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TO ROW TOGETHER OR PADDLE ONE'S OWN CANOE? SIMULATING STRATEGIES TO SPUR DIGITAL PLATFORM GROWTH

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Research paper

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Abstract

This study provides a novel perspective on digital platform dynamics by applying a stochastic cellular automaton (CA) as a promising instrument of inquiry to investigate the impact of social and technical openness on platform growth. Owing to the dynamism of digital platforms caused by technological complexity, network effects, and developer-level factors, there is limited understanding of how early-stage platform owners can successfully sustain platform growth. Research suggests two growth strategies: Adjusting the openness of technical platform resources and governing the developers' accessibility of the distribution channel. Based on experiments that leverage a stochastic CA, we show that platform growth can be achieved through three disparate growth strategy configurations. Our paper contributes to research by synthesizing the technology, market, and individual levels of platform growth analyses through a novel methodological account, and by offering theoretical propositions for future research. Our results can guide platform owners to scrutinize their growth strategies.

Keywords: stochastic cellular automaton, platform growth, platform openness, negotiated platform access.

1 Introduction

The past decade has witnessed a multiplicity of digital platform ecosystems, which have emerged as some of the most pervasive business models (Tan et al., 2015). A digital platform is a modular, layered technology provided by a platform owner, on which interconnected actors (e.g. developers and customers) can build, distribute, and consume complementary services and products, such as digital apps, to advance a platform ecosystem in innovative ways (Parker et al., 2017; Tiwana, 2014). Although a digital platform may entail proprietary elements, to be useful, it must often rely on complementary digital assets (e.g. apps) contributed by actors engaging on the platform (Tilson et al., 2013). While the platform owners mainly provide boundary resources (e.g. application programming interfaces / APIs) and anchor points for the coordination between actors to spawn new digital assets, platforms' economic viability and attractiveness primarily results from complementary assets generated by third-party developers creating a self-sustaining ecosystem (Ghazawneh and Henfridsson, 2013; Tilson et al., 2013).

Since less than 10% of startup platforms are expected to sustain and become profitable (Morvan et al., 2016), existing research highlights that digital platforms' failure rate is mainly caused by a lack of favorable network effects (Ondrus et al., 2015; Parker et al., 2017; Ruutu et al., 2017; Staykova and Damsgaard, 2016). Network effects are generated by the number of actors and the relationships among them (i.e. developers and end-users) and the variety of innovative or useful digital assets on the platform (Ondrus et al., 2015). A sufficient number of developers who provide digital assets that attract paying customers are significant for platform growth and success, especially when a platform's standalone value (i.e. the core platform's value before developers add digital assets) is low (Parker et al., 2017; Staykova and Damsgaard, 2016). In this regard, maintaining attractiveness for third-party developers is an important aspect for digital platforms to succeed in today's dynamic environment (Benlian et al., 2015; Tiwana, 2015). Thus, platform owners have to create the right conditions to enable third-party developers to produce digital applications and thus foster network effects (Ondrus et al., 2015). Research points out that platform owners can utilize two primary strategies to influence network effects and attract additional developers: adjusting the platform's degree of openness (Eisenmann et al., 2009) and negotiating the platform access (Cenamor et al., 2013). First, owners face the key question of how much to open their platform core resources to third-party developers who engage in a platform (Ondrus et al., 2015; Parker et al., 2017). For instance, while Apple's proprietary iOS is closed-source and developer must submit to Apple's rigorous quality review, Google Android made Android's core resources set publicly available and has a more lenient approval process (Boudreau, 2010; Parker et al., 2017). Second, early-stage platform owners may choose to establish contractual relationships with developers to spur asset output and growth, for instance, through vertical integration or subcontracting of development firms (Cenamor et al., 2013; Parker et al., 2017). This negotiated platform access (NPA) allows platform owners to reduce the openness level and increase the number of applications. This decision set led to different market outcomes: while Android as the more open platform attracts more third-party developers and grows faster (Parker et al., 2017), Apple is able to charge higher prices for its platform and generates a 8:1 revenue ratio in contrast to Google's Play Store (Travlos, 2012).

