Extended Generativity Theory on Digital Platforms*

Authors:

Fürstenau, Daniel[1]

Baiyere, Abayomi[2,3]

Schewina, Kai[4]

Schulte-Althoff, Matthias[4]

Rothe, Hannes[5,6]

[1] IT University of Copenhagen, Department of Business IT, Copenhagen, Denmark

[2] Queen's University, Smith Business School, Canada

[3] Copenhagen Business School, Department of Digitalization, Frederiksberg, Denmark

[4] Freie Universität Berlin, School of Business & Economics, Berlin, Germany

[5] University of Duisburg-Essen, Institute for Computer Science and Business Information Systems, Essen, Germany

[6] ICN Business School (Paris, Berlin, Nancy), Department of Information Systems and Supply Chain Management, Berlin, Germany

Accepted at *Information Systems Research*

January 24, 2023

This is a pre-print. Please cite the final version as published in *Information Systems Research*.

Extended Generativity Theory on Digital Platforms

Abstract

The assumption that generativity engenders unbounded growth has acquired an almost taken-for-granted position in information systems and management literature. Against this premise, we examine the relationship between generativity and user base growth in the context of a digital platform. To do this, we synthesize the literature on generativity into two views–*social interaction* (expansion of ecosystem boundaries) and *product view* (expansion of product boundaries)–that jointly and individually relate to user base growth. Both views help us explain how opening a platform relates to the emergence and resolution of conflicting expectations in a platform ecosystem that result in new functions and expanded usage. We adopt a panel vector autoregressive approach combining data from six large transaction platforms that engaged with open source developer communities. We found that the dominant narrative of generativity engendering growth, while generally supported by our analysis, obscures the fact that the inverse is also true; that is, *growth can lead to expansion of product boundaries (inverse generativity),* and that generativity can be bounded; that is, *growth can stabilize ecosystem boundaries (bounded generativity)*. Against this background, we propose an Extended Generativity Theory that presents generativity and growth in an *integrative view* and raises awareness about the limitations of the "unbounded growth" claim. We conclude that there is value in separating the two views of generativity conceptually and analytically, along with their relationship to user base growth, and we call for research on the pathways through which generativity produces growth.

Keywords: digital platforms; generativity; user base growth; product boundaries; ecosystem boundaries; dynamic boundary

This is a pre-print. Please cite the final version as published in *Information Systems Research*.

Extended Generativity Theory on Digital Platforms

1. Introduction

Generativity engenders a system's capacity to generate unbounded growth (Zittrain 2009, Yoo et al. 2010; Tilson et al. 2010). Undoubtedly, the view of generativity in relation to unbounded growth has gained deep roots in scholarship on digital platforms (de Reuver et al. 2018, Constantinides et al. 2018). This proliferation of generativity as the recipe for unbounded growth reflects digital platform's search for growth as they seek to expand their value offerings (Parker et al. 2016, Morgan et al. 2021), expand the reach of their ecosystems (Grover and Lyytinen 2022; Thomas and Ritala 2021), and expand their user base (Rietveld and Schilling 2021; Taeuscher and Rothe 2021). Prior research has shown that the generative capacity of software is rooted in re-programmable functions that leverage input from open communities (Yoo et al. 2012). Consequently, the generative capacities of traditional in-house software systems are considered limited compared to digital platforms external parties can contribute to (cf. Lehman et al. 1997, Lehman and Fernández-Ramil 2004). The quest for growth has led organizations to consider opening up in-house systems as digital platforms to leverage generativity.

The current literature has extended our knowledge about how generativity contributes to growth on and of a digital platform. It has shown that there is no single, unified definition of generativity but there can be different forms of generativity (Faraj et al. 2011, Yoo et al. 2010, Thomas and Tee 2021). Generativity can be viewed from at least two perspectives–*the product* and the *social interaction* view. In the *product view,* generativity manifests in the expansion of product boundaries of a platform, i.e., adding new categories of content, services, or functions to a platform, such as new genres of games to a video game console (Cennamo and Santaló 2019) or new categories of apps to a mobile app store (Ghazawneh and Henfridsson 2013). The *social interaction view* engenders an expansion of ecosystem boundaries in that generativity arises from an increase in social interactions between platform providers and platform complementors. Both groups' expectations can conflict, and they need to negotiate (Faraj et al. 2011, 2016, Shaikh and Vaast 2016) what functions a platform provides and how. While both views consider expanding boundaries, they implicitly assume that generativity engenders growth.

In this study, we caveat this unbounded growth claim by highlighting that this is not always the case. Unbounded growth is assumed despite the nuanced differences in the forms of generativity explored in prior literature. While the literature on generativity has acknowledged the (co-)existence of both, the product and the social interaction view (e.g., Faraj et al. 2011), both have been largely considered silos. There has been limited investigation and theorizing on how these two views separately and jointly relate to user growth. We posit that there is much to uncover in examining how these seemingly disparate views of generativity specifically impact growth in digital platforms, i.e., their expansion in a relevant measure of size (West 2017). This absence in scholarship is unfortunate because the rapid growth (e.g., "growing on steroids"; Huang et al. 2017) of digital platforms is desired but remains elusive. At the surface, generativity may seem to overlap with what is referred to as growth of actors or services (Zittrain 2009, Tilson et al. 2010). For platform providers, however, an important growth measure is the user base (e.g., Rietveld and Schilling 2021; Taeuscher and Rothe 2021), which can be distinguished from the aforementioned expansions of ecosystem or product boundaries. Paying attention to how different strands of generativity contribute to user base growth is important as organizations increasingly recognize the benefits of leveraging digital platforms to access the knowledge of uncoordinated audiences also referred to as the "crowd" (Cusumano et al. 2019, Niederer and van Dijck 2010). This observation has given salience to the value of "platformization" as a channel for growth and innovation (Boudreau 2006, Bygstad and Hanseth 2018), which has spurred many organizations to strive to open their systems to external developers. Hence, our study specifically asks: *How do different forms of generativity on a digital platform relate to user growth?*

We disentangle both views and point out nuances in the interaction between generativity and growth that call for caution in this blanket characterization. We propose an *integrative view* of generativity as a conceptual framework that lays out how both forms of generativity explain dynamic boundaries of a digital platform. We exemplify this view in the context of platforms that open core functions to joint development between professional developers of a platform provider, freelancers, and large uncoordinated audiences. From an integrative view, we consider a dynamic set of components (expanding product boundaries) that results from a continuous process in which providers and a dynamic set of developer complementors (expanding ecosystem boundaries) negotiate conflicting expectations on functions at the service layer of a digital platform. By opening up the service layer (Yoo et al. 2012) of a transaction platform, not an innovation (e.g., Lyytinen et al. 2016) or product platform (e.g., Sandberg et al. 2020) through open source (Parker et al. 2017), providers lay open the inner functionality of core components and allow them to be appropriated–a process previously and predominantly under the control of corporate employees and contracted in-house IT personnel. The integrative view of generativity allows for studying the relationship between generativity, i.e., the expansion of product and ecosystem boundaries, and user base growth in new and unprecedented ways.

Drawing on our integrative view, we employed a panel vector autoregression (PVAR) approach for our analysis. By using panel vector autoregression on a combined dataset from 6 large international e-commerce transaction platform firms, we model the relationship between expansion of product boundaries, expansion of ecosystem boundaries, and user base growth. We employ impulse response function analyses and Granger causality tests and make two surprising findings. First, we find that generativity does not always lead to unbounded growth. While we also find evidence for generativity leading to user base growth, we are surprised to see a stabilizing effect on ecosystem boundaries over time–we refer to this as *bounded generativity*. This observation suggests that generativity is not always ever-expanding *per se* but instead can tend towards a dynamic equilibrium. Second, and contrary to the dominant narrative that generativity leads to growth, we find that the inverse also holds–i.e., user growth can also induce generativity–we refer to this as *inverse generativity*. Based on these findings, we propose an *Extended Generativity Theory* that captures the main insights of our study in six conjectures. The theory contributes to our knowledge of generativity by offering a conceptual bridge for integrating two streams of literature that provide insights into the multi-directional relationship between generativity and growth. Such a theoretical perspective enables us to shed new light on the "unbounded growth" claim that generativity and growth do not interact in unanimously positive and self-reinforcing cycles (e.g., Henfridsson and Bygstad 2013). We conclude by presenting boundary conditions and theoretical and practical implications that should inform and reorient future scholarship on digital platforms.

2. Conceptual Background

2.1 Two Views on Generativity

The internet (Hanseth and Lyytinen 2010, Zittrain 2008, 2009), open source online communities (Faraj et al. 2011, 2016, Shaikh and Vaast 2016), and digital platforms (Constantinides et al. 2018, Foerderer et al. 2018, Hein et al. 2020) are all considered generative systems in that they lead to unbounded growth (Zittrain 2009). On platforms, generativity emerges in the relationship between complementors and a provider (Hein et al. 2020). Complementors use their knowledge and ideas to produce a variety of unforeseen contributions. At the same time, generativity depends on the provider. Platform providers allow people to connect and innovate, while preserving the right to control contributions. Choosing the right degree of openness to spur generativity from complementors, while avoiding negative externalities and identifying threats, is the platform provider's central challenge (Cennamo and Santaló 2019, Constantinides et al. 2018, Parker et al. 2016, de Reuver et al. 2018, Tilson et al. 2010).

Table 1. Views on Generativity in Digital Platforms

View	Foundational sources	Definition and reference to growth	Relation to dynamic boundary
Product view	Zittrain 2008 Yoo et al. 2010 Yoo 2013	*Generativity* refers to the capacity of a platform to enable unbounded growth of new components that expand the product boundaries of a platform beyond its initial conception and further attract more users.	The emergence of a new category of components or the addition of new components to existing categories leads to an expansion of product boundaries. Providers engage in configurational boundary work in that they govern product categories, such as securing boundary resources between the platform and complements or promoting particular complements.
Social interaction view	Faraj 2011 Shaikh and Vaast 2016 Jarvenpaa and Standaert 2018	*Generativity* refers to the capacity of a platform to produce unbounded growth of interactions between human and technology resources that expand the ecosystem boundaries and leads to user growth by resolving emerging conflicts.	The emergence of new interactions between developers and components around conflicts leads to an expansion of ecosystem boundaries. Providers and complementing developers engage in collaborative boundary work as they negotiate what conflicts to solve, how and by whom.

Against this background, generativity can be conceptualized from at least two perspectives–the *product view* and the *social interaction view* (Table 1). Platform providers engage in purposeful efforts to influence the boundaries of their platforms, which is considered boundary work (Langley et al. 2019).

They shape ecosystem boundaries by determining who might become a complementor and can participate in the ecosystem (Kretschmer et al. 2022; Gawer 2021). They shape product boundaries through decisions about what complements are added to the platform.

Product view: The product view of generativity refers to the ability of a platform to expand its product boundaries beyond the current categories. This view highlights the technological potential of generativity to produce “unprompted change” (Zittrain 2008), “a seemingly infinite number of variations and speciations” (Yoo 2013), and “unbounded growth in scale and diversity” of functions (Tilson et al. 2010; Lyytinen et al. 2017). Yoo et al. (2010) outline how, combining layered and modular architecture, platforms create fluid product boundaries. Platforms can be created from (and extended with) product-agnostic components on content, service, network, or device layers. Innovations on each layer lead to cascading effects when layers are loosely coupled (Adomavicius et al. 2008, Boland et al. 2007, Yoo et al. 2010). For example, when new social media or video game applications were added to the app store, iOS and Apple iPhone became more than a combination of a phone and an operating system. Innovations on the service and content layers expanded the product boundaries, and the iPhone became a gaming device and a social media tool. Cennamo and Santaló (2019) conceptualized generativity as the expansion of game genres at the content level of video gaming consoles, considering the positively accumulative effects of generativity on user satisfaction. Pauli and Lin (2020) illustrate how components from internal and external developers expand the product boundaries of IoT platforms at the service layer. Hukal et al. (2020) explain how new tags are introduced that invite more user-based content on platforms like OpenStreetMap. Providers guide what configurations of components they consider beneficial for the platform (Hukal et al. 2020) as they ease collaboration with complementors or even allow competition among complementors to satisfy user demands (Cennamo and Santaló 2019).

Together, providers and complementors have many views on what categories of components should be added to different layers of the platform architecture. At the service layer, any new component of a platform is assessed by third-party and first-party developers against their respective expectations on what functions a component of a particular category needs to fulfill and how it is supposed to perform its task. Platform providers decide what components are added to a platform, highlight what functions are desirable (Constantinides et al. 2018; Zhang et al. 2020), and promote complementors who meet their expectations (Ho and Rai 2017). Similarly, clients have expectations on what functions the platform is supposed to provide as they compare it to competing platforms. By adding new components to existing categories on a platform or by introducing new categories, providers engage in "manipulating patterns of differentiation and integration" of components, which captures configurational boundary work (Langley et al. 2019, p. 704). We refer to this as the *expansion of product boundaries* on a platform.

Social interaction view: The social interaction view of generativity explains how ecosystem boundaries are expanded when complementors become involved in developing components on a platform. Here, an ecosystem for transaction platforms refers to communities of actors who provide heterogeneous complements to the platform's service layer to support forming and leveraging transactions between buyers and sellers (Kretschmer et al. 2022). According to the social interaction view, platforms are not *per se* generative. Their membership structures are generative in that ecosystems produce innovation through meaningful interactions that resolve conflicting expectations between members. When Faraj et al. (2011, 2016) conceptualize the "fluid organization", they note how online communities respond to conflicts in a "generative" or "constrained" way, meaning that generative discussions encourage productive new outcomes, while constrained discussions cause the dialog to halt and die. Kane et al. (2014) study tensions between knowledge change and knowledge retention in social media communities. They argue that generative dialogue fosters discussions about conflicting expectations of retaining or changing knowledge by engaging multiple perspectives. Similarly, Shaikh and Vaast (2016) study developers' discussions about error messages. They find discussions can be generative by "marking the start" from where conflicting expectations are resolved with new digital solutions. Similarly, Lyytinen et al. (2016) lay out how innovation platforms facilitate cognitive and social translation between heterogeneous actors that resolves conflicts and thereby fosters innovation. This view highlights the *social* interactions and structures which enable digital platforms to produce new knowledge (Faraj et al. 2011), new technological components such as enterprise systems (Wareham et al. 2014) or smartphones (Boudreau 2012).

