

The intensity of cross-platform competition greatly influences the extent to which a complementor cospecializes in a focal ecosystem and thus aligns to that ecosystem's shared objectives to create specific complementarities (Cennamo and Santalo 2013, Jacobides et al. 2018) or to pursue individual interests across multiple ecosystems by identifying less with a focal ecosystem's collective (Wareham et al. 2014). Under low platform competition, a single platform system holds de facto monopoly power; the evolution of the ecosystem highly determines the success of the complementor. Under high platform competition, competing platforms hold more similar market importance to complementors that participate in these multiple platform ecosystems because they can reach out to the entire population of end users (i.e., the sum of each platform system's users base) as long as multihoming is viable on the complementors' side[11] (e.g., Corts and Lederman 2009). The intensity of platform competition will affect how complementors respond to the generativity tension.

With intense platform competition, a larger pool of complementors will tend to multihome and limit the level of cospecialization to a single ecosystem (Corts and Lederman 2009, Bresnahan et al. 2015). As platform competition increases, the focal platform ecosystem will increasingly comprise a mix of single- and multihoming complementors. While the former group will identify uniquely with the focal ecosystem and be more inclined to invest in user satisfaction under greater generativity to enhance the platform system value relative to competing systems, multihoming complementors will seek out scale economies for their products (Corts and Lederman 2009). Thus, they will have more limited incentives to make ecosystem-specific investments in terms of product optimization that would enhance user satisfaction of the focal platform[12] (Cennamo and Santalo 2013). Multihoming complementors may now derive extra benefits from the additional sales generated from platforms other than the focal one and have greater incentives than single-homing complementors to free ride on each ecosystem's collective effort when generativity increases. Hence, greater generativity will reflect greater heterogeneity in complementors' motivations when platform competition increases. This heterogeneity can widen the variance of complementors' contributions in terms of user satisfaction with an ambivalent impact on the system reputation and overall platform value. Because of these issues, as we argued above, the positive spillover effect of greater generativity (i.e., the positive interdependence of complementors' contributions) decreases, whereas the free-riding effect becomes more acute. We thus expect that, as competition among platforms intensifies, generativity heightens the negative effect of free riding during the later stages of platform maturity.[13]

Hypothesis 3. *As cross-platform system competition increases, complementors' identification with the focal ecosystem will decrease; greater generativity will accentuate the free-rider effect and lower user satisfaction.*

Research Setting and Data

We conducted our analysis in the U.S. video game industry over the period 1995–2008. Video game console systems, such as Sony's PlayStation or Microsoft's Xbox, cultivate ecosystems of game developers and enable market transactions between gamers on one side and game developers on the other, with indirect network effects across these distinct sides (e.g., Clements and Ohashi 2005, Corts and Lederman 2009). From the early 1970s to the late 2000s, console sales grew from a few hundred units to an $11 billion-plus business. The console industry remained a distinct niche of the broader gaming industry, which has also included games developed for personal computers and hand-held devices such as the Nintendo Gameboy and, more recently, smartphones and online platforms such as Facebook, which are blurring the boundaries of the industry. The present analysis focuses only on the console video gaming sector and on the period prior to the game/mobile/digital convergence of recent years. We consider this setting particularly suitable for our research purposes because we can easily identify what innovation contribution a complement makes to a platform and what game genre it fits into (e.g., sport versus action); basic product-related information, such as each game's selling price, unit sales, introduction date, producer, and platform maturity, as demarcated by technological generations; and whether there are multiple viable platforms or just a few dominant ones. Moreover, offering first-rate games is an important strategic factor in creating higher value for consumers with respect to other consoles and driving platform demand (Binken and Stremersch 2009, Cennamo 2018). The main data set we use comes from the NPD Group,[14] a leading market research firm that covers retailers' data about this and other entertainment industries in the United States. Other scholars have used this source (e.g., Venkatraman and Lee 2004, Clements and Ohashi 2005). Additional information about titles' characteristics and user satisfaction comes from specialized websites such as IGN.com and MobyGames.com. The final data set contains information for the period from September 1995 to June 2008, with a total of 4,145 observations at the console-game title level. Table 1 provides summary statistics and correlations for the variables used in the analysis.

Measures

User Satisfaction. Our dependent variable, *user satisfaction*, captures how well a given game title satisfies users' preferences and expectations about product use (e.g., Tschang 2007) and, thus, consumption utility—that is, how much gamers enjoy it. In our context, user satisfaction reflects how a game's elements, such as the game-play mechanics, graphics, sound, user interface, narrative content, and software-hardware integration, interact to create the consumption experience. We collected information about the evaluation provided by gamers of each game title from IGN.com, which offers historical reviews of games. Each game is rated on a scale of 1 to 10 (10 being the highest) based on consumer feedback. Each game–console combination is assigned a unique rating; a game sold on multiple consoles may receive a different user satisfaction rating for its performance on each console. For instance, *All-Star Baseball 2003* received a rating of 8.3 for the GameCube version and 8.9 for the PlayStation 2 version. This difference may indicate differences in users' preferences between the two consoles or differences in hardware–software integration, such that users value the consumption experience on the GameCube less than on the PlayStation 2.[15]

Generativity. We measure the level of generativity in an ecosystem as the number of game titles of diverse types within a given game genre in the console at the month of individual title launch. This measure captures the variants of newly launched game titles within a given genre, and thus the range of different console–game consumption possibilities for each gaming genre (i.e., the technological affordances of the console as augmented by the different types of games in a genre). Diverse types of games in the sport genre, like a basketball and a racing game, may cater to different users' preferences. (Some may prefer one type as opposed to the other, but others may prefer both types because they tend to their different sport gaming "needs.") We employ also different measures of generativity as a robustness test. Because a game title's rating does not change across time in our database, we considered only the month each title was launched on each console in our estimation models.

Platform Competition. Cross-platform competition is the Herfindhal–Hirshman index (HHI) computed on the basis of unit sales of competing platforms in a given time period. Because the HHI measures the extent of concentration in a market, such that a higher index value denotes lower competition, we take its inverse. Our competition variable takes a minimum of 0 for no competition (i.e., HHI = 1) and positive values for increasing levels of competition (i.e., decreasing values of HHI).

Platform Maturity. Console systems follow different technological generations, with a new generation appearing every five or six years. These iterations are ideal for clearly identifying the distinct maturity stages of a given console's life cycle. We created a dummy variable that takes the value 1 for observations in the late maturity stage, for which we considered game titles launched from the end of the fourth year on, and 0 for observations in the early maturity stage, which considers only game titles launched during the first year of a console's life. Thus, for most platforms, we are essentially considering the first and final years of the life cycle.[16]

Controlled Variables. First, we included in the econometric specification the cumulative installed base (IB) at

Table 1. Summary Statistics and Correlations

Variable	Mean	Standard deviation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
User satisfaction	7.0	1.8								
Generativity	5.0	3.6	−0.01							
Platform competition	2.1	0.6	−0.08*	0.03						
Generation IB	16.7	1.2	0.008	0.16*	0.25*					
Title price	3.8	0.3	0.23*	−0.05	0.11*	−0.34*				
Consoles' average age	83.6	30.1	0.04	0.16*	−0.27*	0.53*	−0.25*			
Multihoming	0.46	0.49	0.01	0.09*	0.003	0.15*	0.01	0.26*		
Developer past sales	10.2	1.8	0.33*	0.14*	−0.05	0.11*	0.16*	0.13*	0.10*	
Platform maturity	0.48	0.49	−0.01	0.18*	−0.06*	0.79*	−0.49*	0.58*	0.02	0.15*

Note. Values for variables *Generation IB, title price*, and *developer past sales* are log-transformed.
*Significant at the 1% level or better.

the generation level to control for the overall market size available to game developers. *Generation IB* is measured as the (logarithm of the) cumulative number of units belonging to a particular generation of consoles that have been sold at the time of a new title's launch. We also controlled for the market maturity stage of the competing consoles by including their average age. This variable is the average of the number of months since the market introduction dates of all the consoles belonging to the same generation. *Title price* is an important strategic variable that game producers can use; we use the log-linear transformation of each title's price. *Multihoming* is a dummy that controls for whether a game was sold exclusively on one platform (0) or on multiple platforms (1). Finally, we accounted for the potential effect that the past performance of a game's producer may have on its user satisfaction: *developer past sales* is the game developer's average sales for the past 12 months on that console. Additionally, we controlled for console- and developer-specific effects to capture firm differences that might explain differences in user satisfaction beyond the effects of generativity, such as a console's brand value and technical features or a developer's skills.[17] Including these individual dummies in the estimation removes any potential bias coming from the association between these time-invariant issues and the model's dependent variables (Greene 2012). We also accounted for unobserved time effects, such as seasonal trends, by including three dummies for the quarters of the year. This controlled variable is particularly relevant for our setting, as sales of games are usually much higher in the last quarter of the year, and it is generally during this period that new games are introduced.