Despite the growing importance of digital platforms, the research has not yet provided a comprehensive understanding of how to balance platform openness and NPA to sustain growth (i.e. increasing the number of platform adopters). Recent studies have pointed out the interrelationships between different growth factors, calling for an integrative perspective (Schreieck et al., 2016). To our best knowledge, the research has either exclusively focused on a technology (e.g. platform openness) or a market perspective (e.g. network effects). Additionally, scholars demanded to account for an individual-level perspective of platform adoption, particularly the technical failure risk of individual third-party and NPA developers, to get an even more complete picture of platform growth (Bergvall-Kåreborn and Howcroft, 2014; Parker et al., 2017). Against this backdrop, we address the following research question: *How do platform openness and negotiated platform access influence digital platform growth over time?* To address our question, we synthesize the three aforementioned perspectives to gain insights into growth patterns in digital platform ecosystems over time. We argue that the development of a stochastic cellular automaton (CA) simulation may be a highly suitable approach to integrate all these perspectives, and explore platform rules and outcomes to generate rich insights and inform platform design (Goldenberg et al., 2001; Schreieck et al., 2016). CA, originally developed by Ulam and von Neumann in the 1940s, is a simulation approach that enables researchers to dynamically examine economic and social phenomena by computer-based simulations (Goldenberg et al., 2001). Although simulations generally and CA in particular may provide useful tools to understand complex platform behaviors over time, the use of simulation as a research approach is still under-represented in the IS discipline compared to other fields (Za et al., 2018). We conducted multiple CA experiments to investigate the effects of degrees of openness, NPA, and individual failure risk to simulate digital platform growth patterns.

Our study offers several contributions to the digital platform literature. First, we extend previous research by synthesizing the technology-oriented and market-oriented perspective, and further include an individual level of analysis by simulating platform growth using stochastic CA. Our findings indicate that low platform openness always leads to platform failures over time, while NPA may serve as mechanisms to mitigate negative effects. Second, we derive theoretical propositions from our experiments that reflect our findings in a systemic way, and elaborate ways to achieve platform growth. Third, we point out different digital platform growth strategies based on our results that can be applied in practice.

The remainder of this paper is organized as follows: In Section 2, we provide an overview of digital platforms and derive the hypotheses that underlie our experimental model. We then briefly describe our stochastic CA modeling approach in Section 3 before presenting our results of three computational experiments in Section 4. In Section 5, we suggest theoretical propositions for the roles of platform openness and NPA in achieving digital platform growth, discussing theoretical and practical implications. In Section 6, we summarize the main contributions and limitations of our study and outline future research avenues.

2 Background and Theoretical Framework

2.1 Digital platforms

Digital platforms can be defined as "building blocks (they can be products, technologies or services) that act as a foundation upon which an array of firms (sometimes called a business ecosystem) can develop complementary products, technologies or services" (Gawer, 2009, p. 45). A platform's *innovation capacity* is the sum of the digital products, technologies, and services produced by platform participants (Parker et al., 2017). Taking this definition, we abstract from the incidental occurrence of deceitful or harmful digital resources, since all major platforms have sophisticated mechanisms in place to identify and remove "copycats" and inappropriate or malicious content (Simon, 2018). Based on Eisenmann et al. (2009) and Ondrus et al. (2015), we adapt the layered perspective on digital platforms as depicted in Figure 1, encompassing the levels of owners, individuals, and technology. At the *owner level*, actors exercise the property rights and control the development of the digital platform, including the responsibility to determine who may participate in the platform network (Eisenmann et al., 2009; Ondrus et al., 2015). For instance, Apple owns the iOS platform, while Google, as the parent organization of the Open Handset Alliance, exerts ownership-like power over Android's development (Amadeo, 2013). We focus on multisided platforms that coordinate interactions between multiple heterogeneous groups (Ondrus et al., 2015). Thus, at the *individual level*, demand-side users are considered to be the end-users, while supply-side users are usually developers, who provide complementary digital products and services (Ondrus et al., 2015).