Actors engaging in generative or constraining discussions become part of an ecosystem through self-selection (Wareham et al. 2014). Thus, boundaries are not only defined by actors formally governing a platform or those employed by an organization but by the voluntary participation of actors who decide to join or leave an ecosystem or participate in knowledge exchange (Dahlander and Frederiksen 2012; Ren et al. 2007). Generativity on platforms emerges from the interaction between human and technological resources who resolve conflicting expectations on how technology helps humans and stumble upon conflicts while new components are being designed (Jarvenpaa and Standaert 2018). Parker et al. (2017) laid out how developers who are not formal members of a platform provider "invert that firm" through these interactions because they become invaluable parts of a platform's value creation. Thereby, ecosystem boundaries expand as new sets of human and technological resources from outside the formal provider organization interact to resolve upcoming conflicts on a platform (Barrett et al. 2015, Eaton et al. 2015). In the virtual environment of a digital platform, such interactions become unbounded from physical constraints, i.e., space and access to these resources (Jarvenpaa and Standaert 2018), which allows for a greater range and a broader diversity of developers to engage with a platform (Grover and Lyytinen 2022; Lyytinen et al. 2016). The social interaction view stresses how platform providers and complementors negotiate what conflicting expectations should be resolved on a platform and by whom. Platforms are a "trading zone" where diverse actors–both formal affiliates and non-affiliates of a provider organization–increasingly engage in collaborative boundary work (Langley et al. 2019) that *expands the ecosystem boundary* as they strive to address new conflicts.

2.2 An Integrative View of Generativity and the Dynamic Expansion of Boundaries

We propose an *integrative view* as a third view that integrates both the product and social interaction views conceptually. While not representing a distinct view of generativity *per se*, the integrative view provides a means to take both views into account concurrently for analytical purposes. It considers both views as expanding boundaries and takes into account that extant literature in both streams have considered each other as context to their lines of argument. We develop the conceptual and analytical utility of this view and its implication in what follows.

Platform providers inherently consider both–the product and social interaction view–when controlling which conflicts they solve on their own as they consider what components are core of the platform (Eaton et al. 2015, Eisenmann et al. 2008). Providers may introduce restrictions at all layers of a platform architecture (Lessig 2002, Yoo et al. 2010). For example, the service layer may be restricted in terms of who can enter, modify, and delete code underlying the functions (Eisenmann et al. 2008, Tiwana et al. 2010). The architecture can be more or less inclusive, making access to the network and devices more or less difficult. Legenvre et al. (2022) lay out how Google has provided components on the network layer as a common resource to open source communities. Baig et al. (2015) provide similar examples by turning to the Guifi network infrastructure. Apple aims to "manage the delicate balance between generativity and control in the platform" (Yoo et al. 2012, p. 1400), with oversight as to what content or services from developers of their ecosystem are featured. On the service layer, a platform provider can spur or constrain developers' work on peripheral components (Eisenmann et al. 2008), concerning, for example, access control (Boudreau 2006, Cennamo and Santaló 2019), version control (Tiwana 2018), or interface control (Ghazawneh and Henfridsson 2013). In the case of Apple's iOS platform, Eaton et al. (2015) identified 30 boundary resources, including the distribution of apps, executable code, objectionable content, data usage, and in-app subscription payments. Such "code control" concerns how developers may download, modify, and upload code to the platform and its components. Similarly, Google decided to open boundary resources of their Android platform to their ecosystem while restricting access to other services, like machine learning algorithms for advertising, to delimit social interaction with derivative components, i.e., 'forks' (Karhu et al. 2018).

Considering the two generativity views, we advance the concept of *a dynamic boundary* as an analytical means for integrating both views. Dynamic boundary refers to the dynamic set of components that result from a continuous process in which providers and complementors negotiate conflicting expectations for functions on the service layer of a digital platform. As depicted in Figure 1, the dynamic boundary represents a 'trading zone' (Kellogg et al. 2006) on which developers from inside the provider organization negotiate with complementors (Langley et al. 2019) about what components ought to be designed and how.

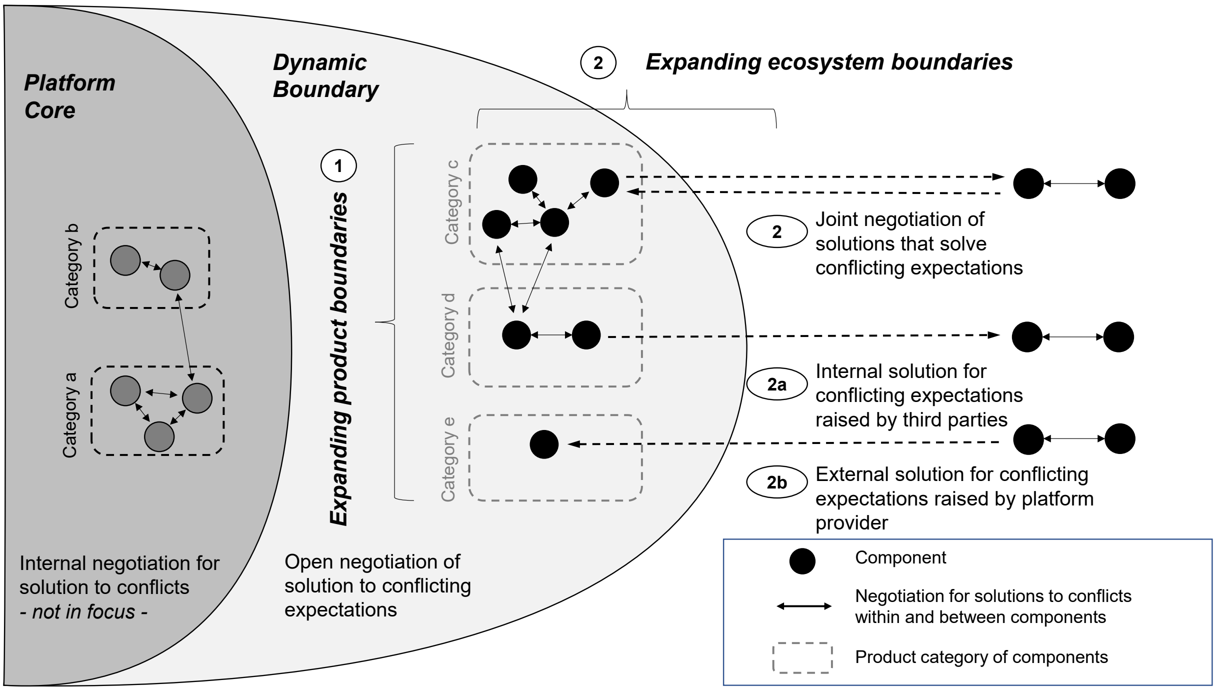


Figure 1. Producing Generativity on the Dynamic Boundary

From a product view of generativity, the dynamic boundary provides (1) openness and permeability to expand product boundaries as more components are added to prevailing categories (Tilson et al. 2010, Lyytinen et al. 2017) or as new categories are introduced. The social-interaction view highlights how conflicting expectations between platform developers and complementors are solved through interacting with components, leading to an expansion of ecosystem boundaries. Internal developers produce components in product categories that they consider core. Components that infer effective use of a platform, such as computationally inefficient algorithms, might result in conflicting expectations of how efficient components ought to be. Components belonging to product categories that are negotiated openly with complementors in the ecosystem reside on the dynamic boundary. This might involve a transparent design of code or a transparent process to flag and discuss conflicts with complementors, for instance, in online communities such as GitHub or StackOverflow.

There are three ways in which ecosystem boundaries are expanded on the dynamic boundary of a platform: (2) *Joint negotiations of conflicting expectations* reveal how components that have originally been created for a platform are modified by complementors applying them for their own needs in the outside environment (cf. Andersen and Bogusz 2019, Karhu et al. 2018). Later, platform providers can reintegrate these adapted components into the dynamic boundary (cf. Kalliamvakou et al. 2016). This is a generative process as it creates derivative innovation that becomes the basis of new variants of a component on the dynamic boundary (Zhang et al. 2014) which might spark platform growth (Kim et al. 2018). This process may also be hostile when complementors "exploit" developed platform functionality and use it for competitive reasons (Karhu et al. 2018). In product categories at the dynamic boundary, complementors' expectations for the design of a component might be influenced by their interest to work with components that are less specific to the platform architecture and allow for more general applications outside of the platform (Andersen and Bogusz 2019, Karhu et al. 2018). Thus, platform providers need to assess whether proposed changes to components, whether as new code or reported issues, meet their expectations on functions of a component and how it relates to the platform architecture. This form of direct negotiation of issues represents the main form of social interaction on the dynamic boundary. There are at least two variations that implicitly expand ecosystem boundaries.

Expanding ecosystem boundaries involves negotiation between platform developers and complementors when (2a) internal components are used to solve conflicting expectations that third-parties resolve in the environment as long as providers remain aware of these solutions. Complementors who use a component from the core for purposes outside of the platform inherently relate components that resolved conflicting expectations on a platform with conflicts they currently face outside of the context of the dynamic boundary. Complementors who adapt platform components in different contexts face more conflicting expectations between how a component is built and how it is supposed to operate in this context. This provides ample opportunities to revise existing code, find new approaches to solve existing conflicts, and eventually help a component become more effective or robust. Adaptations of these derivative components ('forks') remain open and transparent on code platforms like GitHub, which allows platform providers to keep track of these derivatives and monitor changes. As long as platform developers remain aware of changes, these derivative components remain part of an ongoing negotiation about appropriate solutions to potentially conflicting expectations. Finally, the ability to openly negotiate expectations on specific product categories allows (2b) platform developers to solve conflicts raised internally with existing solutions from potential complementors. Hereby, internal developers initiate the solution of existing conflicts at the core with components from third-party developers. Instead of deeply integrating these components into the core, they remain on the dynamic boundary where adaptations are openly presented and can be negotiated with complementors later on.

From the foregoing, both views–social interaction and product view–should individually and mutually contribute to generativity on the dynamic boundary. New product categories added by complementors on the service layer of a digital platform expand both the product and the ecosystem boundary. Similarly, conflicting expectations that arise from adding new components can attract new complementors who specialize in solving such conflicts and expand both boundaries.

2.3 Effects Between Generativity on the Dynamic Boundary and Growth

The most important growth measure for platform providers is the user base (e.g., Rietveld and Schilling 2021; Taeuscher and Rothe 2020), on which generativity is theorized to have a positive impact (Huang et al. 2017). How we understand generativity is informed by two views from prior literature: generativity as an expansion of *product boundaries* and generativity as an expansion of *ecosystem boundaries* through social interaction. Figure 2 shows how expanding product and ecosystem boundaries relate to user base growth in our research model. The distinct relationships are theorized next.

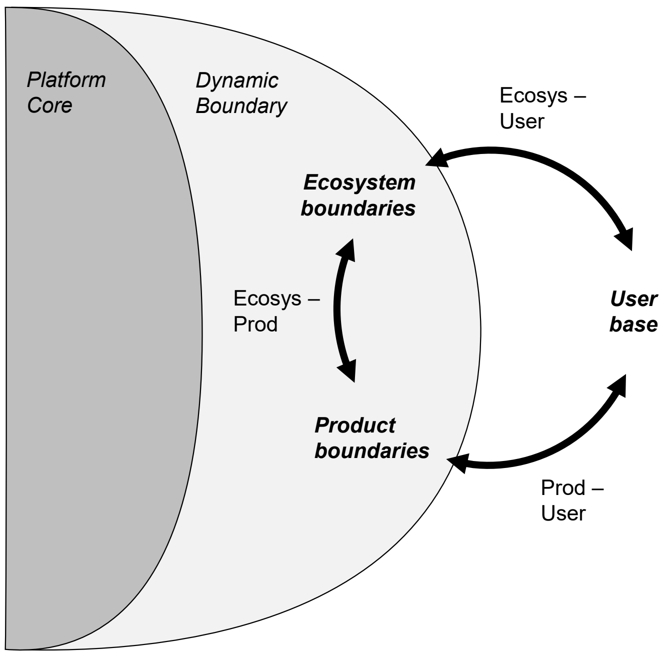


Figure 2. Research model for relationships between generativity, i.e., the expansion of product boundaries (*Prod*) and ecosystem boundaries (*Ecosys*), and user base growth (*User*)

Ecosys–User Relationship. Ecosystem boundaries expand when internal and external developers form temporal communities to negotiate how to solve conflicting expectations that arise from existing components (e.g., Faraj et al. 2011). When ecosystem boundaries expand, complementors incorporate divergent expectations into negotiating what functions are supposed to be at the service layer and how they should be developed. As a result, platform developers and complementors coordinate the development and openly raise upcoming conflicts of expectations so that solutions can be produced and revised more quickly (Parker et al. 2016). Expanding ecosystem boundaries, therefore, allows for continuous adaptation of components on the dynamic boundary that lead to alignment between the expectation of internal and external actors. This helps to adapt components more quickly on the platform to external demand and supports user base growth (Huang et al. 2017). Following prior work, we can also assume that user base growth influences ecosystem boundaries. For example, the case studies of Ghazawneh and Henfridsson (2013) and Eaton et al. (2017) exemplify that with more and more users joining Apple's iOS platform, new conflicts of expectations between users and developers arise because a growing user base could not use their iPhones according to their expectations. This has motivated developers to attend to these conflicts with hacks and jailbreaks, suggesting a relation between user base growth and expanding ecosystem boundaries.

Prod–User Relationship. The product view lays out how an increase of components at the content (Hukal et al. 2020) or service layer (Parker et al. 2017, Yoo et al. 2010) leads to expanding product boundaries that shape the value proposition of a platform from a user's perspective (Autio and Thomas 2020). New functions added to the platform reinforce user growth (Henfridsson and Bygstad 2013) as long as these complements meet user expectations in how platforms in certain markets operate (Cennamo and Santaló 2019). Users, therefore, assess whether components meet their expectations. The flexible nature of a platform as a product (Tilson et al. 2010) allows changing components to a wide range of "temporal and spatial contexts" to increase the user base (Lyytinen et al. 2017). On the dynamic boundary, however, not all components have an equal effect on a user's perception of a platform because users do not directly interact with all components on a service layer. Users can assess whether a component they directly interact with meets their expectations, e.g., recommender systems, payment, or content delivery. Other components improve efficiencies that users are only implicitly aware of, e.g., load balancing of a platform that leads to reduced feedback times. While expanding product boundaries has a positive effect on user base growth, it requires users to notice new components that they directly interact with. Alternatively, they need to at least perceive the issues with new components to arise. Both may require considerable time for new components on the content layer of a platform (Cennamo and Santaló 2019), and potentially even more time at the service layer. A growing number of users will lead to more diverse expectations, providing incentives to further add functions through new components, thus expanding product boundaries. Complementors of Apple's iOS platform, for instance, have regularly turned to user comments to produce new functions and components (Hoffmann et al. 2023).