Empirical Estimation Model

We model user satisfaction rating of game i launched to a console j in genre g at time t as follows:

$$USR_{ijgt} = \mu_j + \omega_i + \beta_0 + \beta_1 G_{jgt} + \beta_2 G^2_{jgt} + \beta_3 G_{jgt} \times PC_{jt} + \beta_4 PC_{jt} + CV + D_t + \varepsilon_{ijgt},$$

where μ_j and ω_i are fixed effects that capture heterogeneity across the different consoles j and developers i and control for time-invariant, unobserved console- and developer-specific effects; G_{jgt} is the level of generativity in console j genre g at time t; PC_{jt} is the level of cross-platform competition faced by console j at time t of title i's launch; CV includes all control variables; β_0 is an intercept; D_t includes the year's quarter dummies; and ε_{ijgt} is the error term. We tried to reduce potential problems of multicollinearity for the squared and interaction terms by standardizing the main components of the explanatory variables before multiplication (Smith and Sasaki 1979). Results from the extra analysis indicated a mean variance inflation factor (VIF) of 1.52 and a max of VIFs of all variables and a condition number (21.31) well below the thresholds (10 and 30, respectively) that indicate potential multicollinearity problems (Belsley et al. 2004, Grewal et al. 2004).

Endogeneity and Identification Strategy

Because we are controlling by both console and developer fixed effects, our identification strategy relies on changes in within-system generativity experienced by the same developer when launching different games for the same console; that is, our estimation results are driven by developers that launch multiple games on the same console, facing a different degree of generativity at each product launch. Differences in within-system generativity experienced by a developer may come from two distinct sources of variation. On one hand, the same developer can release games in different genres, and each genre has a distinct degree of generativity. On the other hand, game developers can release games in the same genre console, but at different times,[18] with the genre having a distinct degree of generativity over time.

However, endogeneity problems might be in place. Particularly, we are concerned that game developers might anticipate a competitor's launch of a first-rate game in a given genre-console. If so, they might be more reluctant to enter the same niche, causing an omitted variable bias, because these unobserved characteristics would be negatively correlated with generativity and positively correlated to user satisfaction. In this case, simply regressing *user satisfaction* on *generativity* may therefore result in estimates that are biased downward. An ideal remedy to this concern would require a natural experiment or exogenous event that shocked the *generativity* variable in a way unrelated to the dependent variable of *user satisfaction*. Unfortunately, in our context, it is hard to find an experiment that satisfies such conditions. A second-best solution is to use instrumental variable(s) that correlate with the endogenous variable in the estimated equation but are uncorrelated with the unobserved variables that explain a game's user satisfaction rating. We used as an instrument the lagged total number of developers ($NDEV$) selling games on a given console's niches other than the focal one. We instrument generativity in console j, niche g, at time t with the number of developers for console j, niches $-g$ at $t - 12$ ($NDEV_{j,t-12,-g}$). The number of developers on a given console has proven to critically affect the level of generativity in a given ecosystem (Boudreau 2012); pairwise correlation analysis reveals a significant positive correlation of 0.36 in our context. However, this measure should be unrelated to user satisfaction of the product to be introduced into that niche for two main reasons. First, although the number of complementors in a given platform ecosystem can affect the amount of complements being produced at the aggregate level, it would hardly influence the rating of the specific complement *directly* other than through the aggregate indirect, spillover, or free-riding effect discussed above. Second, we took the past year's value of the number of developers in other platform genres to minimize any possible correlation between the number of developers on console j, niches $-g$, and the rating of a game introduced into console j, niche g at time t. The identifying assumption of this instrument is hence that developers that eventually shy away from a given genre at time t because they anticipate a rival first-rate title may move to a different genre at t, but not at time $t-12$, before the competition from the first-rate title takes effect. Where the previous year's value could not be observed (for instance, for the console's first year in the market), this variable was set to zero. In line with this logic, in the first-stage estimations, we find that an increase in the number of developers for console j, niches $-g$, leads to greater generativity in niche g (0.17; $p < 0.001$). We instrument for *generativity* squared with the squared instrument, and for the interaction of *generativity* with *platform competition* with the interaction between the instrument and the *platform competition* variable. This procedure is considered good practice when the instrumental variable and the other variable are (as in this case) not interdependent (Baum et al. 2007). We implemented these instruments and estimated our models via standard instrumental variable estimation using the two-stage least squares (2SLS) procedure (Greene 2012). Results of the first-stage estimation are reported in Table 2; they show that our instrumental variables do a reasonably good job of explaining the endogenous variables. The Stock–Wright, Angrist–Pischke, and Anderson–Rubin test statistics all indicate that no weak-instrument problem is present (Stock and Yogo 2005, Angrist and Pischke 2009). Also, the Sargan J test statistic indicates that no overidentification problem is present. We also report that the generativity–user satisfaction relationship switches signs from the early to the later stages of the platform life cycle as our theoretical reasoning predicted. If these results were driven by endogeneity and an omitted variable bias, then this omitted variable bias should be positive at early stages of platform maturity and the same omitted variable bias should be negative later on. These sign changes decrease the likelihood that our results are driven by endogeneity.

Results

Descriptive Evidence

First-rate games, or "superstars" (Binken and Stremersch 2009), contribute substantially to the overall perception of platform value and have been shown to be highly correlated with platform performance sales. Figure 1 shows clear descriptive evidence of the positive correlation between a game's rating and its total sales (in thousands). Games with a very high rating (between 9 and 10) achieve 1.3 million unit sales on average, with some reaching as high as 9.2 million unit sales. In our sample, only about 7% of the full sample's observations fall into this case, 60% of which

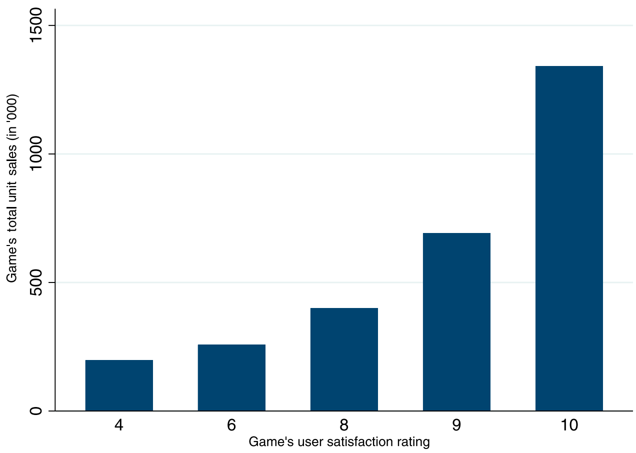
Table 2. First-Stage Results for Instrumented Variables

	First-stage model [Table 3, Model (3)]	First-stage model [Table 3, Model (4)]	
Instrumental variables	(1) Generativity	(2) Generativity	(3) Generativity squared
Past number of developers (*NDEV*)	0.17***	1.46***	11.5***
	(0.01)	(0.26)	(1.63)
$NDEV^2$		−0.05***	−0.41***
		(0.01)	(0.06)
Number of observations	4,145	4,145	4,145
R^2	0.27	0.32	0.16
F-statistic	13***	16***	6***
Angrist–Pischke test	176***	192***	50***

Notes. Model (1) shows first-stage results corresponding to Model (3) of Table 3; the dependent variable to be estimated is the endogenous variable *generativity*. Other models fit the endogenous variables in the full model of Table 3, (4). All models include all exogenous variables (other independent and control variables) of our baseline corresponding models of Table 3, as well as console and developer fixed effects and year-quarter dummies. Results for those coefficients are not reported here for presentation purposes. The Sargan statistic corresponding to the first-stage analysis of Model (4) in Table 3 is 8.74 ($p = 0.12$), which rejects problems of overidentification of all instruments. Stock–Wright test statistics corresponding to the first-stage analysis of Model (4) in Table 3 is 29.35 ($p < 0.001$). This and the Angrist–Pischke test reported in the table reject problems of weak instruments or underidentification.