Owners may choose to calibrate the supply side by *negotiating platform access (NPA)* in two ways. First, to control for the quality of platform assets, owners may privilege (e.g. by granting exclusive access to additional resources) professional developers and firms over entrepreneurs and more inexperienced hobby developers (Benlian et al., 2015; David and Shapiro, 2008). Second, owners may follow a subcontracting strategy or vertical integration of external developers. Developers and firms in a contractual relationship with platform owners engineer assets such as basic functions or apps for the exclusive commercial exploitation through the owner (Parker et al., 2016). For instance, Microsoft engages several internal (i.e. Microsoft Studios) and external (e.g. Mighty Studios) developers who develop specific content exclusively for its Xbox platform. In our study, we sought to primarily focus on this type of NPA, since prior research has shown that establishing contractual relationships with developers may serve as an important mechanism to build an ecosystem-wide governance (Huber et al., 2017). Such agreements may further stimulate growth in early stages of platform evolution (Cenamor et al., 2013; Parker et al., 2017) and may also attract additional *extension* (or independent *third-party*) *developers* (Tuunainen et al., 2011).

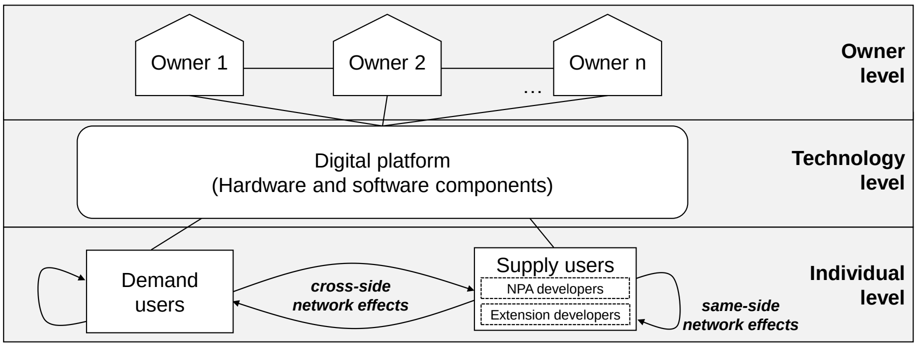

Figure 1. A Layered Perspective on Digital Platforms (adapted from Ondrus et al., 2015).

Extension developers range from individuals to professional firms acting for their own profit (David and Shapiro, 2008) and usually have no contractual relationship with owners; these developers' participation depends on the extent to which a platform owner provides access to its technological infrastructure to generate complementary assets (Parker et al., 2016). Owners have the authority to designate a platform on the *technology level* as open or closed, facing the question how much to open a platform for extension developers, who provide valuable extra services for end-users without incurring extra costs for such development (Parker et al., 2016, 2017). We understand degree of (technical) *openness* as a variable that measures the extent to which a platform owner gives extension developers access to the platform's core resources, for instance by offering APIs and technical documentations (Benlian et al., 2015; Parker et al., 2017). Benlian et al. (2015) operationalizes openness through several indicators, such as the existence of technical documentation, the technical support by provider, learnability of technical standards, the availability of development tools or technical interoperability. Opening the technical core of a platform can have both positive and negative outcomes on innovation capacity and platform profits (Ondrus et al., 2015; Parker et al., 2017). While Android, which is more open, attracts more developers and grows faster than the proprietary iOS (Parker et al., 2017), excessive openness may attract too many opportunistic third-party developers, as the breakdown of Atari's gaming platform impressively demonstrated (Boudreau and Hagiu, 2009). However, if a platform is too closed, owners may deter good extension developers, squandering valuable innovation capacity (Parker et al., 2016). To benefit from extension developers, platform owners must provide access to the technology level that contains the platform ecosystem's fundamental technical architecture. In our context, individual-level actors are subject to so-called *network effects*, which "reinforce in a cumulative manner early gained advantages such as an installed base of users, or the existence of complementary products" (Gawer, 2009, p. 2). In a positive feedback loop, the value of participating in a platform may increase for any given actor, depending on the number of other actors with whom they can interact (Eisenmann et al., 2011; Tan et al., 2015). The minimum number of platform actors required to trigger network effects, is defined as critical mass (Ondrus et al., 2015). Once a given platform has successfully reached critical mass, network effects can protect platform owners' market position against rival platforms (Boudreau, 2011; Ruutu et al., 2017). Network effects can arise on the same-side or on the cross-side between digital platforms' supply and demand user groups. Same-side network effects arise "(…) when adding an additional participant (e.g. end-user) to one side of the platform changes its value to all other participants on the same side" (Tiwana, 2014, p. 35). For instance, adding a further end-user to Skype may increase the software's value to other Skype end-users, because there is now an additional end-user to interact with (Tiwana, 2014). In contrast, cross-side effects are generated when a platform's value for one user group depends on the number of users in a different group (Tiwana, 2014); for instance, an increasing number of merchants who accept credit card payments may increase the number of credit card holders (and vice versa) (Ondrus et al., 2015). We focus on the supply-side, because previous research efforts have underlined developers' strong influence in ensuring platform growth and success (Parker et al., 2017; Qiu et al., 2017).