Ecosys–Prod Relationship. With the expansion of ecosystem boundaries, complementors increasingly interact with components on the dynamic boundary, allowing issues to be uncovered and resolved. A greater diversity of knowledge and goals of developers is brought to the platform by engaging with an ecosystem (Boudreau and Jeppesen 2015). This diversity enables more social interactions between developers on a platform because a wider variety of expectations will be present (Lyytinen et al. 2016), eventually providing room for innovation (Parker 2016). Complementors continuously assess how existing components on the dynamic boundary meet their expectations for functions of similar components in existing categories. Not meeting these expectations leads to irritation and conflicts (Lyytinen et al. 2017) that need to be resolved through collaborative boundary work. New components are proposed if existing conflicts cannot be resolved with components. This might, for instance, lead complementors to propose new components to existing categories, e.g., adding a "database component" that uses a non-relational database like NoSQL instead of a relational database like SQL. While in this case, our knowledge about the relationship between expanding product and ecosystem boundaries is limited, we assume that both are positively self-reinforcing (Henfridsson and Bygstad 2013). When providers highlight what content (Hukal et al. 2017) or what functions they deem desirable (Constantinides et al. 2018, Zhang et al. 2021), or when they promote third-party developers (Ho and Rai 2017), they influence ecosystem expansion. Ghazawneh and Henfridsson (2013), for instance, highlight how Apple's introduction of new SDKs was accommodated by an application review process through which providers influenced what components are added and thereby which conflicts are mainly being attended to by the ecosystem. Similarly, Legenvre et al. (2022) outline how platform providers keep track of complementor's expectations in order to prioritize investments into components on deeper layers of digital infrastructure.

Finally, platforms underly direct network effects (Boudreau and Jeppesen 2015, Eisenmann et al. 2011). We can assume that all three concepts are self-referential: new categories extend old categories, new expectations arise as old conflicts are solved, and more users are attracted to a larger user base. Considering such complex feedback loops requires an endogenous modeling approach, as explained next.

3. Research Methodology

3.1 Data and Context

Our paper studies the relationship between generativity and user base growth on digital platforms. We select *six* large transaction platforms in e-commerce with a well-established focus on achieving user base growth (e.g., Cennamo and Santaló 2013, 2019, Taeuscher and Rothe 2021): eBay, Groupon, Zalando, Otto, Flipkart, and Rakuten. We select the cases as typical examples of transaction platforms in e-commerce, for which we explain the within-case variance of generativity and user base growth (Gerring 2006). While prior studies (e.g., Lyytinen et al. 2016, Karhu et al. 2018, Sandberg et al. 2020) on generativity in platforms have focused on innovation platforms (also product platforms) and hybrids between innovation and transaction platforms, we exclude cases that are primarily innovation platforms, such as WeChat, and hybrids, such as Amazon or Alibaba (Gawer 2021). Innovation platforms and hybrids change strategies for achieving user growth over time and are less likely to delimit access to resources or engage in securing boundary resources at the beginning (Ghazawneh and Henfridsson 2013, Gawer 2021) while doing so at later stages (Karhu et al. 2018). Within these typical cases, we seek to represent geographical diversity by sampling from the three largest e-commerce markets (Americas, Europe, and Asia-Pacific). In doing so, we selected two exemplar cases per region to avoid leaving individual examples without replication (Yin 2009). The selection of cases within regions was based on platform maturity (as represented by age and firm size) and sufficiently meaningful open source activities over extended periods. We selected cases that had several years of open source activity and operated at least 50 active open source repositories.

eBay is an Americas-based veteran e-commerce marketplace. It has $10.27 billion in revenue (2020), approximately 140,000 employees (December 2018), and $1.9 million spent on IT (2020). *Groupon* is an Americas-based e-commerce platform that offers consumers a marketplace of deals worldwide. It has $1.41 billion in revenue (2020), approximately 4,159 employees (2020), and reports $20.3 million in spending on IT (2020). *Zalando* is a European e-commerce platform provider with €8.2 billion in revenue (2019), approximately 13,763 employees, and 31 million active customers. Its IT unit comprises approximately 2,000 employees. *Otto* belongs to the Otto Group, one of the largest e-commerce firms globally headquartered in Europe. It has an annual revenue of €3.2 billion (2019), employs approximately 4,900 people (2019), and has 7.5 million active customers. *Flipkart* is an Asia Pacific-based e-commerce platform based in Bangalore. It offers over 30 million products, has an annual revenue of $6.1 billion (2020), and 31,334 employees (2020). *Rakuten* is an e-commerce and online marketing firm. It has an annual revenue of 14.1 billion USD (as of Q4 2020) and employs 23,444 people. It is based in Tokyo. Rakuten's customers, as of Q4 2020, are nearly 120 million. It has acquired 22 companies as of Q4 2020, spanning FinTech to telecom, with 153 million in funding raised in Q1 2021.

GitHub repositories for all platforms were created in 2011 or 2012, and no software development kits were provided before. We collected data from January 2013 to December 2020, encompassing most of the period when platform providers have been active on GitHub. For *user base growth (*ln *User)*, we used the number of unique monthly visitors (Taeuscher and Rothe 2021). Data was collected from Semrush, a platform supporting SEO analytics and delivering fine-grained user statistics on traffic and clickstream data. Semrush estimates a website's monthly traffic by acquiring clickstream data from over 200 million users worldwide. To avoid the influence of advertising and excessive search engine optimization, we only considered organic traffic data in any month. We aggregated traffic data for all local domains of any platform in our sample, e.g., ebay.com and ebay.at. To re-scale variation and reduce skew, we construct ln *User* as the natural logarithm of the number of monthly unique visitors. Comparison between our user base measure with usage data from Ahref, another third-party data provider, and with first-party data provided as quarterly or annual figures did not indicate distortion of the estimated values from using Semrush as a data source.

We collected data on generativity that stems from the expansion of product boundaries and ecosystem boundaries by turning to GitHub. GitHub allows developers to collaborate on software projects via track and trace activity, versioning support, social networking, and several other features (Wu et al. 2014). It allows the development of complex artifacts based on a publicly accessible code base (Borges and Valente 2018). GitHub encourages the reuse of software code reused beyond the original creator within and across internal and external projects (Zhang et al. 2014). Developers write code that is integrated into the platform on the level of specific code components (i.e., repositories). We extracted data on the entire public organizational accounts of all cases using the GitHub API and aggregated it to platform-months. We combined multiple accounts by a single organization (e.g., eBay and eBay Classifieds) and merged them into a panel dataset.

Our measures for *expanding product boundaries (*ln *Prod)* lean on the work of Cennamo and Santaló (2019). They considered the monthly status of populated "product" categories for video games that complemented their platforms. We turned to categories of software that complemented e-commerce platforms, where we defined 22 component categories (e.g., database tools, testing frameworks, project management, or continuous integration). A BERT machine learning model supported the definition of these categories (see Appendix 1 for an overview of the detailed procedure and the resulting categories). We unambiguously assigned each repository to one category. The coding was performed manually by two coders familiar with open source software on GitHub (inter-coder reliability K=0.75). The remaining discrepancies were resolved in a personal meeting between the coders and supported by a third person. Unlike in Cennamo and Santaló (2019), where users notice component changes at the content layer (i.e., video games), users are more unaware of component changes at the service layer of a digital platform. This has two important consequences for measuring the expansion of product boundaries in digital platforms. First, complementors who provide digital content, like video games or educational courses, compete against each other in product categories. They seek to replace each other's complements (Cennamo and Santaló 2013, Taeuscher and Rothe 2021). On the service layer, developers seek to complement and not replace each other with components in similar categories. An incremental change to content, like versioning a video game (Cennamo and Santaló 2019) from one year to another, is unlike an increment of a service-layer component. The latter might imply a significantly new software with a potentially different purpose and functionality, even if it remains in the same category. Measuring the expansion of product boundaries considers both adding new components to an existing category and introducing components in an entirely new category. To cater to this, we adopted a scale that accounts for the marginal increase within as well as between categories. We define *Prod* as a weighted metric with the current size of a category group as a basis:

$$ln\text{Prod}_{i,t} = ln\sum_{j} \frac{g_{i,t}-g_{i,t-1}}{g_{i,t}} \qquad (1)$$

where j is a category group and $g_{i,t}$ is the number of components (i.e., repositories) on the platform i in period t.

We assessed *expansion of ecosystem boundaries (*ln *Ecosys)* by measuring the extent to which developers resolved existing tensions with changes to components on the dynamic boundary. While in an online community setting (Faraj et al. 2011), conversations around issues of a certain topic materialize in interactions on discussion threads, we measured the intensity in which external developers engage with components on the dynamic boundary by turning to the *number of actively maintained forks* on GitHub. GitHub allows two types of threaded interaction with software code for platforms. Branches allow developers from platform providers to interact openly with code. Forks are copies of platform code that third-party developers interact with (Andersen and Bogusz 2019, Karhu et al. 2018, Zhang et al. 2014). We considered actively maintained forks for our analysis in that we accounted for only those forks where originators made changes after fork creation. We summed them up monthly by organization. As outlined before, platform providers can also monitor forks and adapt their expectations or even pull forks back into the platform core. We tested alternative specifications of *Ecosys,* which gave no indication of an errors-in-variable bias (see Appendix 2).

3.2 Model Specification

Estimating the relationship between the expansion of product boundaries, ecosystem boundaries, and user base growth over time is difficult because of the endogenous feedback effects between constructs at the level of the platform organization. Extant platform research (e.g., Zittrain 2008, Yoo et al. 2010, Cennamo and Santaló 2019, Faraj et al. 2011, Shaikh and Vaast 2016, Jarvenpaa and Standart 2018) suggests the interplay of three dimensions as a dynamic co-evolving system of interdependent variables. This is best described using vector autoregressive (VAR) models. The GMM panel VAR framework sets up a co-evolving system of equations that allows for lagged interdependences, fixed effects, and considers the variables to be endogenous. Specifically, the investigation of the relationship between the variables across multiple platform organizations requested us to turn to panel VAR as it allowed for considering the cases in a combined fashion while accounting for their substantial potential heterogeneity. By holding other variables immune to external shocks, the model allows for identifying the effect of one exogenous shock by the orthogonalized response.

As outlined by Adomavicius et al. (2012), the selection of a (panel) VAR model involves three basic decisions: (1) variable selection, (2) lag length selection, and (3) model form selection. Because we are specifically interested in the interrelationships among product generativity, social interaction, and user base growth, we naturally chose these three variables (i.e., the corresponding time series) to make up the PVAR system.

A three-variable panel VAR (PVAR) model is specified as follows:

$$Y_{i,t} = A_0 + \sum_{j=1}^{p} A_j Y_{i,t\text{-}j} + m_i + e_{i,t} \tag{2}$$

Where $Y_{i,t}$ is the three-variable vector (ln *Prod*, ln *Ecosys*, ln *User*) and A_j represents the corresponding estimated coefficients. The nonzero off-diagonal coefficients of the A_1 matrix represent the feedback interdependency of the variables. The number of lags can be determined using the Modified Akaike information criterion (MAIC). Based on the results of Stata's pvarsoc, we choose to report a PVAR model with lag length 5 as it minimizes the MAIC.

In applying the VAR procedure to panel data, we allow for "individual heterogeneity" in the levels of variables by introducing fixed effects of the platform organization, denoted by m_i in the model, to overcome the restriction that the underlying structure is the same for each cross-sectional unit (platform organization). We use forward orthogonal transformation (FOD), also referred to as Helmert transformation, to preserve the orthogonality condition between lagged regressors and transformed variables, hence allowing us to use lagged regressors as instruments and estimate the coefficients by system generalized method of moments (GMM, Love and Zicchino 2006).

The stationarity of the respective time series is an important consideration that can restrict the application of a panel VAR model. We test for stationarity of the original variables using a Levin–Lin–Chu unit-root test (Levin et al. 2002) demeaned without trend. Based thereupon, we transform the variables using first differencing and reject the null hypothesis that the time series is non-stationary. Transformed variable time-series graphs are reported in Appendix 3.

In addition, to control for any seasonality effects in the time series, we include 11 monthly dummies. This was done in alignment with previous authors that have used this method in management and IS research (e.g., Hu and Bettis 2018). To account for the potential effect that growth strategies might change when digital platforms enter new stages (Gawer 2021; Cusumano et al. 2019), we account for the age of the platforms.

We assess multicollinearity to avoid erroneous conclusions by calculating variance inflation factors (VIF) on an ordinary least-squares regression replicating our GMM model. We do not find any VIF scores above the critical threshold of 5. Co-integration is another serious problem in Panel VAR models that can lead to spurious relationships. The Kao test for co-integration was used (Kao 1999). The test statistics for the Modified Dickey-Fuller t-test, Dickey-Fuller t-test, Augmented Dickey-Fuller t-test, Unadjusted Modified Dickey-Fuller t-test, and Unadjusted Dickey-Fuller t-test are assessed and indicate no co-integration problems. We assess the stability condition of the final PVAR estimates. We use Stata's *pvarstable* command (Abrigo and Love 2016). Specifically, *pvarstable* checks the eigenvalue condition after estimating the parameters of a panel VAR. We find that all the eigenvalues lay inside the unit circle; thus, the panel VAR satisfies the stability condition.

However, it can be difficult to understand the dynamic evolution of a vector across time through coefficients alone (Hu and Bettis 2018). This is because estimated coefficients only show the total reduced-form effects of a past increase in one variable of our model while implying shared feedback on other variables in a recursive form (ibid.). These coefficients demonstrate how a past increase in one variable affects the value of other variables over time. The dynamics between variables over time can be assessed via impulse response (IRF) functions, which allow for determining the effect of one unit increase in one variable on the future values of all variables in the system. Thus, impulse response function simulations are reported as a standard practice in the panel VAR analysis (ibid.). IRF simulations allow us to examine the temporal response of one variable (e.g., product boundary expansion) to one standard deviation, onetime shock (referred to simply as a "shock") in another variable (e.g., user base growth) over time while holding the remaining variable(s) constant. IRF simulations present the estimated distorting feedback on a generativity/growth dimension caused by a shock to another dimension over sequential lags, using the coefficient estimates from the reduced form VAR analysis of the sampled data. Thus, IRFs are more informative than coefficients when revealing interdependencies between variables over time (ibid., Enders 2008, Stock and Watson 2001).