***$p < 0.01$.

Figure 1. (Color online) User Satisfaction and Game Sales



occur in the early stage of platform maturity. Results from an econometric analysis estimating the impact of a game's rating over the game's sales (not reported here) reveals that an increase of 1 unit in the game's rating contributes to an increase in game sales of 91,251 units on average. Taken together, this evidence confirms that the degree of user satisfaction with platform complements' consumption is a key driver of value creation, affecting not just platform sales, but, importantly, complements' sales, which represent the bulk of profits for a platform provider (through the sales fees collected from complementors).

Figure 2 reports trends in generativity and user satisfaction for console systems belonging to the same technological generation. There is no clear evidence of systematic differences in generativity levels as the ecosystem evolves; average user satisfaction instead displays a somewhat downward trend that starts around the second half of a console's life cycle. Figure 3 shows the median-spline plots relating a game's user satisfaction rating to generativity, broken down by early and late stages of platform maturity. We can appreciate a downward sloping trend in the generativity–user satisfaction relationship for the subsample of late maturity stages. In all, this is descriptive evidence consistent with our core logic of an asymmetric effect of generativity depending on platform maturity. Clearly, these are just trends that might capture other cofounding factors. Results of formal analysis are provided below.

Main Results

Table 3 reports the second stage's baseline estimation results of the 2SLS procedure. Models (1) and (2) also report results from standard ordinary least squares (OLS) estimation. In both models, *generativity* has a significant negative impact on *user satisfaction*. This finding confirms the potential endogeneity problem discussed above, which should bias the effect of generativity downward. When we correct for endogeneity in Models (3) and (4), we find that *generativity* has a positive and significant impact on user satisfaction in all models, consistent with the prediction of Hypothesis 1a of the positive spillover effect of generativity. However, in Model (4), where we add the squared term of *generativity*, we find that high levels of generativity have a negative and statistically significant impact (the squared term coefficient being −0.05; $p < 0.001$). This result is consistent with the prediction of Hypothesis 1b of a free-riding negative effect, showcasing the tension that generativity creates in ecosystems. As we shall see below, this inverted-U relationship between *generativity* and *user satisfaction* can be explained by the differential impact of *generativity* at different stages of platform maturity.

Table 4 reports results for the impact of generativity at distinct stages of platform maturity. Our theory

Figure 2. (Color online) Generativity and User Satisfaction Trends

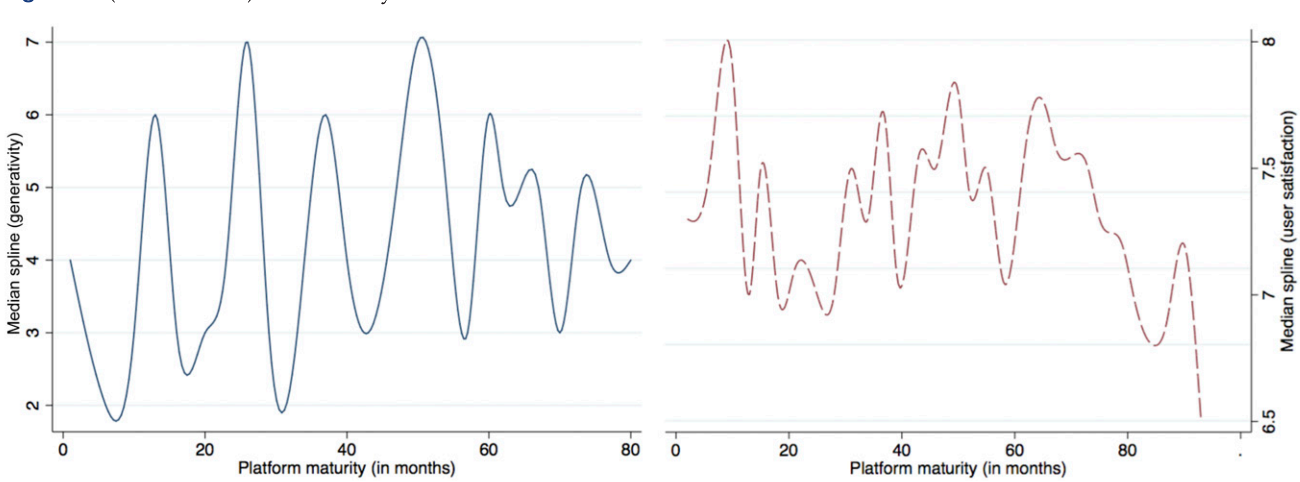
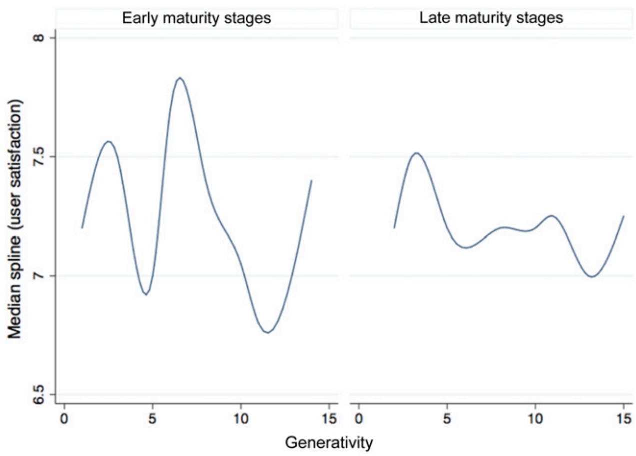


Figure 3. (Color online) Generativity and User Satisfaction at Different Maturity Stages



predicts that, at the later stages, as free-riding problems become more acute with increasing generativity, generativity will negatively affect user satisfaction. To test this hypothesis (Hypothesis 2), we ran the baseline models of Table 3 in two subsamples reflecting the early and late stages of platform maturity. The

Table 3. Generativity and User Satisfaction: Baseline Results

	OLS		2SLS	
Variable	(1)	(2)	(3)	(4)
Generativity	−0.03***	−0.03***	0.12***	0.17***
	(0.01)	(0.01)	(0.04)	(0.04)
Generativity^2		−0.001		−0.05***
		(0.00)		(0.01)
Generation IB	0.13***	0.13***	0.08*	0.18***
	(0.04)	(0.04)	(0.04)	(0.05)
Title price	1.47***	1.46***	1.37***	1.39***
	(0.11)	(0.11)	(0.11)	(0.12)
Platform competition	−0.10*	−0.10	−0.12*	−0.11
	(0.06)	(0.06)	(0.06)	(0.07)
Consoles' average age	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Multihoming	−0.16***	−0.16***	−0.22***	−0.11
	(0.06)	(0.06)	(0.06)	(0.07)
Developer past sales	0.21***	0.21***	0.17***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)
Constant	−2.42	−2.40	−0.79	−2.25
	(1.67)	(1.67)	(1.79)	(1.88)
Number of observations	4,145	4,145	4,145	4,145
R^2	0.25	0.25	0.11	0.14
F-statistic	11.93***	11.62***	10.89***	9.65***

Notes. The dependent variable is the game rating of user satisfaction. Models (1) and (2) report OLS estimations, whereas coefficients in Models (3) and (4) are from instrumental variable 2SLS estimations. All models include fixed effects at the console and game publisher levels and year-quarter dummies.

*$p < 0.10$; ***$p < 0.01$.

early stage subsample comprises 1,164 observations, whereas the late stage subsample has 1,105 observations. Model (1) shows that *generativity* has a positive statistically significant effect on *user satisfaction* in the early stage (0.09, $p < 0.05$), and that this effect is reinforced by *platform competition*, although the latter is not statistically significant. In contrast, Models (3) and (4) show a negative and statistically significant effect of *generativity* on *user satisfaction* in the late-stage subsample (−0.11, $p < 0.05$ and −0.10, $p < 0.1$). This result is consistent with our Hypothesis 2. Also, note that these results also hold when controlling for potential curvilinear effects of *generativity;* the squared term is no longer significant, which indicates that the asymmetric effect of generativity is not driven by the highest levels of generativity at a given maturity stage. We also find that the interaction term with *platform competition* is negative and statistically significant at later stages in both models. This is evidence corroborating our Hypothesis 3. In the last two models, instead of running the analysis in two separate samples, we used the *platform maturity* dummy interacted with our focal variable of interest, *generativity.*[19] This sample has a total of 2,269 observations: the sum of the observations of the two subsamples of Models (1) and (3). While the main effect of generativity is positive and significant in Model (5), its interaction with platform maturity has a negative and statistically significant effect (−0.19, $p < 0.001$). These results also hold when controlling for the curvilinear effect of *generativity* and the moderation effect of *platform competition* in Model (6). These findings bring additional support for our key hypotheses. It is also noteworthy that the *maturity* dummy variable has no significant effect on *user satisfaction* except when it is interacted with our focal variable, *generativity*. This result suggests that the maturity stage of a console has no direct influence on the average user satisfaction from games' consumption; thus, platform maturity cannot in itself explain the degrading user satisfaction.