2.2 Hypothesis development

We sought to answer recent calls for research that integrates the market-oriented (i.e. network effects, NPA) and the technology-oriented perspective (i.e. platform openness) to gain a deeper understanding of platform growth and innovation (Schreieck et al., 2016). We predict that platform openness and NPA trigger network effects on the supply-side of a digital platform, which in turn can lead to increased platform innovation capacity in terms of application output. The way owners design and govern their platform is key to understanding platform growth. Openness is essential to platform growth, since it increases the attractiveness to extension developers, and may thus result in a higher number of platform assets (Benlian et al., 2015; Ondrus et al., 2015; Parker et al., 2017). Same-side network effects may attract further extension developers, for two reasons. First, the number of available assets that can be built on increases opening opportunities for complementary products and hence may attract further extension developers (Gawer, 2014; Tiwana, 2014). Second, from a developer perspective, a large number of developers and therefore a greater number of applications is expected to attract revenue-generating end-users (Tuunainen et al., 2011). We follow the assumption that, as more applications appear on a platform, they attract more extension developers in a positive feedback loop, increasing the value for potential end-users (Cusumano, 2010a). We specifically focus on the same-side network effects between developers. Notably, openness does not affect vertically-integrated NPA developers, who usually have full access to the technology stack owing to their contractual partnership with the owner, and are not attracted by a growing user base (Parker et al., 2016). Thus:

H1: *Platform openness positively influences positive network effects.*

Despite the positive effects on network effects, platform openness also has drawbacks. Designating a platform as open entails a tradeoff between seizing most of the profits and access to extension developers' capabilities (Benlian et al., 2015; Parker et al., 2017). Thus, platform owners face the necessity to carefully balance control and openness (Parker et al., 2017; Tiwana et al., 2010). Adverse degrees of openness can lower owners' profits: possible benefits may be lost to extension developers (Eisenmann et al., 2006; Ondrus et al., 2015), and customers' switching costs may be lowered (Eisenmann et al., 2009; Ruutu et al., 2017). In light of these observations, negotiated platform access, defined as the total number of contracts with developers per platform, can help platform owners to mitigate this drawback (Parker et al., 2017). Thus, a platform owner may decide to increase the number of contractual relationships with developers to maintain an adequate digital asset output rate while reducing the degree of openness, to increase owners' control about core platform resources and margins. All additional contractual NPA developers produce complementary applications that, in turn, attract end-users through increased functionalities or user experiences provided on the platforms. Besides this process, we assume that further extension developers are attracted by an increasing number of NPA developers (Tuunainen et al., 2011). Further, we argue that negotiated platform access has the potential to increase positive network effects on both the supply-side and the demand-side, since the increased asset output has the potential to attract more end-users. Thus:

H2a: *Negotiated platform access can substitute for platform openness.*

H2b*: Negotiated platform access positively influences positive network effects.*

Our rationale is that any additional developer increases the sum of digital assets on a platform and therefore a platforms' innovation capacity, enhancing the potential to attract more end-users. The evidence suggests that platforms with more developers are more profitable than those with fewer developers (Boudreau, 2010; Parker et al., 2017). The literature on digital platforms stresses the importance of achieving positive network effects, necessary to generate sustainable platform growth (Boudreau, 2011; Ruutu et al., 2017). Research suggests that platform profits increase proportionally to the actor population growth (Eisenmann et al., 2006; Voigt and Hinz, 2015). At the same time, increasing the number of developers is also associated with an increase in the number of digital assets available on a platform (Ceccagnoli et al., 2012). We argue that a higher number of developers generated through network effects and NPA contracts leads to higher innovation capacity (Parker et al., 2017). Therefore, we posit that positive network effects and NPA increase a platform's innovation capacity (i.e. number of digital assets) through increased participation of developers. Thus:

H3a: *Negotiated platform access relates positively to a digital platform's innovation capacity.*

H3b: *Network effects relate positively to a digital platform's innovation capacity.*

However, any developer, as a human agent, is prone to technical risks and failure. Although some studies have included an abstract representation of developers, their characteristics were not considered (Bergvall-Kåreborn and Howcroft, 2014; Schreieck et al., 2016). We argue that the impacts of network effects and NPA on platforms' innovation capacity are moderated by individual *developers' dead application risk* and extension *developers' churn* (Parker et al., 2017; Tiwana, 2015). First, we define dead application risk as the likelihood that a given developer produces a technical failure in the process of developing a digital application (Parker et al., 2017) or not reaching a significant end-user adoption level for an app (Tiwana, 2015b). Thus, we assume that developers produce failures on a platform (Parker et al., 2017), impeding a digital platform's innovation capacity. Second, empirical evidence also suggest that the platform owner's implementation of platform openness and developer's perceptions of autonomy influence developer's continuous development intentions (Goldbach et al., 2018). Consequently, we argue that with increasing developer churn (or, attrition rate), the potential of producing additional assets decreases and therefore the platform's innovation capacity. Hence:

H4a: *Dead application risk is negatively associated with a platform's innovation capacity.*

H4b: *Developer churn is negatively associated with a platform's innovation capacity.*

3 Research Approach

From a theoretical perspective, the evolution of a digital platform over time can be considered a growth process (Parker et al., 2017). However, we have a limited understanding of digital platforms' initial growth conditions (e.g. degree of openness and negotiated platform access) (Tan et al., 2015). De Reuver, Sørensen, and Basole (2018) point out the need to explore factors for developer participation and platform growth, proposing the use of "computational/synthetic platform 'markets' to mimic and explore rules and outcomes of the ecosystem and use the insights gained to inform design" (p. 132). We argue that a simulation approach is suited to investigate multiple interdependent conditions and their effects on platform growth in detail. A simulation may be understood as any artifact that "imitates the behavior of the system under investigation" (Za et al., 2018, p. 269) and uses mathematical laws to explain or predict phenomena. Specifically, simulation involves creating a mathematical model with underlying theoretical logic to simplify real-world problems (Davis et al., 2007). This representation is then coded into software that executes the model under varying experimental conditions to generate theoretical insights into the dynamic behaviors of complex interactive systems, such as digital platforms. As recommended when simulating a phenomenon that involves dynamic local interactions between entities situated in a system that evolves over time (Za et al., 2018), we used an agent-based stochastic *cellular automaton (CA)* to investigate platform growth under different conditions. Researchers have often applied CA as a flexible and versatile technique to explore network effects with many heterogeneous agents (e.g. consumers or firms) (Goldenberg and Efroni, 2001). CA modeling also enables researchers to simultaneously investigate constructs that act on a market (e.g. network effects, NPA), technology level (i.e. platform openness), and individual level (i.e. dead application risk).

CA models allow one to describe a real-world phenomenon by configuring parameters that characterize the environment and a set of functionalities (behavior) and attributes (the internal states) of agents engaging in this environment (Za et al., 2018). A CA model has three foundational components (Mitchell, 1998). The first component of a CA model is the *cellular space*. Every model's space consists of a d-dimensional lattice, which has N cells (i.e. agents). Our model is built on a two-dimensional lattice (d = 2) with an array of 100 x 100 cells (N = 10,000), which represents a digital platform. Every cell in a lattice takes one of finite numbers of possible discrete states. In our model, different cell state types either represent a non-adoption of a platform by a developer (i.e. a dead cell) or different developer types (i.e. extension and NPA developers), either producing an outcome (e.g. an app) or a technical failure. The second component of a CA model is its *neighborhood configuration*.