4. Results

4.1 Empirical Analysis with the PVAR Model

Descriptive Statistics. Table 2 displays the descriptive statistics and Appendix 4 correlations among variables and their five lagged values. The number of observations for these variables is 576, resulting in a balanced panel data set that comprises 6 companies and 96 platform-months. The average monthly increase in ln *User* is 0.1. This corresponds to an increase of 1.3M users per month with a similar growth rate among all 6 platforms. The average number of active forks each month that accounts for expansion of ecosystem boundaries (ln *Ecosys*) is 1.88 (with mean ln *Ecosys* of 0.63), ranging between 5.03 forks per month for Zalando and 0.35 forks per month for Otto.de (i.e., in the extreme case, Zalando's repository is forked 25 times in a month). The logged average number of new components each month accounting for an expansion of product boundaries (ln *Prod*) is 3.05. This corresponds to a marginal increase of 0.35 per month. In the following, we used the PVAR package in Stata, developed by Love and Zicchino (2006), for the GMM estimation.

Table 2. Descriptive Statistics of Key Variables

	Obs	Mean	SD	Median	Min	Max
1. ln *Prod*	576	3.05	0.74	3.28	0.69	3.90
2. ln *Ecosys*	576	0.63	0.76	0	0	3.26
3. ln *User*	576	17.10	1.97	17.51	10.81	19.95

PVAR Estimates Through GMM Method. We aim to examine whether generativity drives user base growth and vice versa after controlling for other factors such as individual effects, time effects, and platform age. We estimate a panel VAR model that examines the dynamic interactions among user base growth and two measures of generativity: expansion of ecosystem and product boundaries. Table 3 presents the system GMM estimates from the PVAR model. Overall, the PVAR model estimates 3 x 15 coefficients. The effect size of GMM estimates in a PVAR model with multiple lags, however, cannot be interpreted straightforwardly (Chen et al. 2015). We, therefore, report on the main observations of the GMM estimates but rely on IRF graphs in the next subsection for a more detailed interpretation.

Table 3. System GMM Results of PVAR Model

Dep. Var.	ln *User*		ln *Prod*		ln *Ecosys*	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ln *User t-1*	0.068†	0.037	0.003	0.004	-0.025	0.139
ln *Prod t-1*	0.234	0.296	0.141	0.115	-0.140	0.647
ln *Ecosys t-1*	-0.017	0.016	**0.007***	0.004	-0.836***	0.056
ln *User t-2*	-0.040	0.038	**0.011****	0.004	0.017	0.072
ln *Prod t-2*	0.064	0.153	0.058	0.085	-0.525	0.641
ln *Ecosys t-2*	-0.022	0.028	**0.012****	0.004	-0.558***	0.079
ln *User t-3*	0.046	0.099	**0.020*****	0.005	**-0.138****	0.044
ln *Prod t-3*	-0.072	0.227	0.168**	0.063	-0.601	0.595
ln *Ecosys t-3*	-0.039	0.030	**0.009***	0.004	-0.402***	0.078
ln *User t-4*	-0.034	0.028	**-0.017*****	0.004	-0.072	0.046
ln *Prod t-4*	**0.521***	0.214	0.174**	0.059	**-0.928***	0.463
ln *Ecosys t-4*	**0.044†**	0.026	**0.008***	0.004	-0.260***	0.068
ln *User t-5*	0.006	0.025	-0.003	0.004	-0.036	0.046
ln *Prod t-5*	0.104	0.190	0.091	0.061	0.141	0.564
ln *Ecosys t-5*	0.022	0.017	0.004	0.003	-0.139**	0.049

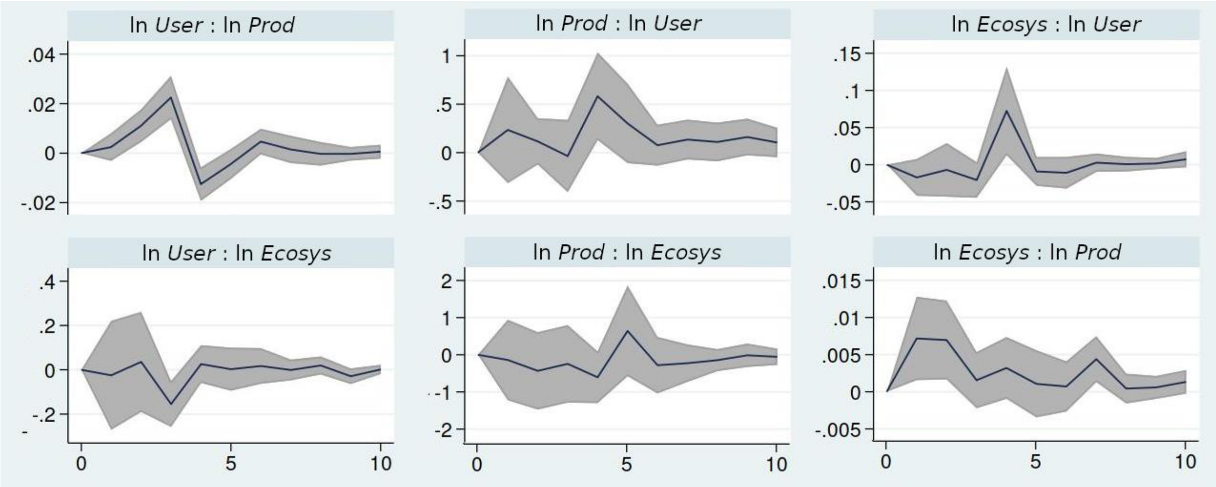
Notes. The model coefficients are estimated using the GMM method in the *PVAR* model, as described by Holtz-Eakin et al. (1988). The panel-specific fixed effects are removed using forward orthogonal deviation or Helmert transformation. First-order differencing is used to achieve stationarity of the variables. The model includes 11 additional monthly dummy variables and age. The model included six panels. † Indicates p<0.10, * p<0.05, ** p<0.01, *** p<0.001; grey indicates diagonals; bold indicates non-diagonal, significant effects.

The first observation in Table 3 is that the time series for each variable exhibit different self-referential patterns. As seen from the diagonals, the effects are complex and show a mixed feedback structure. Turning to the core of our interest, the results show interesting interdependencies among generativity and growth variables, as indicated by the non-zero off-diagonal effects. The most notable of these effects are significant relations between ln *Prod* and ln *User*, ln *Prod* and ln *Ecosys*, ln *Ecosys* and ln *User*, ln *Ecosys* and ln *Prod*, ln *User* and ln *Prod*, and ln *User* and ln *Ecosys*. These effects exhibit a complex and mixed feedback structure, and impulse-response simulations will help to entangle these effects.

4.2 Impulse-Response Functions

Figure 3 provides six impulse response functions for the estimated PVAR model with 90% confidence intervals generated from Monte Carlo simulations. Each plot in Figure 3 shows the corresponding response of a variable over time given a one-unit increase of a "shocked" variable at time *t*.

Figure 3. Impulse-Response Simulation Results of the PVAR Analysis



Notes. We show impulse-response simulations (command *pvarirf*) with 10 steps and 500 draws Monte Carlo sampling of confidence intervals (in grey) with 10%. The graphs show responses in one-standard deviation shocks to the first-differenced variables (ln *User*, ln *Prod*, ln *Ecosys*). We used axis rescaling to account for differences in variable scales.

A shock to ln *Ecosys* results in a positive response of ln *Prod*, as can be seen when considering the lower right graph–consistent with GMM estimates. Notably, the response becomes most clearly nonzero after two months and touches the zero band again a few months later. Considering the graph in the lower center, a shock to expansion of product boundaries (ln *Prod*) shows no clear nonzero response of ln *Ecosys*. Although the responses spike several times (most clearly after 5 months), the confidence interval is broad and not significantly different from zero. Therefore, the IRFs also remind us to be cautious when assuming a positive relationship between product boundary and ecosystem boundary expansion. Considering the response from shocks to ecosystem boundary expansion to users (upper right graph) reveals an increase of ln *User* at *t* – 4. There are several spikes within the first months, which we found nonzero upon closer scrutiny. A shock to ln *Prod* is followed by an increase in ln *User (upper center graph)* before the effect on the user base diminishes, suggesting that there is limited evidence in the data for a nonzero positive effect from product boundary to user base growth.

Considering the inverse relationships from ln *User* on ln *Prod* and on ln *Ecosys* reveals interesting patterns. From the impulse-response function at the upper left, we find nonzero positive and negative responses of user base growth on product boundary expansion. From the graph in the lower-left corner, we also find nonzero positive and negative responses of user base growth on ecosystem boundary expansion. Overall, the responses are neither consistently positive nor negative. However, they reveal oscillating patterns, indicating a complex and asymmetric relationship. Given that we operate on panel data from multiple organizations aggregated over several years, it is natural that the effect can vary over time and for different platforms in the panel, as our results corroborate. Taken together, the visualization of the IRFs on how the platforms evolve, including the response results at t=4, is consistent with the PVAR coefficient estimates shown in Table 3.

Analysis of Granger-Causality. We analyzed structures of the causal relationships between variables by following a Granger-causality approach (Adomavicius et al. 2012). This is a statistical hypothesis test to determine whether one time series significantly contributes to the forecast of another (Granger 1969). We applied five lags to test the null hypothesis that user base growth does not involve Granger causality when affecting product boundaries (see Appendix 5). This hypothesis was rejected at the 1% level of significance, suggesting that user base growth Granger-causally affects product boundaries (ln *User* → ln *Prod*). Similarly, we tested user base growth does not involve Granger causality when affecting ecosystem boundary expansion. This null hypothesis can be rejected at the 5% level of significance, suggesting that user base growth causally affects ecosystem boundaries (ln *User* → ln *Ecosys*). Furthermore, we found indication at the 10% level of significance of unidirectional causality from changes in ecosystem boundaries to changes in product boundaries (ln *Ecosys* → ln *Prod*), and from changes in product boundaries to user base growth (ln *Prod* → ln *User*).

To further validate our findings, we conduct multiple robustness checks. An alternative specification of product boundary expansion (ln *Prod*) using absolute growth in the number of components is largely consistent with the reported effect (see Appendix 6). We also introduced alternative specifications for ecosystem boundaries (ln *Ecosys*) to check for robustness. We, first, weighted our measure of active forks by how many commits have been made after the forks have been created. Second, we considered merged “pull requests” from forks and weighted these by their respectively added or deleted lines of codes. Both alternative specifications support our main model (see Appendix 2).

The result of expanding product boundaries leading to user growth was further confirmed by an additional random-effect panel regression, as indicated by the Hausman test (see Appendix 7). Additionally, to further test the impact of product boundary expansion on user growth, an alternative model considers changes to the components in the core. For this purpose, we turned to an alternative source of data for constructing our variable representing product boundaries: Built-With[1], a public repository that tracks the use of frontend and backend technologies for webbased services. Appendix 8 demonstrates the results for the Built-With model with a lag length of 5, ln *User* as the dependent variable, ln *Prod* and ln *Ecosys* as independent variables, and controls using random effects. It indicates significant results for a lag of 4 (b=4.637; SD=1.565; p≤0.01), which aligns with our main finding.

4.3 Summary

In summary, we reveal nonzero off-diagonal coefficients that represent feedback interdependencies among the expansion of product boundaries, expansion of ecosystem boundaries, and user base growth in digital platforms. We find supporting evidence (see Table 3 and Figure 3) that some off-diagonal coefficients are nonzero, and thus there is feedback interdependency between generativity and user base growth with large effect sizes. Specifically, our analysis suggests a positive relationship between the expansion of ecosystem and product boundaries and, therefore, a mutual dependency. However, product boundaries seem to stabilize ecosystem boundaries over time (negative coefficient). Additionally, our results suggest a positive relationship between expansion of product boundaries and user base growth, and a positive relationship between ecosystem boundary expansion and user base growth. The analysis also indicates a complex but overall positive relationship between user base growth and product

[1]Built-With (www.built-with.com) contains data on at least 58,000 web technologies (shopping carts, analytics, hosting etc.) and includes over 673 million websites. The website’s technology lookup groups web technologies into various categories (e.g., analytics and tracking, widgets, payment, content delivery network) that are directly detected from the online service, which we used to construct an alternative measure of product boundary expansion. The website also reports the date at which these technologies were first and last detected and thus allows for dynamic analysis of expanding or compressing product boundaries.

boundaries and a stabilizing inverse relation between user base growth and ecosystem boundaries. Figure 4 presents the reduced form model, as supported by the analysis.

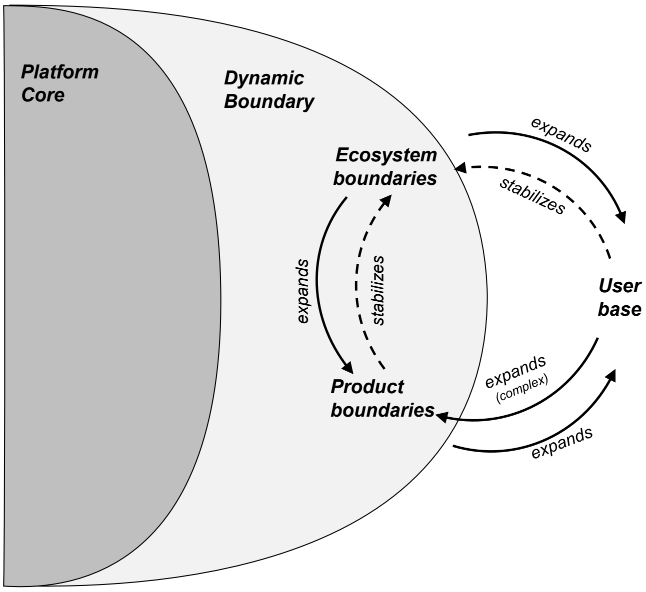


Figure 4. An Integrative View of Generativity and Growth on Digital Platforms as Supported by the PVAR Model

Relationship between Ecosystem and Product Boundary Expansion. We operationalized two concrete expressions of generativity, and our empirical analysis shows that both are interrelated. Specifically, we find that expanding ecosystem boundaries drives expansion of product boundaries. Considering the weighted nature of our measure, this means that product boundaries are also expanded as we find more interactions between complementors and components within the dynamic boundary. New components are added to existing categories, or components are added to entirely new categories. This effect is also confirmed using an alternative measure of product boundaries (see Appendix 6) and is consistent with the Granger-causality analysis.

Vice versa, we find some evidence for a stabilizing relationship between product and ecosystem boundaries. This relationship is less nuanced than the other effects. It is supported by the IRFs and suggests that an expansion of the ecosystem boundaries drives the expansion of product boundaries, but not the other way around.