The differences in complements' user satisfaction caused by generativity are also economically significant. According to the coefficients of Model (2) and (4) in Table 4, if *platform competition* were zero, an increase of two standard deviation of *generativity* would be associated with an increase in *user satisfaction* of 1.08 (the mean of *user satisfaction* is around 7) in the early stages of a console's life cycle and a decrease in *user satisfaction* of 0.72 in the late stages. Such a variation has an important economic impact because titles with ratings of around 7 generate, on average, 382,510 unit sales (with some titles generating up to 3.3 million unit sales), whereas those rated around 8 generate an average of 481,345 unit sales (with some titles generating up to 5.6 million unit sales). With an average per-unit retail price of around

Table 4. Generativity Effect at Different Platform Maturity Stages

	Early stage		Late stage		Maturity: 1 = late stage	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Generativity	0.09**	0.15*	−0.11**	−0.10*	0.21***	0.24***
	(0.04)	(0.09)	(0.05)	(0.05)	(0.05)	(0.07)
Generativity^2		−0.02		−0.01		−0.01
		(0.02)		(0.01)		(0.01)
Generativity × platform competition	0.02	0.05	−1.01**	−1.3**		−0.15
	(0.14)	(0.14)	(0.4)	(0.52)		(0.19)
Generativity × maturity					−0.19***	−0.21**
					(0.06)	(0.07)
Maturity					0.59	0.63
					(0.38)	(0.43)
Generation IB	0.19	0.19	−0.97	−1.02	0.08	0.15
	(0.15)	(0.15)	(0.86)	(0.88)	(0.08)	(0.12)
Title price	2.02***	2.01***	1.31***	1.31***	1.53***	1.54***
	(0.34)	(0.34)	(0.18)	(0.19)	(0.16)	(0.16)
Platform competition	−0.43**	−0.46**	1.39	1.52	−0.23*	−0.32*
	(0.20)	(0.21)	(0.93)	(0.96)	(0.14)	(0.16)
Consoles' average age	−0.01	−0.01	0.001	−0.001	0.001	0.001
	(0.01)	(0.01)	(0.002)	(0.003)	(0.002)	(0.002)
Multihoming	−0.04	−0.05	−0.23*	−0.23*	−0.21**	−0.20**
	(0.11)	(0.11)	(0.12)	(0.13)	(0.08)	(0.09)
Developer past sales	0.26***	0.25***	0.12***	0.10**	0.19***	0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Constant	−2.21	−2.55	13.47	14.63	−0.72	−1.52
	(2.73)	(2.8)	(17.04)	(17.41)	(2.0)	(2.27)
Number of observations	1,164	1,164	1,105	1,105	2,269	2,269
R^2	0.34	0.34	0.28	0.28	0.23	0.23
F-statistic	6.69 ***	6.47***	5.30***	5.05***	7.73***	7.44***

Notes. The dependent variable is *user satisfaction* (game rating). Coefficients in Models (1)–(6) are from instrumental variable 2SLS estimation. All models include fixed effects at the console and game publisher levels and year-quarter dummies.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

$45 in our data, this difference represents an increase in sales revenue of $4.4 million per title, on average, at early stages, and a loss of $4.3 million per title, on average, at late stages.

Results from the analysis on the impact of generativity on the dispersion of user satisfaction bring additional evidence of the theoretical mechanisms we discuss in the section, "Generativity Tension and the Implications for User Satisfaction." As we advanced, we observed that free-riding problems worsen as the platform ecosystem matures and average user satisfaction degrades because of underlying greater dispersion in users' preferences and evaluations of how well novel, diverse types of complements can satisfy their consumption needs. Essentially, when free riding is present, an increase in generativity will affect the mean level of platform user satisfaction by influencing the dispersion of user satisfaction from complement consumption in the system (what Wareham et al. 2014, p. 1197 refer to as "undesirable variance"). In fact, the mechanism through which free riding affects the provision of valuable complements critically depends on, first, the coexistence of first- and second-rate complements in the marketplace, and second, the manifestation of asymmetric information problems that prevent consumers from perfectly distinguishing ex ante between these products. Hence, the negative impact of generativity on user satisfaction should be driven by an increase in the games' rating dispersion that accentuates the free-riding problem discussed above.

We test this mechanism by modeling the variance of *user satisfaction* on *generativity* over the platform's entire life cycle and at different maturity stages. Table 5 reports the results of this estimation. Variance is computed as the ratio of the number of titles with a user satisfaction rating below the mean (at the console-genre-quarter level) over the number of titles with a rating above the mean. This measure is intended to capture a more precise glimpse of the nature of dispersion in user satisfaction; that is, whether higher *generativity*

Table 5. Generativity and Dispersion in User Satisfaction

	No. of low-rated games/No. of high-rated games					
	Full sample		Early stage		Late stage	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Generativity	0.1***	0.1***	0.08	0.04	0.1***	0.2***
	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)	(0.07)
Generativity × *platform competition*		−0.3***		−0.2*		0.3
		(0.11)		(0.1)		(0.6)
Number of observations	762	762	242	242	169	169
R^2	0.17	0.30	0.21	0.37	0.5	0.5
F-statistic	1.42***	1.28***	0.8***	1.0***	1.68***	1.78***

Notes. The level of analysis is the console-genre-quarter. Variance is computed as the ratio of the number of titles with a user satisfaction rating below the average (at the console-genre-quarter level), low-rated games, over the number of titles with a user satisfaction rating above the average, high-rated games. All models report 2SLS estimation results and include fixed effects at the console and game publisher levels and year-quarter dummies. All models also include the following control variables: *generation IB, title price, platform competition*, and *consoles' average Age*. These variables are averages at the console-genre-quarter level; results for these coefficients not reported here.

$^{*}p < 0.10$; $^{***}p < 0.01$.

increases the mean-adjusted variance of *user satisfaction* by increasing the dispersion in terms of the proportion of developers producing low- versus high-rated titles. If that is the case, in line with our prediction of free-riding problems, higher levels of generativity imply more provision of second-rate complements by developers at late stages when the free-rider effect becomes most acute. Results from the full-sample models do indeed show that an increase in *generativity* leads to greater dispersion in user satisfaction. Comparing the early and late stages, the effect of generativity on user satisfaction dispersion is indeed higher at late stages. This finding reinforces the idea that the relative force of the free-rider effect is stronger during later stages of platform maturity.

We also took a closer look at each developer's behavior to better understand whether this increase in supply of second-rate titles at late stages is attributable to more free riders entering at later stages of the platform life cycle, or to changing incentives for early contributors of first-rate games. Table 6 reports statistics for this classification exercise for the two largest consoles (PlayStation and PlayStation 2) in our sample. Two points are noteworthy. First, the majority (more than 83%) of developers of first-rate games at early stages "switch" and become free riders at late stages (producing low rank games, i.e., titles whose rating falls within the first and second quartiles of the games' rating distribution). Second, half of all the developers of second-rate games at late stages were already in the platform at earlier stages *and* produced *also* first-rate games at some point,[20] whereas roughly 34%–43% are "pure" free riders: firms that entered the platform at late stages with low-rated games. This result suggests, then, that most of the free-rider effect of generativity is a moral hazard problem (Akerlof 1970), but a selection problem (attracting providers of low-value complements) is also present.

How do this free-rider effect and the degrading user satisfaction impact the value being generated within a platform system? By negatively affecting a user's consumption benefits, a greater influx of second-rate complements should negatively affect value in the ecosystem to the extent that it reduces the volume of transactions (and their dollar value), and thus the revenues generated by complementors and the platform in aggregate terms. To gain a sense of the economic impact of the free-rider effect, we replicated the analysis of user satisfaction dispersion performed at the quarter level and estimated the effects of games with low ratings launched in a genre in a given quarter on the total sales of games with high ratings (those with a rating greater or equal to 8) launched in the same quarter-genre [Table 7, Models (1) and (2)], on the market share performance of the platform in that quarter [Table 7, Models (3) and (4)], and on the platform's and active games' unit sales in that quarter [Table 7, Models (5) and (6)]. We found that an increase of one standard deviation in the proportion of low-rated (to high-rated) games in a given quarter decreased sales of high-rated games by 745,484 units on average. Considering the average price (in our sample) of $49 for these games, this effect amounts to an average loss in revenues of about $36.5 million. Also, an increase of one standard deviation in the proportion of low-rated games is associated with a drop of about 3.3% market share of the platform in that quarter. Taken together, these results indicate that the free-rider effect has an important, negative economic impact.