The pattern of local connections to other cells is called the cell neighborhood. The neighborhood defined by von Neumann (Figure 2) is one of the most common ones and refers to four adjacent cells that share an edge with a focal cell. We utilize the Von Neumann neighborhood, since studies have successfully applied this neighborhood in adoption and diffusion contexts.

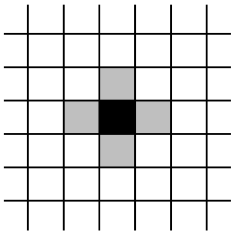

Figure 2. Von Neumann Neighborhood (gray cells = neighbors of the central black cell).

The third component of a CA model is *transition rules*. At each discrete time step *t+1*, cells synchronously update their state based on a function accounting for their neighbors' states at time *t*. In our experiments, we used different functions and parameters to describe varying degrees of platform openness, negotiated platform access, network effects, and dead application risk, which we will describe in the next section. As outlined by Parker et al. (2017), unforeseen technological failure and uncertainty play key roles in platform growth. Thus, we grounded our transition rules on *stochastic processes*, which consider random variation of conditions over time. A CA is stochastic "if the value of the state variable at the next time step is conditioned by the realization of a random variable, which is compared to a pre-determined numerical value that is a function of the initial state variable" (Guinot, 2002, p. 702). In other words, stochastic cell transition rules are performed by external means of probabilities, instead of discrete values (Almeida and Macau, 2011). In contrast, a purely deterministic CA would evolve the same way in each experiment, given that initial parameter configurations are the same. Our simulation approach was guided by the recommendations of Davis et al. (2007), who suggest developing a simple model that covers the underlying theoretical logic of the simulation model. This is represented by the hypotheses described in section 2.2. Thus, we created the CA model as computational representation of the underpinning theoretical model by utilizing the source code of a CA framework (Klüver et al., 2012). This framework allows researchers to implement stochastic transition rules and cell movement effects. Using varying parameters and starting conditions, we conducted three experiments to examine the growth patterns of different synthetic platforms. Based on the simulation results, we developed theoretical propositions as well as managerial implications as the final step.

4 Cellular Automaton Model and Simulation Results

4.1 Computational implementation of hypotheses

Our stochastic CA model simulates platform growth by integrating characteristics of three main perspectives on digital platforms: the technology (i.e. platform openness), market (i.e. NPA and network effects), and individual perspectives (i.e. dead application risk). First, since we seek to understand how effects from an individual developer's perspective lead to platform growth on an aggregate level, we based the probability of *platform openness* on recent empirical findings on perceived platform openness (Benlian et al., 2015). Thus, to approximate the adoption probability (q) based on platform openness, we relied on the squared estimated path coefficients (Hair et al., 2016) between the developer's perceived platform openness and the developer's satisfaction provided by Benlian et al. (2015). As noted by Song et al. (2013), developer satisfaction is a key determinant of mobile platform adoption. Previous research has demonstrated that self-reported measures are often strongly correlated with objective ones (Dess and Robinson, 1984). For this simulation, we therefore assume that high developer satisfaction is a suitable proxy for platform adoption and that Android is a suitable example of an open platform (Parker et al., 2017). Interestingly, Benlian et al.'s (2015) data suggests that iOS developers perceive a greater influence of platform openness on satisfaction than Android developers (i.e. $0.640^2 = 41\%$ vs. $0.519^2 = 27\%$). We used the approximation for the platform openness' probability to distinguish different degrees of platform openness. For our simulations of synthetic platforms, we defined Android as an anchor for a high platform openness (100%) and further assumed that a medium openness is 50% of this value (and 25% for low platform openness). We also accounted for closed platforms, which have an extension developer adoption probability of 0. Arguably, without access to the platform's core resources, extension developers cannot adopt the platform to create complementary assets. To examine how network effects drive platform growth, the CA model relies on market-level modeling techniques. In the context of digital platforms, the research highlights that actors' individual decision process to adopt a given platform is mainly affected by other actors' adoption choices (Song et al., 2013; Venkatraman, 2004). We assume that every additional developer who participates in a given platform improves the utility for all others by its specific utility level. This increase in utility is mainly driven by knowledge spillovers from platform actors' interactions and collaborations (e.g. reusable code) (Venkatraman, 2004). Building on social network theories (Fang et al., 2013; Hartmann, 2010; Hill et al., 2006) and studies from the stochastic CA field (Goldenberg et al., 2010), we developed an individual time-dependent and openness-based likelihood for extension developers to adopt a digital platform:

$$Ao(q)_{(i,t)} = [1-(1-q)^{n_{i,t}}]$$

where ($n_{i,t}$) defines the number of extension developers who participate on a given platform at time period (t) and interact with actor (i) (Goldenberg et al., 2010). Specifically, the exponent ($n_{i,t}$) represents every platform actor's neighborhood in the simulation. We argue that the proposed probability equation is particularly suitable, because it allows researchers to capture the influence of network effects through the exponent ($n_{i,t}$), i.e. the number of cells' neighbors who adopt a given state (Fang et al., 2013). For instance, for $(q) = 0.27$ (high platform openness) and $(n_{i,t}) = 1$, the resulting adoption probability (Ao) is 27%. With more neighbors, the adoption probability increases owing to positive network effects (e.g. 71% provided that a given cell has four neighbors with the same cell type).

Second, platform owners may utilize *NPA developers* to trigger network effects, which may attract additional extension developers and end-users. To model the NPA mechanism, we followed previous research findings that indicate that NPA positively moderates the relationship between complementary products and platform adoption (Cenamor et al., 2013). Further, these findings are in line with the notion that more complementary digital applications attract more end-users as well as extension developers, leading to reinforcing network effects (Cusumano, 2010b). Thus, we defined (x) as the probability of each NPA developer (i) at time-step (t) to attract additional extension developers, implying that additional NPA content attracts end-users, which – in turn – attracts further extension developers. For parsimoniousness, we assumed a positive and monotonous slope as suggested by Cenamor et al. (2013) and defined that every additional digital asset produced by NPA developers attracts one additional end-user and therefore one additional extension developer to join the platform. We followed Fang et al. (2013), who used the cascade method to derive the probability equation and to compute the probability of an individual adopting a product or opinion in a digital platform over time. The more NPA developers are enlisted on a platform, the higher the probability that extension developers will participate. Following this assumption, the NPA-induced adoption probability can be expressed by the formula:

$$An(x)_{(i,t)} = [1-(1-x)^{n_{i,t}}]$$

where $n_{i,t}$ defines the number of NPA developers that participate on a given platform at a point in time (t) and interacting with actor (i) and the openness probabilities (x). Thus, by assuming that $n_{i,t}$ ranges from 0 to 4, we derived the final NPA probabilities. In case that extension and NPA developers share a common neighborhood, we calculated a combined probability by multiplying both formulas:

$$Aon(q,x)_{(i,t)} = [1-(1-q)^{n_{q,i,t}}\,(1-x)^{n_{x,i,t}}]$$

Third, while platform openness and NPA can spur network effects, individual developers (both NPA developers and extension developers) often face the *risk of producing dead applications* that are not further developed or fail to reach a significant number of end-users (Parker et al., 2017; Tiwana, 2015b). For instance, Koetsier (2013) indicated that between 41% and 69% of apps in mobile platforms were never updated and had less than 10 reviews. Reasons for such failures are manifold and pertain for instance to low developer programming skills, technical failures (Goldbach et al., 2018; Kude, 2014; Song et al., 2013) or excessive coordination costs with other platform applications (Tiwana, 2015b). Considering these observations, we argue that more experienced developers, such as NPA developers, are more likely to have significant coding experience than extension developers and are more likely to generate successful assets (David and Shapiro, 2008). Thus, we define (*r*) as an individual developer's probability of producing a dead application, and *(1-r)* as the probability of producing a successful application. While this rate is generally suggested to range at around 41% (Koetsier, 2013), we set the individual failure probability (*r*) of NPA developers as 20% lower owing to their professional background and smaller failure rate. In contrast to Parker et al.'s (2017) formal model, which assumes a declining number of developers over time, we argue that technical failures don't necessarily lead to developer churn. Developers who fail to produce a successful asset may still be committed to start a subsequent entrepreneurial asset development process (Qiu et al., 2017; Sinha et al., 2012). Thus, in our CA model, we defined (*l*) as a developer's probability to discontinue developing for the platform and (1-*l*) to describe the probability to continuously contribute assets to the platform. However, this probability is only valid for extension developers, since NPA developers have employment relationships with platform owners.