Relationship Between Product Boundary Expansion and User Base Growth. Our analysis provides evidence that expanding product boundaries lead to user base growth. The GMM estimates and the impulse-response functions indicate a positive and lagged effect that was confirmed by an additional random-effects panel regression (Appendix 7). Both the Granger-causality analysis (Appendix 5) and an alternative operationalization of our product boundary variable (Appendix 6) further substantiate our finding suggesting that product boundary expansion drives user base growth.

Relationship Between Ecosystem Boundaries and User Base Growth. We found evidence that expanding ecosystem boundaries leads to user growth. Beyond the IRFs, the effect was supported by additional robustness checks that include different specifications of ecosystem boundaries (see Appendix 2). Granger-causality analysis supports our findings at a 10% significance level.

Relationship Between User Base Growth and Generativity. Our results provide evidence for an inverse relationship between user base growth and the expansion of product boundaries. The effect is pronounced by IRFs in the second and third months after a shock to the user base and switches from positive to negative in the fourth month. This suggests that the effect of a growing user base on product boundaries is complex. Granger-causality analysis supports our findings that user base growth, overall, drives expansion of product boundaries at a 5% significance level.

Our results also suggest that user base growth and ecosystem boundaries have an inverse relationship. The effect is pronounced in the third month after a shock to the user base. Evidence suggests that the effect was stabilizing, i.e., a negative directionality on a relationship with an ecosystem boundary expansion measure. The Granger-causality analysis supports at the 5% significance level that user base growth temporally precedes changes in ecosystem boundaries.

5. Discussion and Implications

5.1 Towards an Extended Generativity Theory

Based on our findings, we revisit the claim that generativity produces "unbounded growth" and propose an "Extended Generativity Theory" to reorient our thinking about generativity and its interdependent relationship with growth. The proposed theory is laid out in six conjectures and offers a new conceptual apparatus for engaging with established views on generativity in future scholarship—see Figure 5. In that, it does not refute established theorizing on generativity, as our study provides robust support for existing knowledge on the unilateral relationships between generativity and growth. Rather, the Extended Generativity Theory provides a much-needed clarification and recalibration of the nuances and boundary conditions for theorizing on generativity. The theory contributes to the literature on generativity and growth in digital platforms in several ways.

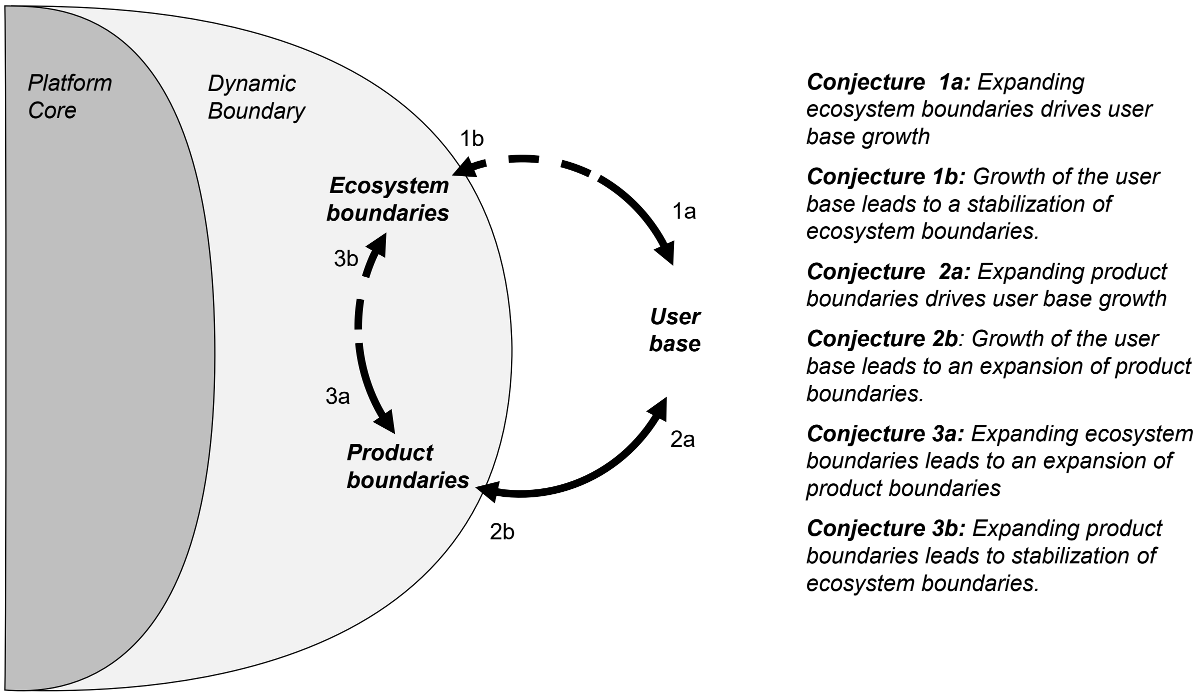


Figure 5. The Extended Generativity Theory: Bounded- and Inverse-Generativity on Digital Platforms

First, our study calls for caution and sensitivity in the dominant assumption of prior literature that generativity engenders "unbounded growth" (e.g., Yoo et al. 2010; Tilson et al. 2010; Zittrain 2009). We capture this observation with the notion of *bounded generativity.* Second, our study potentially reorients traditional thinking about the directionality between generativity and user base growth by indicating the existence of an inverse relationship between these two–what we refer to as *inverse generativity.* Third, in operational terms, the theory recognizes and consolidates prior views of generativity into what we call the *integrative view.* With this view, we bridge siloed discussions where one stream of literature on generativity considers the other as context. Based upon this integrative view, we can capture a platform's *dynamic boundary* in the context of the service layer of transaction platforms. We thereby exemplify the role of technical mediation for user base growth, which complements the much-accentuated network effects between users and suppliers of products and services at the content layer.

In essence, our theory, as captured in Figure 5, provides clarity on the relationships between the two views on generativity via the integrative view that explains user base growth on digital platforms. In what follows, we elaborate on each of these theoretical building blocks and their implications for theory, boundary conditions, and future research.

5.2 Bounded Generativity: When Unbounded Growth Does Not Emerge from Generativity

A key takeaway by a casual reader of the literature on generativity would be that it undoubtedly carries the potential for unbounded growth. This assumption is implicit in the discourse around generativity and in fact, part of many of the definitions of generativity (e.g., Yoo et al. 2010, Zittrain 2009). Our study lends further credence to this. *How then can our result not support this thinking for the social interaction view of generativity, i.e., expansion of ecosystem boundaries?* We elaborate on this surprising finding in what follows.

In overview, our study calls for sensitivity in the claim that unbounded growth emerges from generativity. We align with prior knowledge on the relationship between generativity and growth by first validating that both the expanding product and ecosystem boundaries lead to growth (Cennamo and Santaló 2019, Lyytinen et al. 2017, Faraj et al. 2011, Yoo 2010, Zittrain 2009). Reproducing conceptual remarks found in prior literature on generativity in an empirical setting lends further credence to our findings. For this reason, we conjecture that:

Conjecture 1a: Expanding ecosystem boundaries drive user base growth.

Conjecture 2a: Expanding product boundaries drive user base growth.

Conjecture 3a: Expanding ecosystem boundaries leads to an expansion of product boundaries.

Interestingly, however, our findings also indicate that ecosystem boundaries stabilize as more users enter a platform over time. This stands in contrast to the unbounded growth narrative. Stabilization in these ecosystem boundaries implies that, after a period of seemingly unbounded expansion, fewer conflicting expectations between complementors and providers arise. Considering that the relationship between ecosystem boundaries and user base growth is not mutually reinforcing, the user base growth trajectory begins to coalesce around a point–it is *bounded* (see Figure 5). In essence, our study provides a nuanced empirical validation of the "unbounded growth" claim (Tilson et al. 2010, Yoo et al. 2010), and simultaneously calls to question the universality of this assumption.

We offer two explanations for this unexpected finding. First, there might be a dynamic equilibrium for the expansion of ecosystem boundaries because user base growth leads to the stabilization of ecosystem boundaries. This might be due to the maturing status of the platform. At the onset of a platform, available functions and features that complementors would expect diverge more. Various conflicting expectations between complementors and platform providers need to be addressed, such as perceived bugs, issues mainly known by domain experts (e.g., e-commerce) or technology experts (e.g., machine learning), and upcoming ideas to solve emerging problems. At this early point, a platform benefits from an unbridled expansion of the ecosystem, because with the increasing interest of complementors and a growing user base, new expectations on functions are raised by third-parties. From here, new conflicting expectations arise that can be resolved by complementors. However, over time, key conflicts are resolved for the various component categories, leading to fewer issues around a platform or in its domain. Together, these signal a stabilization of the generative power due to maturing of the platform. This is interesting as one would expect that with a growing user base, the number of new conflicts that need to be resolved increases. Even if users who are early adopters significantly differ from users entering a platform at later stages (Rietveld and Schilling 2021), the change in expected functions does not translate into conflicting expectations that are resolved by complementors. Rather, we suggest that, as the platform matures, an increase in the numbers of users does not necessarily lead to the expansion of ecosystem boundaries, but contributes to its stabilization.

Second, ecosystem boundaries might be influenced by the limited number of complementors a platform can attract. While the growth of the user base attracts more complementors to engage with a platform (Boudreau and Jeppesen 2015, Parker et al. 2017), the pool of developers in the environment who can be attracted to become complementors is finite. It is important to note that the negotiations around such conflicting expectations in themselves have the valence to be both "generative" (i.e., encouraging productive outcomes) and "constraining" (i.e., halting dialog) as noted by (Faraj et al. 2011, 2016). For most platforms in a domain, most of the developers that are interested in what a platform stands for or what technologies it uses (Jarvenpaa and Standaert 2018) would have joined over time through voluntary self-selection (Wareham et al. 2014). Except if a provider fundamentally changes platform positioning or the underlying technology, it can further expand boundaries of its ecosystem. This could be a worrying realization for managers, as this "stabilizing" finding may explain why lively ecosystems might gradually fade into oblivion after periods of high-intensity engagement. In this sense, the expansion of an ecosystem boundary is not ever-expanding. On the contrary, ecosystem expansion is still bounded even if the entire environment, i.e., the whole developer population, puts all its attention on interacting with components of a particular platform.

Conjecture 1b: Growth of the user base leads to a stabilization of ecosystem boundaries.

Conjecture 3b: Expanding product boundaries leads to stabilization of ecosystem boundaries.

It is striking to note that while the expansion of ecosystem boundaries contributes to an expansion of product boundaries, the inverse does not hold. On the contrary, the expansion of product boundaries only stabilizes ecosystem boundaries. The former relationship suggests that third-party developers who engage in solving issues on a platform also produce new components, which leads to an expansion of product boundaries (Boudreau and Jeppesen 2015, Lyytinen et al. 2016; Hukal et al. 2020). A plausible explanation for the latter lies in the configurational boundary work in which providers take the upper hand and weigh their own expectations for the platform against those of their complementors and users. When adding new components to existing categories, developers from the platform provider prioritize monitoring and integrating those components that reduce conflicting expectations. Over time, and as complementors introduce new components, platforms attract multiple components for each category so that every expansion of product boundaries leads to a convergence of expectations between platform developers and complementors. Adding components in new categories will add new conflicting expectations to the platform initially. However, the more important conflicts within each new category will be resolved more quickly so that the interest of complementors to engage in further interactions diminishes, leading to reduced social interactions. Thus, social interaction is not only limited by the diversity of expectations of third-party developers who join the dynamic boundary (Lyytinen et al. 2016, 2017), but also by the components that are already established in a particular component category. Hence, even if there may be few physical constraints for more interactions on digital platforms (Jarvenpaa and Standaert 2018), ecosystem boundaries are affected by product boundaries.

Our claim here is not to say that prior research is wrong in claiming that generativity leads to unbounded growth. The study suggests a need for clarity and precision in describing what growth we are referring to and which view of generativity we subscribe to. We thus call for sensitivity in referring to the relationship between specific strands of generativity and specific forms of growth rather than unchecked statements of "generativity leads to unbounded growth" of actors, services, or components–that is liable to fall flat under empirical scrutiny. Our study can be seen as an empirically grounded foundation and a call for further validation and exploration of the relationships between generativity and growth of the user base on digital platforms.

5.3 Inverse Generativity: When Growth leads to Generativity rather than vice versa

Reversing the saying "honey attracts bees" to "bees attract honey" would be an apt analogy to our counterintuitive observation that user base growth can also lead to an increase in product boundaries. By extension, the more users a platform attracts, the more novel component categories will be added to the service layer of a digital platform. This contrasts with the mantra that generativity leads to growth, as in this case, growth can also lead to generativity.

Conjecture 2b: Growth of the user base leads to an expansion of product boundaries.

Although this inverse directionality is not intuitive, it suggests complex inner workings between generativity and user base growth on the dynamic boundary, as our findings suggest. Even more so, our results show that inverse generativity precedes the positive impact of generativity on user base growth. At the onset, ecosystem boundaries typically contribute to expanding product boundaries. Platform developers become increasingly aware of issues being raised and solved by third-parties. Eventually, this leads to expanding product boundaries as new components within and across product categories are added. Interestingly, user base growth affects further expansion of product categories because platform developers might learn from emerging usage data what component categories need further expansion. This exemplifies how developers of platform providers continuously notice new issues while using that information to expand their product boundaries. This inverse generativity finding suggests the potential of the dynamic boundary as a strategic tool that an organization can wield for innovation on its platform.

Taken together, inverse and bounded generativity indicate generativity is not ever-growing but presents a dynamic equilibrium. Ecosystem boundaries stabilize and expansion of product boundaries becomes mainly affected by user base growth. The six conjectures of our "Extended Generativity Theory" (see Figure 5) posit that generativity and growth do not interact in unanimously positive and self-reinforcing cycles. Instead, the contribution from expanding ecosystem boundaries to user base growth seems to be complemented by an expansion of product boundaries. The contribution of ecosystem expansion to user base is a frequently ignored pathway for attracting users to a platform, but one that exemplifies the importance of considering both views of generativity. Our results emphasize the importance of community building and generative discussions as a prerequisite for the "unfolding" of successful growth (Faraj et al. 2011, 2016, Shaikh and Vaast 2016). Like Cennamo and Santaló (2019), who argue that there is an optimal point for generativity affecting user satisfaction, we conjecture that more user base growth is not necessarily an indication of ecosystem expansion on a digital platform. Our study shows that, while the expansion narrative is supported for product boundaries at the service layer of a digital platform, it is bounded for the expansion of ecosystem boundaries. This finding calls for caution on claims in how interactions between developers unilaterally expand product boundaries in platforms to increase the user base (Grover and Lyytinen 2022, Lyytinen et al. 2017) or where the relationship between complementors and the range of services on a platform is considered unanimously self-reinforcing (Henfridsson and Bygstad 2013, Koutsikouri et al. 2018). Instead, expansion of product boundaries might be impacted more by user base growth than by expansion of ecosystem boundaries.