Table 6. Free-Riding Typology

Free-riding typology	PlayStation (PS)	PlayStation 2 (PS2)	Description
Switchers early-late	83%	87%	83% (87%) of PS (PS2) publishers of high-rank titles (4th quartile) in the early stage switch to producing titles of lower rank (1st and 2nd quartiles) at the late stage
Switchers late-late	54%	41%	54% (41%) of PS (PS2) publishers of high-rank titles (4th quartile) in the late stage *also* produce titles of lower rank (1st and 2nd quartiles)
Free-riding late stage			
Free riders (selection)	34%	43%	Among all the publishers of low-rank titles at the late stage, 34% (43%) of PS (PS2) publishers entered the platform at the late stage and never produced a high-rank title
Free riders (moral hazard)	49%	49%	Among all the publishers of low-rank titles at the late stage, 49% (49%) of PS (PS2) publishers had produced at least 1 high-rank title (at the early or late stage), i.e., they are either early-late or late-late switchers

Robustness Analysis

One potential issue that concerned us was the identification strategy for the effect of generativity. We are assuming that complementors can observe the level of generativity in a given product niche at year t and accordingly decide whether to launch the product and its target level of user satisfaction. However, it might be that this decision is taken upon observing the level of generativity in the market at the time when game development is under way. Given that it takes about six months to a year, on average, to develop a console game, we replicated the analysis by lagging our key generativity variables at $t-6$ and $t-12$;[21] the results did not change. In our setting, also, console providers produce their own game titles, that is, first-party complements. If the free-rider effect is the key driving mechanism of our results, as we argued above, we should expect console providers to be immune to such behavior, and generativity should have no impact on the level of a game's user satisfaction supplied by the platform provider itself. We replicated the analysis only for the subsample of first-party games and found no significant effect of generativity on user satisfaction. However, this lacking effect could be due to the rather limited number of observations (n = 227). We thus ran the analysis in the full sample, interacting the

Table 7. The Economic Impact of the Free-Rider Effect

	High-rated games' total sales		Platform market share		Platform and game unit sales	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Generativity	943,151***	945,777***	0.02***	0.01	1,136,241***	1,094,521***
	(174,431)	(174,261)	(0.01)	(0.01)	(148,494)	(156,811)
Generativity × Platform Competition		328,474		0.12***		686,987***
		(518,003)		(0.03)		(562,138)
Ratio low-rated/high-rated Games	−1,355,426***	−1,325,534***	−0.06***	−0.03**	−825,378***	−743,882***
	(357,578)	(375,604)	(0.01)	(0.02)	(324,838)	(340,042)
Number of observations	537	537	762	762	762	762
R^2	0.43	0.43	0.53	0.65	0.58	0.58
F-statistic	3***	3***	16***	12***	7***	7***

Notes. The dependent variable is *average total sales of high-rated games* (active games in the given quarter with a user satisfaction rating greater than or equal to 8) in Models (1) and (2), *console market share* relative to other active consoles of the same generation in the given quarter in Models (3) and (4), and *platform and games unit sales* (active games in the given quarter) in Model (5) and (6). Analysis is at the console-genre-quarter level; all variables are averages at the quarter level. Reported coefficients are from instrumental variable 2SLS estimations. Control variables (*generation IB*, *title price*, *platform competition*, and *consoles' average age*) are included but not reported here for presentational convenience. All models include fixed effects at the console level and year-quarter dummies.
$^{**}p < 0.05$; $^{***}p < 0.01$.

dummy *first party* (which takes a value of 1 for titles supplied by the platform provider) with *generativity*. Again, we find that generativity does not affect the rating of first-party games.

We also tested the sensitivity of our findings to alternative measures of *generativity*. Our measure captures changes in game types within a given genre at a given time period, thus reflecting variety of complements. However, it might be that, in a given month, two or more games of the same type, for example, baseball games, are released in the same sport genre. Accordingly, to capture a pure variety measure accounting only for the number of unique complements of diverse type, we build a new measure, *unique variety:* the unique counting of newly launched games of diverse types in a genre at time *t*. Consider the following example taken from our sample. In September 1999, five different games were released for SEGA's Dreamcast console in the "sports" genre, of which two were "football" games, two were "racing" games, and one was an "extreme sports" game. Our (original) baseline measure of generativity counted five games; our new unique variety measure only counts three (one for each of the three diverse types of sport games released). An even stricter measure we use is *novelty*. Because generativity also refers to innovations that are not originally intended or anticipated by the core technology's innovator, one might consider a strict measure of generativity as only those original innovations of diverse types, in our context, the number of diverse types of games with novel intellectual property.[22] As reported in Table 8, we find very similar results with these alternative measures. We also replicated the analysis including an additional control variable, *months to next-generation consoles*, which accounts for the number of months at time *t* to the launch of the first next-generation console. The concern is that part of the degrading user satisfaction at maturity stages may be caused by a portion of platform users deferring their complement consumptions to next-generation platforms.[23] When controlling for this possible effect, our main results still hold (results not reported here).

To further test the robustness of our findings, in particular, that the free-riding effect is attributable to decreasing incentives and investments by complementors at later stages, we manually collected extra data about the characteristics of each game title (where this information was available) to construct measures that could capture the underlying development and marketing investment (and effort) behind each game project. These results are reported in Table 9. Specifically, for the development investment, we constructed a new variable, *project size*, measuring the number of individual developers employed during the entire development period of a game title, to capture the extent of the development effort.[24] Table 9 shows how generativity is negatively (positively) related to the number of individual developers working on a given game project in late (early) stage of platform maturity. This result is consistent with our logic of negative free-riding incentives becoming more pronounced at late stages of platform maturity because we again find evidence for the asymmetric impact of generativity at earlier and later stages.

As a proxy for the marketing investment in a game's promotional campaign, we constructed the variable *awareness* to capture consumers' awareness of a game during the week it was launched into the market, measured via Google Trends analytics. This number indicates how many searches were carried out for a particular game, relative to the total number of searches on Google over time. As such, it should reflect, on one side, consumers' preferences and expectations about game use, and, on the other side, the level of game publishers' advertising and promotional campaigns.[25] We found that generativity has a negative impact on consumers' awareness during later stages. We interpret this finding as a greater difficulty for consumers to find out about a new game launched on a platform at late stages under increasing levels of generativity (i.e., more game introductions). Because of reduced awareness, consumers' ability to assess a game's consumption benefits ex ante is also further hampered. Because these effects are associated with greater free-riding incentives, enhanced generativity at late stages will reduce investments in promotional campaigns by game providers. One possible alternative explanation of the reduced levels of investments and of user satisfaction is that game sales become more concentrated in each genre over time. This could be the case if, after some initial periods in each genre, one or two games dominate the market, while the rest of participants become fringe competitors until the end of the platform life cycle. This market dynamic could reduce the incentives of the majority of developers to invest in user satisfaction.[26] Against this possibility we shall note two aspects. First, from simple descriptive statistics, we can confirm that the average level of sales concentration, both at the developer and game levels, is relatively low and shows high variance.[27] This implies that, while *some* titles and *some* developers may capture a relatively large portion of sales in the market at a given point in time, there is large variance in market concentration[28] in our sample. Second, the market is quite competitive and contestable also because games become obsolete very quickly (games get "consumed"), with most of a game's sales happening in the first two-three months following its market launch (Binken and Stremersch 2009). This implies that market leadership, if achieved by a game developer, is short-lived. If one or two games

Table 8. Generativity: Alternative Measures

Variable	Generativity = unique variety		Generativity = novelty	
	(1)	(2)	(3)	(4)
Generativity	0.53***	0.57***	0.56***	0.75***
	(0.12)	(0.12)	(0.19)	(0.23)
Generativity × platform competition		−0.24		−0.24*
		(0.16)		(0.15)
Generativity × maturity	−0.44***	−0.50***	−0.38*	−0.65***
	(0.14)	(0.15)	(0.20)	(0.26)
Maturity	0.74	0.77	0.17	0.35
	(0.44)	(0.47)	(0.34)	(0.37)
Number of observations	2,268	2,268	2,268	2,268
R^2	0.13	0.18	0.09	0.17
F-statistic	7***	7***	7***	6***

Notes. The dependent variable is *user satisfaction*. Reported coefficients are from instrumental variable 2SLS estimations. Control variables (*generation IB*, *title price*, *platform competition*, *multihoming*, *developer past sales*, and *consoles' average age*) are included but not reported here for presentational convenience. All models include fixed effects at the console level and year-quarter dummies.
*$p < 0.10$; ***$p < 0.01$.

achieve dominance in a given Christmas period in a given genre type, this leadership is unlikely to persist until the end of the platform life cycle. On the contrary, it is very likely that in the next Christmas period, other players will dethrone the once-successful incumbents.

Overall, we conclude that the additional robustness tests and analyses presented in this section offer additional support for the theorized underlying mechanism.

Discussion

We focused on the inherent tension that generativity, a key property of platform-based technology ecosystems, has on value creation. Mainstream theory from the multisided market literature has mainly stressed the reinforcing, indirect network effects between complement availability and platform user value. Accordingly, a greater variety of complements should enhance value creation. Yet, not all complements are equal in the way they address and satisfy consumers' needs and utility. When user satisfaction from complement consumption is a key driver for users' platform adoption and usage (e.g., Binken and Stremersch 2009, Cennamo 2018) but can be only imperfectly observed ex ante, some complement providers may free ride on the market's cocreation effort (Gupta et al. 1999) made by providers of first-rate complements and opportunistically enter the

Table 9. Development and Marketing Effort

Variable	*Awareness*		*Project size*	
	Early stage	Late stage	Early stage	Late stage
Generativity	0.15	−3.08***	6.47	0.98
	(1.23)	(1.10)	(5.05)	(3.61)
Generativity^2	0.08	−0.01	0.36	−1.48**
	(0.38)	(0.11)	(1.34)	(0.64)
Generativity × platform competition	−3.38	−14.23*	12.5	−92.35***
	(3.89)	(8.44)	(8.73)	(34.5)
Number of observations	357	848	1,109	1,006
R^2	0.13	0.05	0.42	0.34
F-statistic	1.01***	1.45***	9.28***	7.11***

Notes. The level of analysis is as in Tables 3 and 4, the console-genre-title at the month of launch of the title. The dependent variable is *awareness* for the first two models and *project size* (of the game title in the genre at the month of the title's launch) for the consecutive models. All models report 2SLS estimation results and include fixed effects at the console and game publisher levels and year-quarter dummies. All models also include the control variables *generation IB*, *title price*, *platform competition*, *multihoming*, *consoles' average age*, and *developer past sales*; results for these coefficients not reported here.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

market with average-quality complements. As we advanced, generativity reflects mixed incentives for the provision of first-rate complements because of both a positive spillover effect and a negative free-rider effect. Its impact on user satisfaction is ambiguous; ultimately, it depends on whether the negative free-rider effect is outweighed by the positive spillover effect of generativity. We provided empirical evidence that supports our framework in showing that the effect of generativity on complements' user satisfaction is asymmetric depending on the stage of platform system maturity. Also, consistent with the free-rider mechanism underlying the results, we provided additional evidence that generativity also increases the variance of complements' user satisfaction. It also reduces both the development innovation effort and the marketing promotional investments of complementors at later maturity stages. This effect is due to both a shift in existing complement providers' incentives and a new entry of free riders.

Our findings illustrate the organizational challenges platform ecosystem orchestrators face when managing their complementors to create value for users. Enhanced generativity ensuing from greater ecosystem participation generates tension in the value-creation process. The way platform ecosystem orchestrators handle this process will affect the platform system's configuration, its overall value, and, eventually, the market share of the technology (e.g., Zhu and Iansiti 2012, Cennamo and Santalo 2013). Our findings also stress the importance of accounting for the different dynamics that may emerge throughout the platform evolution and identify the relative importance of the main factors affecting platform ecosystem evolution at distinct stages. For instance, our finding that generativity positively affects user satisfaction of complements in the early stage suggests that platforms may create more value by stimulating greater generativity early on because it will boost the complements' variety and consumption utility. However, as the platform matures, these two value-creation drivers are in tension, and average user satisfaction will degrade. Because generativity will increase the variance of complements' user satisfaction, it continues to have a negative impact on users' expectations and, ultimately, the platform system's reputation. (e.g., Roger and Vasconcelos 2014). How these opposing forces affect a platform's overall value and market performance at a given time remains an open question of interest for future research.

Such analysis may contribute to the emerging debate between scholars focusing primarily on network effects, and hence network size, as a driver of platform system success (e.g., Armstrong 2006, Corts and Lederman 2009) and those arguing that, ultimately, the resilience of a platform ecosystem depends on the value of the innovation produced therein beyond its variety (e.g., Zhu and Iansiti 2012, Cennamo and Santalo 2013), as greatly affected by the ecosystem governance (Wareham et al. 2014) and other platform characteristics (Penttinen et al. 2018). This would open a broader research agenda on whether multiple platform systems can coexist in the market based on a different focus on variety versus consumption utility of complements (e.g., Zhu and Iansiti 2012) and/or platform ecosystem configurations (e.g., Cennamo and Santalo 2013). Could the benefits of a greater variety of complements from enhanced generativity compensate the platform system for degrading user satisfaction? When and in which sectors might this be the case? In sectors where complements' user satisfaction is a critical factor for success, our contributions suggest that platform strategies too focused on leveraging generativity to maximize network effects might be ill designed. Yet, platforms that fail to leverage generativity may not gain enough complementary products or be forced to bargain with the few complementors they attract to secure an adequate variety of first-rate complements. Managers then face a dilemma of consumption utility versus variety, and value capture versus value creation. Interestingly, the resulting net effect also depends on something platform managers cannot directly control but nonetheless aspire to shape: platform competition. Understanding how managers resolve these tensions, or fail to do so, while governing the evolution of the platform ecosystem may prove invaluable for our understanding of platform ecosystem dynamics and competition.

Previous studies have identified the tensions arising from generativity for ecosystem evolution, and they have highlighted the technology and governance design aspects affecting complementors' participation and their level of generativity (e.g., Tilson et al. 2010, Tiwana et al. 2010, Yoo et al. 2012, Henfridsson and Bygstad 2013, Anderson et al. 2014, Wareham et al. 2014). The collective action perspective we advance here extends this line of research by offering a new lens for analyzing ecosystems as collective organization. By uncovering the underlying mechanisms affecting the positive or negative feedback from generativity, it helps us to understand how patterns of self-organizing can emerge from the feedback of generativity and lead to complementarities among ecosystem participants' contributions. This approach is important in developing a greater understanding of the distinct nature of coordination and organizing logic in ecosystems compared with other organizing forms (e.g., markets, hierarchies, alliances). More research is needed along this line. Although complementors act in plain autonomy in their self-economic interest, their actions and contributions to the shared objective of the ecosystem might be nonetheless steered somehow through stimuli other than generativity feedback. In fact, platform ecosystem governance is gaining increasing attention of late in research as well as in practice to gain a better understanding of how to govern activity of the "unfiltered" (Zittrain 2008, p. 70) large and varied audience active on platforms and limit its negative consequences without constraining generativity. This dilemma calls for a fresh view on governance. As Tiwana et al. (2010, p. 680) suggest, platform ecosystems cannot be viewed through the lens of the classical principal agent relationship; the "role of control mechanisms...is one of coordination" that could guarantee alignment of firms' interests by continuously shaping the direction for their contribution toward the shared ecosystem's objective. The significant need for coordination, which cannot be dealt with in markets, but also does not require the hierarchical control typical of centralized organizations, is in fact what drives the emergence of ecosystems in the first place (Jacobides et al. 2018). Similarly, Yoo et al. (2012, p. 1402) advance that, in ecosystem contexts, "the notion of organizational incentives may come to be understood as less of a structural feature of the organization and as more of an adaptive emergent coordination mechanism." In this sense, and in line with recent contributions (Wareham et al. 2014), our study calls for the platform owner to install appropriate governance mechanisms to manage the tensions inherent in ecosystems, specifically the spillover and free-rider effects of generativity in our case. Wareham et al. (2014) discuss potential selection mechanisms for screening out providers that would otherwise contribute to ecosystem fragmentation and instability. These mechanisms may work out to guarantee identification of the complementor with the ecosystem and its commitment to the collective good at the time of entry and initial contribution to the ecosystem. However, they might have a limited effect in coordinating complementors' contributions on an ongoing basis. How can the platform owner retain complementors' collective-oriented incentives over time with increases in participation and generativity? What can platform owners do to alleviate the free-riding problem without discouraging participation? One option is to set strict screening mechanisms to assess complement value case by case and provide complementors with marketing support or lower royalty fees to incent them to offer first-rate complements. However, such dyadic collaboration agreements are not viable with a large number of providers (e.g., Hagiu 2009, Cennamo and Santalo 2013), and they might even raise selection problems for the platform owner, who lacks ex ante the relevant information about the value of providers' complements (Hagiu and Wright 2015). A traditional partnership program, where the platform owner identifies ex ante a set of reputable providers and offers them favorable conditions on the expectation of value-adding provision, can lead to moral hazard issues without removing free-riding incentives. This is why some suggest that the platform should rely on the self-selection governance mechanism of a quasi-market-type relationship (e.g., Armstrong 2006, Hagiu and Wright 2015). However, this mechanism would expose the platform to the negative free-riding effect we document; platform owners may discover, to their dismay, that the solution is worse than the problem (e.g., Cennamo and Santalo 2013, Wareham et al. 2014). The platform owner might set participation rules and incentives that align participants' interests (e.g., Grewal et al. 2010), and restrict access for providers of second-rate complements. However, such governance mechanisms would not provide incentives for higher user satisfaction beyond the minimum threshold. They are also trade-offs with the open-access, quasi-market mechanisms required to attract an increasing number of complementors and install generativity (e.g., Boudreau 2012, Wareham et al. 2014).