Here, we see a resurfacing of the chicken and egg dilemma that new platform businesses often face (e.g., Parker et al. 2016)–i.e., whom do platforms dedicate most effort to attracting first–users or complementors? Our findings suggest that attending to user base growth could lead to innovation on the platform via stimulating expansion of product and ecosystem boundaries generativities through inverse relations (see Figure 5), but more research would be needed to fully unravel this. This is important because prior research has already highlighted that the challenge for organizations opening up their core is a two-sided challenge of how to attract users and complementors to the platform (Constantinides et al. 2018, de Reuver et al. 2018, Parker et al. 2016). While learning from users has been highlighted as an important determinant of improving digital infrastructures (e.g., Huang et al. 2017; Henfridsson and Bygstad 2013), it is a continuous task that shapes product boundaries.

5.4 An Integrative View of Generativity

Much of the literature on generativity has adopted singular views in which generativity is seen either from a social interaction view or from a product view. While this is not necessarily a problem and there remain valid reasons to adopt such undiluted views, we acknowledge that the uniqueness of our findings stems from the vantage position offered by adopting the integrative view. The integrative view offers a conceptual bridge that facilitates an engagement with different streams of literature on generativity and allows for insights into the dynamic and complex relationships between generativity and user base growth. We exemplify this by turning to our notion of a dynamic boundary, where generativity plays out on the service layer of a digital platform.

By pointing out how generativity at the service layer engenders growth, we present a complementary perspective to other studies that have focused on producing generativity from complements on the content layer (e.g., Hukal et al. 2020, Cennamo and Santaló 2019) or at deeper layers of the digital infrastructure (Legenvre et al. 2022). Organizations that open core functions (Tiwana et al. 2010) via platformization (Boudreau 2006, Bygstad and Hanseth 2018) produce a dynamic boundary. Here, user base growth is attained through boundary work (Langley et al. 2019) between complementors and platform providers as the latter decides to produce new components in a platform ecosystem. Complementors and platform providers reveal their expectations for functions of a platform and negotiate how to address conflicting expectations. These negotiations are knowledge flows (Faraj et al. 2011) that materialize in lines of code for new or for changed components. Thereby both parties jointly engage in collaborative boundary work (Comeau-Vallée and Langley 2020) that stabilizes or expands of ecosystem boundaries. This speaks to the role of social and cognitive translations between platform providers and complementors (e.g., Lyytinen et al. 2016). Together, both parties seek to reduce emerging conflicts over time (Jarvenpaa and Standaert 2018). We lay out how platform providers and complementors simultaneously engage in different forms of boundary work (Langley et al. 2019) as they change or add component categories on a platform and set rules (e.g., Eaton et al. 2015) for whether and how categories can be amended. Changes to component categories not only shape the platform as a product (Yoo et al. 2010; Tilson et al. 2010), it also impacts what functions users and complementors might expect from a platform. Together, both types of boundary work change what component categories are offered on the dynamic boundary of a platform and how these emerge from negotiation of conflicting expectations.

By considering both views on generativity–product and ecosystem view–as boundary work, the integrative view provides a conceptual bridge. It highlights how the dynamic boundary of a platform becomes a 'trading zone' for functions that providers and complementors expect from a platform. This is important, because the individual expectations might depend on platform types or even domains. We lay out that transaction platforms are considered cleverly tuned (Eaton et al. 2015) if internal and external contributions afford user base growth–see Figure 5. We stress the point that on the service layer of a transaction platform, complementors do not directly compete (cf. Cennamo and Santaló 2019). Other than on hybrid or innovation platforms, the ecosystem might also be less affected by negative effects of multihoming (e.g., Karhu et al. 2018). In comparison to such platforms like iOS, users, complementors and platform providers are also more likely to differ in their expectations for functions of that platform. It would be up to future research to investigate whether these distinct expectations help platform providers leverage generativity from different stakeholders by other means than user base growth, such as through capturing value from divergent monetization strategies (Parker et al. 2016), through securing the platform (Ghazawneh and Henfridsson 2013) or by opening deeper layers of the architecture while producing proprietary services on top (Sandberg et al. 2020).

5.5 Boundary Conditions and Limitations

Multiple boundary conditions are worth noting. We study digital transaction platforms where providers invite third-parties to contribute components to the service layer of their platform and where they allow them to use components outside of the platform and for their goals. These complementors engage with the platform and resolve issues by changing the software code of components on the dynamic boundary. Changed components can be integrated into the platform core or used outside the platform context.

Our theorizing does not concern how generativity and growth relate on the content layer. Here, changes can be easily perceived by users and complementors compete against each other within categories (Cennamo and Santaló 2019). Complement exclusivity, complementor multihoming (Cennamo and Santaló 2013), or complementor attributes like status (Taeuscher and Rothe 2021), play important roles in explaining user base growth. In our setting, platform providers learn from expanding ecosystem boundaries about issues and how they can be solved. These learnings can be translated into new functions for components provided on the dynamic boundary of a platform. In addition, we assumed that interactions between complementors and providers in the ecosystem and interactions with users are distinct. This assumption might not apply to content, where users can more easily become complementors themselves. These assumptions, however, provide rich opportunities for future research seeking to explain prerequisites for platform governance and whether strategies such as envelopment are determined by the nature of a component. Expanding product boundaries assumes that components on the dynamic boundary entail categories beyond the initial conception of the platform provider. Thus, providers may not be aware of changes to components when these changes are being made (Zittrain 2008; Cennamo and Santaló 2019). Faraj et al. (2011) speak to an expansion of ecosystems where actors "may not be aware of the others' ideas" (p. 1235). In our context, interactions on the dynamic boundary materialize in software code, where changes and their originators are transparent to the public. We assume that developers from platform providers engage in boundary work in that they notice changes to components on the dynamic boundary and compare these to their own expectations of what functions their platform is supposed to provide and how. In other contexts, platforms continuously track and assess changes to components on the dynamic boundary, for instance, by introducing a review system for components (e.g., Ghazawneh and Henfridsson 2013) or a reputation system for new content (e.g., Hukal et al. 2020).

In addition, an important boundary condition is that developers engaging in ecosystem expansion are substantially distinct from platform users. In our empirical context, developers raise and resolve conflicting expectations regarding components on the dynamic boundary. Users are suppliers or buyers of products on a transaction platform. These actors have distinct intentions to engage with the platform and potentially diverging expectations on what components are necessary and how they should operate.

Engaging with an expanding ecosystem and observing user base growth gives providers opportunities to incorporate potentially different learnings for further development of their platform.

It is important to note that because PVAR analysis controls the individual platform organization and monthly fixed effects, our results represent interdependency between three constructs representing generativity and user base growth at the average level of all platforms across time rather than at the individual platform or month level. The interdependency structure will probably vary across and/or within individual platforms across time. One would expect that, sometimes, platform- and/or month-level analyzes would find some other types of feedback interdependency, contemporaneous, and/or lagged. Even for the same type of feedback interdependency, interdependency may vary across platforms or across time. For example, user base values for two platforms were lower for several months at the beginning of the observation period. We learned Semrush changed a data collection technique for Eastern Asian domains during that time, which is why some user data was unobserved. While this data can be considered completely random, we performed a complementary robustness test by imputing values using linear transformation and an added stochastic component. After comparing our final measure for user base growth with user data from another third-party data provider and with first-party data, we consider this measure reliable.

While we selected a sample that spans major regions and represents platforms at different stages, limitations might arise from sampling. We did not include innovation platforms and hybrids, which include leading platforms like Amazon or Alibaba. Because of their extensive engagement in building innovation platforms like infrastructure-as-a-service platforms (AWS, AlibabaCloud) these providers have access to broad open source initiatives. In addition, we assumed that complementors only create and actively maintain forks when they face considerable issues between platform providers and themselves. However, our data did not allow us to observe problems that arise from mismatches between platform providers and complementors directly, because those would entail cognitive and social dimensions (Lyytinen et al. 2016). Some of the limitations carry important boundary conditions for the Extended Generativity Theory. We invite future work to investigate different platform designs or regional contexts to further carve out these conditions.

5.6 Practical Implications

As managers contend with the realization that the in-house expertise and resources at their disposal are limited, the drive to consider opening their systems to access these external value contributors is likely to rise (Morgan et al. 2021). This study provides such managers with a key insight that informs them about activities around a platform's dynamic boundary that might lead to user growth. Specifically, our study raises awareness that investments into more generativity do not necessarily translate into user growth. This makes management of generativity an inherently economic task where managers who stimulate the expansion of ecosystem boundaries consider further investments in light of potential learnings from the ecosystem. Digital platform providers that intend to achieve user growth and leverage external knowledge resident within the crowds need to focus on how that learning translates into expanding product boundaries, i.e., new components in new categories. This is likely not going to be just a challenge of selecting between expanding product boundaries or expanding ecosystem boundaries, but one that embraces an integrative view and considers the interrelationship between these two views on generativity.

References

Abrigo MRM, Love I (2016) Estimation of panel vector autoregression in stata. *Stata J.* 16(3):778–804.

Adomavicius G, Bockstedt JC, Gupta A (2012) Modeling supply-side dynamics of it components, products, and infrastructure: An empirical analysis using vector autoregression. *Inf. Syst. Res.* 23(2):397–417.

Adomavicius G, Bockstedt JC, Gupta A, Kauffman RJ (2008) Making sense of technology trends in the information technology landscape: A design science approach. *MIS Quart.* 32(4):779–809.

Andersen JV, Bogusz CI (2019) Self-organizing in blockchain infrastructures: Generativity through shifting objectives and forking. *J. Assoc. Inf. Syst.* 20(9):1242–1273.

Autio E, Thomas LDW (2020) Value co-creation in ecosystems: Insights and research promise from three disciplinary perspectives. Nambisan S, Lyytinen K, Yoo Y, eds. *Handbook of Digital Innovation* (Edward Elgar, Cheltenham), 107–132.

Baig R, Roca R, Freitag F, Navarro L (2015) Guifi.net, a crowdsourced network infrastructure held in common. *Comput. Networks* 90:150–165.

Barrett M, Davidson E, Prabhu J, Vargo SL (2015) Service innovation in the digital age: Key contributions and future directions. *MIS Quart.* 39(1):135–154.

Boland RJ Jr, Lyytinen K, Yoo Y (2007) Wakes of innovation in project networks: The case of digital 3-d representations in architecture, engineering, and construction. *Organ. Sci.* 18(4):631–647.

Borges H, Tulio Valente M (2018) What's in a github star? Understanding repository starring practices in a social coding platform. *J. Syst. Softw.* 146:112–129.

Boudreau K (2006) Too many complementors? Evidence on software developers. SSRN eLibrary.

Boudreau, K (2012) Let a thousand flowers bloom? An early look at large numbers of software app developers and patterns of innovation. *Organ. Sci.* 23(5): 1409-1427.

Boudreau K, Jeppesen LB (2015) Unpaid crowd complementors: The platform network effect mirage. *Strateg. Manag. J.* 36(12):1761–1777.

Bygstad B, Hanseth O (2018) Transforming digital infrastructures through platformization. Bednar PM, Frank U, Kautz K, eds. *Proc. 26th Eur. Conf. Inf. Syst.* (Association for Information Systems, Atlanta), 1-13.

Cennamo C, Santaló J (2013) Platform competition: Strategic trade-offs in platform markets. *Strateg. Manage. J.* 34(11):1331–1350.

Cennamo C, Santaló J (2019) Generativity tension and value creation in platform ecosystems. *Organ. Sci.* 30(3):617–641.

Chen CM, Delmas MA, Lieberman MB (2015) Production frontier methodologies and efficiency as a performance measure in strategic management research. *Strateg. Manage. J.* 36(1):19-36.

Comeau-Vallée M, Langley A (2020) The interplay of inter- and intraprofessional boundary work in multidisciplinary teams. *Organ. Stud.* 41(12):1649–1672.

Constantinides P, Henfridsson O, Parker G (2018) Platforms and infrastructures in the digital age. *Inf. Syst. Res.* 29(2):381–400.

Cusumano MA, Gawer A, Yoffie DB (2019) *The Business of Platforms: Strategy in the Age of Digital Competition, Innovation, and Power* (Harper Business, New York).

Dahlander L, Frederiksen L (2012) The core and cosmopolitans: A relational view of innovation in user communities. *Organ. Sci.* 23(4):988–1007.

Eaton B, Elaluf-Calderwood S, Sørensen C, Yoo Y (2015) Distributed tuning of boundary resources: The case of apple's ios service system. *MIS Quart.* 39(1):217–243.

Eisenmann TR, Parker G, Van Alstyne M (2008) Opening platforms: How, when and why? Gawer A, ed. *Platforms, Markets and. Innovation* (Edward Elgar, Cheltenham, UK), 131-162.

Eisenmann T, Parker G, Van Alstyne M (2011) Platform envelopment. *Strateg. Manag. J.* 32(12):1270–1285.

Enders W (2008) *Applied Econometric Time Series* (John Wiley & Sons, New York).

Faraj S, Jarvenpaa SL, Majchrzak A (2011) Knowledge collaboration in online communities. *Organ. Sci.* 22(5):1224–1239.

Faraj S, von Krogh G, Monteiro E, Lakhani KR (2016) Special section introduction - Online community as space for knowledge flows. *Inf. Syst. Res.* 27(4):668–684.

Foerderer J, Kude T, Mithas S, Heinzl A (2018) Does platform owner's entry crowd out innovation? Evidence from google photos. *Inf. Syst. Res.* 29(2):444-460.

Gawer A (2021) Digital platforms' boundaries: The interplay of firm scope, platform sides, and digital interfaces. *Long Range Plann.* 54(5):102045.

Gerring J (2006) *Case Study Research: Principles and Practices* (Cambridge University Press, Cambridge, UK).

Ghazawneh A, Henfridsson O (2013) Balancing platform control and external contribution in third-party development: The boundary resources model. *Inf. Syst. J.* 23(2):173–192.

Granger, CW (1969) Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37(3):424-438.

Grover V, Lyytinen K (2022) Special issue editorial: Platform competition in the digital era - Overview and research directions. *MIS Q. Exec.* 21(1): 3.

Hanseth O, Lyytinen K (2010) Design theory for dynamic complexity in information infrastructures: The case of building internet. *J. Inf. Technol.* 25(1):1–19.