One potential solution could be setting incentive programs for investing in user satisfaction, where the platform owner offers rewards such as marketing endorsements (Rietveld et al. 2016) to selected complements *after* observing those complements' user satisfaction and initial market performance.[29] In our setting, for instance, Sony and Nintendo have long supported providers' efforts through selective comarketing, remarketing endorsed games under their Greatest Hits and Nintendo Selects brands, respectively. The platform owner sets only minimum requirements to be eligible for these comarketing programs (such as sales levels) and then selects among the eligible games (Rietveld et al. 2016). Thus, instead of entering ex ante into dyadic relational bargaining, the platform owner simply sets a standard policy that can be applied only ex post after the utility of a provider's product is revealed, effectively screening for quality while offering a universal incentive for user satisfaction investments. We would thus expect the platform owner to be more likely to endorse complements as the negative free-riding effect becomes more acute. This scheme has the advantage of possibly disciplining free-riding behavior of complementors, providing them with the incentives (the prospect of the possible endorsement reward by the platform owner) for investments in user satisfaction, and yet stimulating generativity. Similarly, in the mobile app context, Apple is endorsing prospectively valuable apps by featuring them in the "App of the Day" or "This Week's Favorites" list in its App Store. This example also suggests that platform owners might increasingly need to align the design of the platform architecture (the market infrastructure layer in this specific example) with the coordination of the collective organization to effectively influence value-enhancing interactions in the ecosystem. Whether, or better, *when*, this is the case and what other governance mechanisms platform owners can implement to balance out tensions in ecosystems without constraining complementors' autonomy and ecosystem generativity are questions that might lead to a fascinating research agenda for future research.

Limitations and Future Research

One limitation of our study is that we did not consider the screening mechanisms platform owners employ when assessing a game title for licensing. Platform owners may, for example, demand lower royalties or offer better financial conditions in the face of greater generativity. Depending on how such agreements are designed and implemented, they may partly attenuate—or, in some cases, exacerbate—the free-riding problem, thus creating an additional source of variation that we could not capture directly in our analysis. More generally, our focus was on the consequences and not the sources of generativity. But the question of how the different (technological and governance) factors affect generativity in platform ecosystems is an interesting one, worthy of deeper examination. Also, given the importance of a complementor's talent for the generativity of the ecosystem, platform owners have established practices to cultivate and promote this talent. Some platform providers even provide formal training and forms of evaluating complementors' skills. Our finding of a strong, negative free-rider effect of generativity as the platform matures suggests that such practices are not as effective in promoting talent to the extent of compensating for the loss in user satisfaction associated with the free-rider effect. Nonetheless, how these practices affect the actual talent of complementors and their capacity to produce better content is an interesting aspect to study; it could also help us to better appreciate how the platform complementor interaction evolves over time.

Second, one characteristic of the video game industry that may drive our results is the short life cycle of the product: on average, game titles sell strongly for 3 months, but first-rate titles, or superstars, can receive sales for 10–15 months (Clements and Ohashi 2005, Binken and Stremersch 2009). Developers may decide to maximize the profitability of each title by settling for relatively competitive standards of user satisfaction. In other sectors, where goods have longer consumption lives, firms might have more incentives to maximize ex ante the level of quality provided in their durable goods; free-riding problems would still be present, but they might have different effects. Fourth, complementors that inhabit multiple ecosystems may face technical problems of platform complement product integration that may degrade the consumption experience of multihoming complements (compared with complements specializing in a single platform). Our analysis controls for the main-effect differences between multi- and single-homing complements and for platform technological and other unobserved differences, but it is agnostic/it does not control for the underlying motivations for multihoming strategy.[30] Future research might explore the relationship between the multihoming strategy and collective action problems, as enhanced by cross-platform competition, in more detail. Fifth, as a boundary condition, our theoretical reasoning applies for those platforms in which third-party independent firms need to allocate platform-specific investments to increase the utility of users on the other side of the platform when utilizing that platform. The more important this platform-specific investment is, the more likely we consider our theory applicable to the context. Hence, our hypotheses should hold in contexts like apps for smartphone operative systems, shopping malls in which the shops must invest effort and money to sustain both their own images and the mall's reputation, or the developers of applications for cloud computing platforms (e.g., Dropbox,[31] Salesforce, etc.). On the contrary, our theory should be less applicable in contexts with lower platform-specific investments like pure two-sided marketplaces (e.g., credit cards) or crowdfunding platforms (e.g., Kickstarter).

Finally, a critical condition for our theoretical logic is that a complement's value can be only imperfectly observed ex ante by consumers. Consumers may form expectations about the utility of a game title when deciding to buy it at launch, but it is only after they have played the game that they can properly assess how well it meets their expectations. Once a game has been played by a mass of gamers, new buyers who follow them can rely on the information they provide through reviews to guide their purchase decisions. If "rational" gamers anticipate this and postpone their purchase decision accordingly, second-rate titles are far less likely to be selected; hence, there might be less of an incentive to free ride. In our context, this is seldom the case for two main reasons. First, the bulk of game sales is generally concentrated in the Christmas holiday season, when gamers are impulsively interested in buying and playing new games. Second, because games are hedonic goods with relatively short life cycles, gamers hardly postpone their purchasing decision to make a better-informed one.[32] In other contexts, the conditions for free riding, or its effects, may manifest in different forms. More broadly, we hope the insights our study provides will stimulate future work on value creation in platform ecosystems and uncover other potential tensions ensuing from generativity and ways to address them.

Acknowledgments

The authors thank the editor, Ann Majchrzak, and two anonymous reviewers for their detailed and constructive feedback during the revision of the manuscript. Michael Jacobides, Luis Diestre, Charles Baden-Fuller, Gianvito Lanzolla, Elena Novelli, Wesley Koo, Dovev Lavie, and Jan Ondrus gave them valuable comments, which have helped structure their argumentation. They also acknowledge feedback from seminar participants at the IE Business School, Bocconi University, Cass Business School, London Business School's Ghoshal Strategy Conference, Rotterdam School of Management, Essec Business School (Singapore), Esade Business School, and participants at the Academy of Management Meeting and Strategic Management Society Conference.

Endnotes

[1] Ecosystems are complex forms of interfirm collaborations among cospecialized firms linked by interdependent activities with linked economic prospects acting as a collective entity (for a thorough discussion of the distinct nature of ecosystems compared with other organizational forms, see Jacobides et al. 2018).

[2] Whereas products are designed for prespecified uses (that cannot be modified or extended in use), platforms continue to change their possible uses through the different types of complements (Yoo 2012) and, accordingly, their consumption benefits.