Hein A, Schreieck M, Riasanow T, Setzke DS, Wiesche M, Böhm M, Krcmar H (2020) Digital platform ecosystems. *Electron. Mark.* 30(1):87–98.

Henfridsson O, Bygstad B (2013) The generative mechanisms of digital infrastructure evolution. *MIS Quart.* 37(3): 896-931.

von Hippel EA, von Krogh G (2003) Open source software and the "private-collective" innovation model: Issues for organization science. *Organ. Sci.* 14(2):209–223.

Ho SY, Rai A (2017) Continued voluntary participation intention in firm-participating open source software projects. *Inf. Syst. Res.* 28(3): 603-625.

Hoffmann P, Shmagina V, Halckenhaeusser A, Lueker N (2023) The influence of user feedback on complementary innovation in platform ecosystems: NLP evidence on the value of multihoming. Bui TX, Sprague RH, eds. *Proc. 56th Hawaii Int. Conf. Syst. Sci. 2023* (Shidler College of Business, Honolulu). Forthcoming.

Holtz-Eakin D, Newey W, Rosen HS (1988) Estimating vector autoregressions with panel data. *Econometrica* 56(6):1371–1395.

Hu S, Bettis RA (2018) Multiple organization goals with feedback from shared technological task environments. *Organ. Sci.* 29(5):873–889.
Huang J, Henfridsson O, Liu MJ, Newell S (2017) Growing on steroids: Rapidly scaling the user base of digital ventures through digital innovation. *MIS Quart.* 41(1):301–314.
Hukal P, Henfridsson O, Shaikh M, Parker G (2020) Platform signaling for generating platform content. *MIS Quart.* 44(3):1177–1205.
Jarvenpaa SL, Standaert W (2018) Digital probes as opening possibilities of generativity. *J. Assoc. Inf. Syst.* 19(10):982–1000.
Kalliamvakou E, Gousios G, Blincoe K, Singer L, German DM, Damian D (2016) An in-depth study of the promises and perils of mining GitHub. *Empir. Softw. Eng.* 21(5):2035–2071.
Kane GC, Johnson J, Majchrzak A (2014) Emergent life cycle: The tension between knowledge change and knowledge retention in open online coproduction communities. *Manage. Sci.* 60(12):3026–3048.
Kao C (1999) Spurious regression and residual-based tests for cointegration in panel data. *J. Econom.* 90(1):1–44.
Karhu K, Gustafsson R, Lyytinen K (2018) Exploiting and defending open digital platforms with boundary resources: Android's five platform forks. *Inf. Syst. Res.* 29(2):479–497.
Kellogg KC, Orlikowski WJ, Yates JA (2006) Life in the trading zone: Structuring coordination across boundaries in postbureaucratic organizations. *Organ. Sci.* 17(1):22–44.
Kim Y, Jarvenpaa SL, Gu B (2018) External bridging and internal bonding: Unlocking the generative resources of member time and attention spent in online communities. *MIS Quart.* 42(1):265–283.
Kretschmer T, Leiponen A, Schilling M, Vasudeva G (2022) Platform ecosystems as meta-organizations: Implications for platform strategies. *Strateg. Manage. J.* 43(3):405 -424
Koutsikouri D, Lindgren R, Henfridsson O, Rudmark D (2018) Extending digital infrastructures: A typology of growth tactics. *J. Assoc. Inf. Syst.* 19(10):1001-1019.
Langley A, Lindberg K, Mørk BE, Nicolini D, Raviola E, Walter L (2019) Boundary work among groups, occupations, and organizations: From cartography to process. *Acad. Manag. Ann.* 13(2):704–736.
Legenvre H, Autio E, Hameri AP (2022) How to harness open technologies for digital platform advantage. *MIS Q. Exec.* 21(1):6.
Lehman M, Fernández-Ramil JC (2004) Software evolution. Madhavji NH, Fernández-Ramil JC, Perry DE, eds. *Software Evolution and Feedback: Theory and Practice* (John Wiley & Sons, Chichester, UK), 7–40.
Lehman MM, Fernández-Ramil JC, Wernick PD, Perry DE, Turski WM (1997) Metrics and laws of software evolution - The nineties view. Werner B, ed. *Proc. 4th Int. Softw. Metr. Symp. 1997* (Institute of Electrical and Electronics Engineers, Albuquerque, NM), 20-32.
Lessig L (2002) *The Future of Ideas: The Fate of the Commons in a Connected World* (Vintage, New York).
Levin A, Lin CF, Chu CSJ (2002) Unit root tests in panel data: Asymptotic and finite-sample properties. *J. Econometrics* 108(1):1–24.
Love I, Zicchino L (2006) Financial development and dynamic investment behavior: Evidence from panel var. *Q. Rev. Econ. Financ.* 46(2):190–210.
Lyytinen K, Sørensen C, Tilson D (2017) Generativity in digital infrastructures: A research note. Galliers R, Stein MK, eds. *The Routledge Companion to Management Information Systems* (Routledge, London), 253-275.
Lyytinen K, Yoo Y, Boland RJ Jr (2016) Digital product innovation within four classes of innovation networks. *Inf. Syst. J.* 26(1):47-75.
Morgan, L, Gleasure, R, Baiyere, A, Dang, HP (2021) Share and share alike: How inner source can help create new digital platforms. *Calif. Manage. Rev.* 64(1):90-112.
Niederer S, van Dijck J (2010) Wisdom of the crowd or technicity of content? Wikipedia as a sociotechnical system. *New Media Soc.* 12(8):1368–1387.
Parker G, van Alstyne MW, Choudary SP (2016) *Platform Revolution: How Networked Markets Are Transforming the Economy and How to Make Them Work for You* (Norton & Company, New York).
Parker G, van Alstyne MW, Jiang X (2017) Platform ecosystems: How developers invert the firm. *MIS Quart.* 41(1):255–266.

Pauli T, Lin Y (2020) The generativity of industrial iot platforms: Beyond predictive maintenance? Krcmar H, Fedorowicz J, eds. *Proc. 40th Int. Conf. Inf. Syst. 2019* (Association for Information Systems, Atlanta), 1–6.
Ren H, Tian J, Nakamori Y, Wierzbicki AP (2007) Electronic support for knowledge creation in a research institute. *J. Syst. Sci. Syst. Eng.* 16(2):235–253.
Rietveld J, Schilling MA (2021) Platform competition: A systematic and interdisciplinary review of the literature. *J. Manage. 47*(6):1528-1563.
de Reuver M, Sørensen C, Basole RC (2018) The digital platform: A research agenda. *J. Inf. Technol.* 33(2):124–135.
Sandberg J, Holmström J, Lyytinen K (2020). Digitization and phase transitions in platform organizing logics: Evidence from the process automation industry. *MIS Quart.* 44(1):129-153.
Schreyögg G, Sydow J (2010) Crossroads: Organizing for fluidity? Dilemmas of new organizational forms. *Organ. Sci.* 21(6):1251–1262.
Shaikh M, Vaast E (2016) Folding and unfolding: Balancing openness and transparency in open source communities. *Inf. Syst. Res.* 27(4):813-833.
Stock JH, Watson MW (2001) Vector autoregressions. *J. Econ. Perspect.* 15(4):101–115.
Taeuscher K, Rothe H (2021) Optimal distinctiveness in platform markets: Leveraging complementors as legitimacy buffers. *Strateg. Manag. J.* 42(2):435–461.
Tilson D, Lyytinen K, Sørensen C (2010) Digital infrastructures: The missing is research agenda. *Inf. Syst. Res.* 21(4):748–759.
Thomas LD, Ritala P (2021) Ecosystem legitimacy emergence: A collective action view. *J. Manage.* 48(3):515-541.
Thomas LD, Tee R (2021) Generativity: A systematic review and conceptual framework. *Int. J. Manage. Rev.* 24(2):255-278.
Tiwana A (2018) Platform synergy: Architectural origins and competitive consequences. *Inf. Syst. Res.* 29(4):829–848.
Tiwana A, Konsynski B, Bush AA (2010) Research commentary - platform evolution: Coevolution of platform architecture, governance, and environmental dynamics. *Inf. Syst. Res.* 21(4):675–687.
Wareham JD, Fox PB, Cano Giner JL (2014) Technology ecosystem governance. *Organ. Sci.* 25(4):1195–1215.
West G (2017) *Scale: The Universal Laws of Growth, Innovation, Sustainability, and the Pace of Life in Organisms, Cities, Economies, and Companies* (Penguin Press, London).
Wu Y, Kropczynski J, Shih PC, Carroll JM (2014) Exploring the ecosystem of software developers on github and other platforms. Fussel S, Lutters W, eds. *Proc. 17th Conf. Comput. Support. Coop. Work 2014* (Association for Computing Machinery, Baltimore), 265–268.
Yin RK (2009) *Case Study Research: Design and Methods*, 4th ed. (Sage, Thousand Oaks, CA).
Yoo Y (2013) The tables have turned: How can the information systems field contribute to technology and innovation management research? *J. Assoc. Inf. Syst.* 14(5):227–236.
Yoo Y, Boland RJ Jr, Lyytinen K, Majchrzak A (2012) Organizing for innovation in the digitized world. *Organ. Sci.* 23(5):1398–1408.
Yoo Y, Henfridsson O, Lyytinen K (2010) The new organizing logic of digital innovation: An agenda for information systems research. *Inf. Syst. Res.* 21(4):724–735.
Zhang Y, Li J, Tong TW (2020) Platform governance matters: How platform gatekeeping affects knowledge sharing among complementors. *Strateg. Manag. J.* 43(3):599-626.
Zhang Z, Yoo Y, Zhang B, Wattal S, Kulathinal R (2014) Generative diffusion of innovations and knowledge networks in open source projects. Myers MD, Straub DW, eds. *Proc. 35th Int. Conf. Inf. Syst. 2014* (Association for Information Systems, Atlanta), 1–10.
Zittrain J (2008) *The Future of the Internet - And How to Stop It* (Yale University Press, London).
Zittrain J (2009) Law and technology - The end of the generative internet. *Commun. ACM* 52(1):18–20.

Appendix

Appendix 1: Scheme for Expansion of Product Boundaries

Category
1. Database Tools
2. Monitoring Tools
3. Testing Frameworks
4. Platform-as-a-Service
5. Frameworks (Full Stack)
6. Java Tools
7. Machine Learning Tools
8. User Management and Authentication
9. Code Review
10. JavaScript Utilities and Libraries
11. Logging Tools
12. Microservices Tools
13. Load Balancer / Reverse Proxy
14. Continuous Integration
15. API Tools
16. Project Management
17. Cluster Management
18. Container Tools
19. Search Tools
20. Git Tools
21. Mobile
22. Other

Notes. BERT: Bidirectional encoder representations from transformers (Devlin et al. 2019) was used in the creation of the category scheme. It is a natural language processing model that is pre-trained on Wikipedia. We fine-tuned the model to our domain by feeding it over 5,000 descriptions of technology products (e.g., "MySQL is…", "Java has…", "JavaScript…") from StackShare (2021), a public repository for considering technology products used within companies, and their respective Stackshare categories (e.g. database tools, machine learning tools). We then applied the fine-tuned model to GitHub repository descriptions and titles to assign Stackshare category suggestions to the repositories. Based on these suggestions, two coders manually assigned a category to each repository and merged categories with less than ten occurrences, with more frequent ones by collective agreement. Reference: Devlin J, Chang M-W, Lee K, Toutanova K. (2018) BERT: Pre-training of deep bidirectional transformers for language understanding. arXiv:1810.04805.

Appendix 2: Robustness Checks Ecosystem Boundaries

Alternative GMM Coefficient estimates of PVAR Model using alternative specification of the ecosystem boundaries variable (ln *Ecosys*) through *active forks weighted by number of commits* after diverting from the original component

Dep. Var.	ln *User*		ln *Prod*		ln *Ecosys*	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ln *User t-1*	0.067†	0.036	0.002	0.004	0.001	0.242
ln *Prod t-1*	0.250	0.303	0.142	0.115	0.815	1.744
ln *Ecosys t-1*	-0.002	0.005	**0.002†**	0.001	-0.800***	0.056
ln *User t-2*	-0.040	0.034	**0.010****	0.003	0.180	0.281
ln *Prod t-2*	0.090	0.155	0.053	0.085	0.126	1.678
ln *Ecosys t-2*	-0.009	0.010	**0.003†**	0.001	-0.548***	0.072
ln *User t-3*	0.043	0.098	**0.020****	0.006	**-0.314***	0.139
ln *Prod t-3*	-0.056	0.236	0.159*	0.063	0.686	1.755
ln *Ecosys t-3*	-0.013	0.012	0.002	0.001	-0.410***	0.072
ln *User t-4*	-0.032	0.026	**-0.017*****	0.004	-0.109	0.124
ln *Prod t-4*	**0.552***	0.238	0.167**	0.059	-1.153	1.381
ln *Ecosys t-4*	0.010	0.008	**0.003***	0.001	-0.249***	0.069
ln *User t-5*	0.008	0.023	-0.004	0.004	-0.075	0.122
ln *Prod t-5*	0.118	0.195	0.083	0.061	2.138	1.570
ln *Ecosys t-5*	0.002	0.004	0.001	0.001	-0.142*	0.056

Notes. The model coefficients are estimated using the GMM method in the *PVAR* model as described by Holtz-Eakin et al. (1988). The panel-specific fixed effects are removed using forward orthogonal deviation or Helmert transformation. First-order differencing was used to achieve stationarity of the variables. Model included 11 additional monthly dummy variables and age. The model included six panels. † indicates $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$; grey indicates diagonals; bold indicates non-diagonal significant effects.

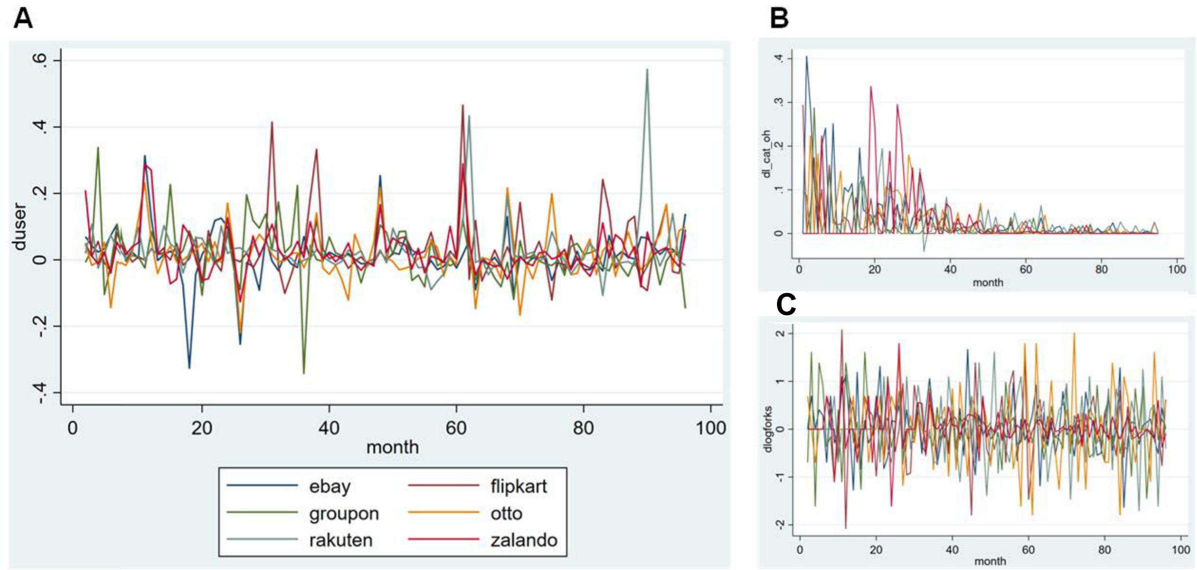
Alternative GMM Coefficient estimates of PVAR Model using alternative specification of the ecosystem boundaries variable (ln *Ecosys*) through *merged pull requests coming from forks*, *weighted by their respective additions and deletions in lines of codes* (logged)

DV:	ln *User*		ln *Prod*		ln *Ecosys*	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ln *User t-1*	0.060†	0.035	0.000	0.003	0.050	0.280
ln *Prod t-1*	0.264	0.330	0.147	0.114	1.319	3.030
ln *Ecosys t-1*	0.010	0.007	**-0.001†**	0.001	-0.566***	0.056
ln *User t-2*	-0.036	0.031	**0.010****	0.003	0.212	0.218
ln *Prod t-2*	0.059	0.156	0.058	0.084	0.997	3.263
ln *Ecosys t-2*	0.010	0.009	0.000	0.001	-0.375***	0.060
ln *User t-3*	0.048	0.099	**0.021*****	0.005	-0.500	0.361
ln *Prod t-3*	-0.008	0.221	0.162**	0.062	2.176	2.888
ln *Ecosys t-3*	0.002	0.004	0.000	0.001	-0.281***	0.056
ln *User t-4*	-0.030	0.028	**-0.019*****	0.004	**-0.724****	0.234
ln *Prod t-4*	**0.486***	0.216	0.167**	0.056	-1.463	2.169
ln *Ecosys t-4*	-0.005	0.005	0.000	0.001	-0.196***	0.055
ln *User t-5*	0.018	0.027	-0.005	0.004	**-0.435†**	0.257
ln *Prod t-5*	0.205	0.232	0.082	0.061	-2.372	2.503
ln *Ecosys t-5*	-0.010	0.009	0.000	0.001	-0.123*	0.050

Notes. The model coefficients are estimated using the GMM method in the *PVAR* model as described by Holtz-Eakin et al. (1988). The panel-specific fixed effects are removed using forward orthogonal deviation or Helmert transformation. First-order differencing was used to achieve stationarity of the variables. Model included 11 additional monthly dummy variables and age. The model included six panels. † indicates $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$; grey indicates diagonals; bold indicates non-diagonal significant effects.

Appendix 3: Time Series Analysis

Time Series Plot of First-Differenced Variables of the Panel VAR System, (A) ln *User*, (B) ln *Prod*, (C) ln *Ecosys*



Appendix 4: Correlation Table

Correlations among key variables and their lagged values

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. ln *Prod*	1																	
2. ln *Ecosys*	0.28	1																
3. ln *User*	0.48	0.40	1															
4. ln *Prod* $_{t-1}$	0.99	0.28	0.47	1														
5. ln *Ecosys* $_{t-1}$	0.30	0.71	0.40	0.30	1													
6. ln *User* $_{t-1}$	0.48	0.40	0.99	0.47	0.41	1												
7. ln *Prod* $_{t-2}$	0.99	0.28	0.47	0.99	0.30	0.47	1											
8. ln *Ecosys* $_{t-2}$	0.31	0.75	0.41	0.31	0.71	0.41	0.31	1										
9. ln *User* $_{t-2}$	0.47	0.40	0.98	0.47	0.41	0.99	0.47	0.41	1									
10. ln *Prod* $_{t-3}$	0.99	0.28	0.47	0.99	0.30	0.47	0.99	0.32	0.46	1								
11. ln *Ecosys* $_{t-3}$	0.32	0.71	0.41	0.33	0.75	0.42	0.33	0.72	0.42	0.33	1							
12. ln *User* $_{t-3}$	0.47	0.40	0.97	0.47	0.41	0.98	0.47	0.42	0.99	0.46	0.42	1						
13. ln *Prod* $_{t-4}$	0.99	0.28	0.46	0.99	0.98	0.46	0.99	0.32	0.46	0.99	0.33	0.46	1					
14. ln *Ecosys* $_{t-4}$	0.33	0.71	0.42	0.36	0.41	0.41	0.34	0.75	0.42	0.34	0.72	0.42	0.34	1				
15. ln *User* $_{t-4}$	0.47	0.41	0.96	0.47	0.97	0.97	0.46	0.42	0.98	0.46	0.43	0.99	0.45	0.42	1			
16. ln *Prod* $_{t-5}$	0.98	0.28	0.46	0.99	0.46	0.46	0.99	0.32	0.45	0.99	0.33	0.45	0.99	0.34	0.45	1		
17. ln *Ecosys* $_{t-5}$	0.34	0.70	0.42	0.34	0.42	0.42	0.35	0.72	0.42	0.35	0.75	0.42	0.35	0.72	0.42	0.35	1	
18. ln *User* $_{t-5}$	0.46	0.41	0.96	0.46	0.97	0.97	0.46	0.42	0.97	0.46	0.43	0.98	0.45	0.43	0.99	0.45	0.43	1

Appendix 5: Granger Causality

Granger Causality Tests with Stata command *pvargranger,* displayed are *p*-values

	ln *User*	ln *Ecosys*	ln *Prod*
ln *User*	-	0.038*	0.000***
ln *Ecosys*	0.514	-	0.061†
ln *Prod*	0.093†	0.336	-

† indicates $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Appendix 6: Robustness Checks Expansion of Product Boundaries

GMM Estimates

Alternative GMM Coefficient estimates of PVAR Model using alternative specification of Expansion of Product Boundaries (ln *Prod*) through number of product categories that have at least one technology

Dep. Var.	ln *User*		ln *Prod*		ln *Ecosys*	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ln *User t-1*	0.060†	0.035	0.008	0.006	-0.037	0.136
ln *Prod t-1*	-0.296	0.184	0.162	0.116	-0.194	0.533
ln *Ecosys t-1*	-0.013	0.015	**0.011***	0.004	-0.839***	0.057
ln *User t-2*	-0.035	0.038	0.006	0.007	0.010	0.074
ln *Prod t-2*	-0.104	0.178	0.077	0.085	-0.167	0.555
ln *Ecosys t-2*	-0.015	0.025	**0.017****	0.005	-0.560***	0.082
ln *User t-3*	0.060	0.106	**0.015*****	0.004	**-0.149****	0.044
ln *Prod t-3*	-0.015	0.190	0.083	0.064	-0.570	0.483
ln *Ecosys t-3*	-0.028	0.025	**0.012****	0.005	-0.409***	0.079
ln *User t-4*	-0.021	0.029	**-0.009***	0.004	-0.066	0.048
ln *Prod t-4*	**0.664***	0.322	0.159*	0.067	**-0.962***	0.384
ln *Ecosys t-4*	**0.054†**	0.030	**0.009***	0.004	-0.269***	0.069
ln *User t-5*	-0.002	0.020	-0.003	0.003	-0.043	0.047
ln *Prod t-5*	0.195	0.242	0.049	0.066	0.349	0.469
ln *Ecosys t-5*	0.029	0.018	0.005	0.003	-0.140**	0.049

Notes. The model coefficients are estimated using the GMM method in the *PVAR* model as described by Holtz-Eakin et al. (1988). The panel-specific fixed effects are removed using forward orthogonal deviation or Helmert transformation. First-order differencing was used to achieve stationarity of the variables. Model included 11 additional monthly dummy variables and age. The model included six panels. † indicates p<0.10, * p<0.05, **p<0.01, *** p<0.001; grey indicates diagonals; bold indicates non-diagonal significant effects.

Alternative GMM Coefficient estimates of PVAR Model using alternative specification of Expansion of Product Boundaries (ln *Prod*) through number of technologies

Dep. Var.	ln *User*		ln *Prod*		ln *Ecosys*	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ln *User t-1*	0.072†	0.039	0.001	0.006	-0.018	0.142
ln *Prod t-1*	0.420	0.362	0.123	0.084	-0.080	0.611
ln *Ecosys t-1*	-0.021	0.017	0.006	0.004	-0.833***	0.055
ln *User t-2*	-0.036	0.036	**0.020****	0.007	0.012	0.072
ln *Prod t-2*	0.332	0.239	0.005	0.064	-0.759	0.594
ln *Ecosys t-2*	-0.025	0.029	**0.008†**	0.005	-0.557***	0.077
ln *User t-3*	0.037	0.097	**0.018*****	0.004	**-0.132****	0.044
ln *Prod t-3*	-0.165	0.204	0.236**	0.077	-0.374	0.607
ln *Ecosys t-3*	-0.041	0.031	0.007	0.004	-0.400***	0.077
ln *User t-4*	-0.046	0.033	-0.005	0.004	-0.063	0.049
ln *Prod t-4*	**0.248†**	0.148	0.177**	0.066	-0.716	0.503
ln *Ecosys t-4*	0.041	0.026	**0.008†**	0.004	-0.257***	0.068
ln *User t-5*	0.001	0.025	-0.004	0.005	-0.036	0.044
ln *Prod t-5*	-0.041	0.209	0.105†	0.061	-0.253	0.577
ln *Ecosys t-5*	0.021	0.017	0.004	0.003	-0.141**	0.049

Notes. The model coefficients are estimated using the GMM method in the *PVAR* model as described by Holtz-Eakin et al. (1988). The panel-specific fixed effects are removed using forward orthogonal deviation or Helmert transformation. First-order differencing was used to achieve stationarity of the variables. Model included 11 additional monthly dummy variables and age. The model included six panels. † indicates p<0.10, * p<0.05, ** p<0.01, *** p<0.001; grey indicates diagonals; bold indicates non-diagonal significant effects.

Appendix 7: Panel Regression with DV ln User

Panel regression (Stata command *xtreg*) results for lag length 5 with ln *User* as dependent variable, ln *Prod* and ln *Ecosys* as independent variables and controls using random effects as indicated by Hausman test

	DV: ln $User_t$	
IV:	*b* (SE)	*p*-value
ln *Prod* t_t	-0.524 (0.282)	**0.063**
ln *Prod* t_{t-1}	0.196 (0.276)	0.478
ln *Prod* t_{t-2}	0.025 (0.259)	0.924
ln *Prod* t_{t-3}	-0.119 (0.248)	0.632
ln *Prod* t_{t-4}	0.547 (0.239)	**0.022**
ln *Prod* t_{t-5}	0.126 (0.231)	0.587
ln *Ecosys* t_t	-0.020 (0.024)	0.416
ln *Ecosys* $_{t-1}$	-0.033 (0.032)	0.291
ln *Ecosys* $_{t-2}$	0.034 (0.034)	0.316
ln *Ecosys* $_{t-3}$	0.051 (0.034)	0.134
ln *Ecosys* $_{t-4}$	0.036 (0.032)	0.264
ln *Ecosys* $_{t-5}$	0.025 (0.025)	0.321
11 monthly dummies and age included		
R^2 within	0.076	
R^2 between	0.000	
R^2 overall	0.074	
Wald $\chi^2(24)$	41.05*	
N	540	

Notes. **Bold** indicates *p*-values < 0.1. We used first-differenced variables. 11 binary monthly variables and age were included in the model as controls.

Appendix 8: Alternative Data Source for Product Generativity

Built-With is a public repository for web technologies used by companies on their respective website. Their database contains at least 58,000 web technologies (shopping carts, analytics, hosting, widgets, frameworks etc.) and lists over 673 million websites. Built-With lists both the first detection and the last detection of a web site's web technologies, hence we could acquire the detailed technology profile for the six companies of our panel in a time series.

GMM Coefficient estimates of PVAR Model using an alternative data source (Built-With) for Product Boundary Expansion (ln *Prod*)

Dep. Var.	ln *User*		ln *Prod*		ln *Ecosys*	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ln *User t-1*	0.065†	0.038	**-0.016****	0.005	-0.027	0.139
ln *Prod t-1*	-0.011	0.025	0.317***	0.043	**-0.411†**	0.212
ln *Ecosys t-1*	-0.016	0.016	0.001	0.003	-0.835***	0.058
ln *User t-2*	-0.042	0.039	-0.002	0.004	0.007	0.074
ln *Prod t-2*	-0.009	0.031	-0.077**	0.028	**0.304***	0.134
ln *Ecosys t-2*	-0.017	0.027	0.000	0.004	-0.571***	0.087
ln *User t-3*	0.049	0.104	-0.016	0.011	-0.139	0.042
ln *Prod t-3*	0.006	0.056	0.094**	0.033	**-0.501***	0.216
ln *Ecosys t-3*	-0.033	0.028	-0.003	0.004	-0.414***	0.084
ln *User t-4*	-0.035	0.028	-0.006	0.004	-0.082	0.052
ln *Prod t-4*	-0.048	0.045	-0.058*	0.025	-0.005	0.106
ln *Ecosys t-4*	**0.047†**	0.028	-0.001	0.005	-0.272***	0.073
ln *User t-5*	0.002	0.023	-0.004	0.005	-0.061	0.049
ln *Prod t-5*	**0.065†**	0.037	0.038*	0.019	-0.240	0.156
ln *Ecosys t-5*	0.024	0.018	0.003	0.003	-0.148**	0.050

Notes. The model coefficients are estimated using the GMM method in the *PVAR* model as described by Holtz-Eakin et al. (1988). The panel-specific fixed effects are removed using forward orthogonal deviation or Helmert transformation. First-order differencing was used to achieve stationarity of the variables. Model included 11 additional monthly dummy variables and age. The model included six panels.. † indicates p<0.10, * p<0.05, ** p<0.01, *** p<0.001; grey indicates diagonals; bold indicates non-diagonal significant effects.