[3] Heterogeneity in complement quality can originate not only from complementors' heterogeneity in skills, resources, and entrepreneurial vision about the way to address user needs, but also from heterogeneity in how complementors respond to platform practices for courting this talent.

[4] In contrast to a buyer–supplier or alliance relationship, the platform owner does not specify what must be supplied or how it will be rewarded; hence, it cannot directly control the level of platform-specific investment or the complement's level of quality or complementarity. The platform only sets up the technological infrastructures for providers and users to connect and the incentive mechanisms to indirectly influence providers' and users' decisions (Grewal et al. 2010, Wareham et al. 2014).

[5] Some authors argue that these issues are minimized, if not eliminated, in platform ecosystems because of the unique quasi-market relationship between complement providers and consumers (e.g., Hagiu and Wright 2015). The argument proposes that because complement providers retain residual claims over their individual demand, and thus the returns from their costly efforts, and autonomously choose what to produce and how to price and market it, they are motivated to undertake costly quality investments with respect to the product in question. Moral hazard problems are duly eliminated, and decisions on quality investments will be based exclusively on the expected benefits associated with the platform's network size (Armstrong 2006, Corts and Lederman 2009, Hagiu and Wright 2015).

[6] We conceive of complement quality as the overall key features of the complement and the way it integrates with the platform technology that determine how well the complement meets a user's preferences and satisfies her consumption needs as assessed by the user. Thus, we use complement quality interchangeably with user satisfaction from a specific platform complement's consumption.

[7] Greater generativity helps the platform's user market get started and expand, which enlarges the potential value to be captured by complementors and, thus, the ex ante incentives of complementors to make investments that enhance the platform's user satisfaction. In turn, by contributing to the shared system reputation, this will increase the positive spillover effect. A reinforcing positive feedback loop may emerge.

[8] This is the opposite of the crowding effect (e.g., Boudreau 2012)—i.e., more complements of same type exerting a negative externality on each other (i.e., a competitive substitution effect).

[9] Naturally, first-rate complements might still capture most of the demand for complements, insofar as their superior value can be signaled to platform users, for instance, through free demos or user review recommendations. However, these are imperfect mechanisms that do not eliminate users' uncertainty entirely. Moreover, for these user reviews to become available, early users must buy the complement without the option of relying on this information for consumption utility assessments. Therefore, a nonnegligible proportion of users may purchase without knowing exactly how much they will like the product and must rely more on expectations based on the platform's reputation, which becomes more volatile as a result of increasing variance in complement user satisfaction.

[10] Complementors' innovation activities can be self-reinforcing under greater generativity—members mutually adjust to each other's activity through feedback mechanisms in a way that the collective self-organizes toward an evolutionary trajectory that merges individual and collective welfare (e.g., Yoo et al. 2012, Henfridsson and Bygstad 2013).

[11] Multihoming is viable to the extent that the cost of adapting the product to the technical specifications of multiple platforms is negligible relative to its production cost as well as to the potential benefits of multihoming (Corts and Lederman 2009).

[12] Multihoming complementors will need to address different audiences of platform users, with possibly distinct characteristics and preferences about platform usage (e.g., Cennamo and Santalo 2013, Bresnahan et al. 2015) and the types of complements that satisfy their consumption needs.

[13] An alternative logic for why cross-platform participation would amplify the negative effect of generativity on user satisfaction could be that complementors may have more limited control over the quality of their products because of technical complexity and constrained resources that would make it more difficult to port complements to multiple platforms. Against this alternative explanation, in the results section, we present some evidence pointing to decreasing effort and investments under greater generativity and platform competition, controlling for complementor fixed effects, which is consistent with the theoretical logic we advance here. We acknowledge the comment of an anonymous reviewer pointing to this aspect.

[14] More details on the data collection methods of the NPD Group are provided on the entertainment market research section of its website (http://www.npd.com/corpServlet?nextpage=entertainment-categories_s.html).

[15] Unfortunately, user ratings from IGN.com are not available for three of the fifth-generation consoles (the Atari Jaguar, 3DO, and Sega Saturn), most probably because these platforms were not particularly successful and soon exited the market. Titles sold on these platforms, therefore, do not enter our final data set.

[16] Few consoles (specifically, Sony's PlayStation and PlayStation2 and Microsoft's Xbox) remained active for longer and indeed continued to marginally expand in user base after the launch of next-generation consoles, overlapping for a while in the market with next-generation consoles.

[17] Because developers differ in their talents, platform owners often set up different practices for stimulating talent and attracting the most talented developers. Console fixed effects control for differences across consoles in these practices (to the extent that they do not change over time).

[18] Note that most games compete in the marketplace for only three months around Christmas, with superstars, games of exceptionally high quality, extending their sale period up to 10–15 months (Clements and Ohashi 2005, Binken and Stremersch 2009).

[19] *Generativity* and the interaction with *maturity* are both endogenous. We followed the same procedure adopted for the interaction between *generativity* and *platform competition* and used as an instrument the variable used to instrument *generativity* interacted with the *maturity* dummy.

[20] This excludes that the developers producing low-quality games were those with limited skills/resources as a plausible alternative explanation and highlights the dynamic governance problem for platform ecosystem orchestrators—free riding cannot simply be solved through ex ante selection mechanisms.

[21] Accordingly, we have lagged further the instruments to maintain a 12-month lag between the instrumented and instrumental variables.

[22] Games, in fact, can be based on existing concepts (e.g., characters, movies etc..), use licensed content (e.g., movies' characters, stories, and content), or be completely novel and based on original intellectual property.

[23] We acknowledge an anonymous reviewer for pointing out this possibility.

[24] We collected this information from the website Mobygames.com, which has a comprehensive and reliable data set on games developed over the years for all platforms, and which has already been used by other scholars (e.g., Corts and Lederman 2009). We could find information for over 90% of the games present in our data set.

[25] Data were normalized using the most-searched-for game in each platform genre as the reference and presented on a scale from 0 to 100. However, because data on Google Trends analytics are available only since 2004, we could not compile information about earlier games. This missing information shrank our sample size to 1,205 observations.

[26] We acknowledge an anonymous referee for suggesting this alternative explanation to our findings.

[27] In particular, on a scale between 0 and 1 (1 being highly concentrated market), the average sales concentration (measured through the Herfindhal index) at the publisher-platform-genre level is around 0.26, with a standard deviation of 0.19, whereas sales concentration at the game title-platform-genre level is around 0.30, with a standard deviation of 0.28.

[28] If the market would consolidate around few complements in each of the product categories, we should observe an increasing market exit rates by developers and a decrease in (or no) generativity in the maturity stage of the platform market; we observe, in fact, an increase in generativity. Also, this logic is at odds with the findings we report in Table 6 (why would developers of high-ranking titles in the early stage, which are the ones that would secure market leadership, switch to producing titles of lower rank in late stages?) and Table 7 (why would an increase in the ratio of low-rated (to high-rated) games lower sales of high-rated games that should have secured market leadership?).

[29] These incentives schemes have features similar to "sales contests" (e.g., Kalra and Shi 2001, Chen and Xiao 2005), where firms seek to boost sales volumes by rewarding individuals for their efforts after observing their relative (instead of absolute) levels of performance, awarding only the winner of the contest (winner-take-all format), or sharing the award among multiple winners based on relative rank (rank-order tournament format), with larger amounts awarded to higher ranks.

[30] Current literature generally tends to emphasize scale economies as the main rationale for multihoming strategies (e.g., Corts and Lederman 2009, Bresnahan et al. 2015), but this leaves out the question of why a great portion of complementors specialize in a single platform system instead of exploiting economies of scale. We believe there is scope to improve our understanding and related theory of multihoming by moving beyond this simple perspective and incorporating issues related also to collective action and ecosystem identification.

[31] Since 2014, Dropbox has opened its enterprise business service to third-party developers to offer a large variety of applications integrating the cloud storage service for enterprise use. See, for example, https://www.v3.co.uk/v3-uk/news/2384545/dropbox-woos-enterprise-app-developers-with-open-api.

[32] Purchases are often driven by the desire to be among the first to play/complete a game and display that achievement to peers via social media (e.g. PlayStation Trophies). Indeed, on average, a game title receives most of its sales during the two to three months following its release (e.g., Binken and Stremersch 2009). The gaming press also generates prerelease hype that raises expectations and tends to make games "day 1" purchases for fans, almost regardless of the lack of available information. For instance, *Grand Theft Auto V* sold 11 million units in its first 24 hours.

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