Based on these considerations, we implemented 25 stochastic transitions rules; 18 refer to *network effects* (NE), six to the *technical failure* rate (TF) and the *outcome* (O) of *negotiated platform access* (NPA) and *extension developers* (ED). One transition rule defines the influence of *platform openness* (PO) on *extension developers* over time. In modeling network effects and platform openness, we implemented an attribute, *age*, as the number of transitions that each *dead cell* (DC) has assumed. Every single rule relates to one of the four criteria: network effects (NE), platform openness (PO), outcome, technical failure of extension developers (O-/TF-ED), and outcome and technical failure of negotiated platform access (O-/TF-NPA). The detailed transition rules are available upon request from the authors.

4.2 Experimental design and analyses

For simulating synthetic platforms, we conducted three computational experiments to assess the influences of platform openness, NPA, network effects, and dead application risk on innovation output and growth. Table 1 presents the CA model parameters for our three experiments.

Parameter	**Experiment**
Manipulated parameters across experiments (initial values)	
Openness (q)	{Experiment 1: high (0.27); Experiment 2: medium (0.13); Experiment 3: low (0.07)}
NPA engagement by platform owner $(x)^{n(i,t)}$	{0; 5; 10; 15; 20; 25; 30; 35; 40} % of total cell space
Constant parameters across experiments	
Dead application risk (r), 1 – (r) (ED)	41% (dead application), 59% (successful application)
Dead application risk (r), 1 – (r) (NPA)	21% (dead application), 79% (successful application)
Churn (l) (ED)	50% (adapted from Sinha et al., 2012)
ED = extension developers; NPA = vertically-integrated (e.g. contracted) developers	

Table 1. Overview of CA Model Parameters to Simulate Network Effects.

For every experiment that considers different degrees of openness (low to medium), we conducted nine sub-experiments, accounting for every NPA engagement level as shown in Table 1. Owing to the dynamic model behavior, this model cannot reach an attractor – a state to which a model converges, given sufficient simulation time (Jaeger and Monk, 2014). Thus, every simulation was stopped after 100 time-steps (*t*). We always worked with an array of 100 x 100 cells. We conducted 50 simulations for each of these settings, and to standardize the simulation results, we calculated the arithmetical mean value from each simulation. We also utilized a validity mode for the simulations that checks every transition rule's validity. We calculated growth rates for extension developers and generated digital applications under varying NPA configurations to interpret the simulation results.

As illustrated in Figure 3, the highest *growth in digital applications* across all experiments was when setting the parameter NPA to 5%, mainly owing to the nature of the new, low-saturated market suggested for experiments 1 to 3, represented by the initial high number of dead cells. Accordingly, the growth rate is initially high and, with growing market saturation, decreases constantly. NPA combined with a *high openness* had a moderate positive influence on the growth in the number of digital applications. Here, 5% NPA yielded 128,544 apps in 100 time-steps, compared to 113,431 apps without NPA. When the NPA parameter was set to 10%, the growth rate decreased to 10% during the same simulation. The NPA values 15%, 20%, 25%, and 30% achieved a growth rate in applications between 9% and 8%. By setting NPA to 35% and 40%, the growth rate fell to the lowest level (6%). In situations with *medium openness*, NPA had a constantly positive influence on platform growth when the parameter was set to 5%, generating 66,052 apps, compared to 43,562 without NPA. In this case, NPA generated a 52% growth rate in digital applications. However, higher NPA values again led to a decreasing marginal growth rate. By setting NPA to 10%, platforms with a medium openness achieved a 28% growth rate. When we set the NPA to 15%, the growth rate continued to fall to 20%. This effect was further intensified by setting the NPA to 20%, where the growth rate fell to 14%. By setting the NPA to 25% and 30%, platforms with medium openness achieved a constant growth rate of 12%. However, setting the NPA to 35% and 40% generated a decreased marginal growth rate. In platforms with *low openness*, the NPA had a significant impact on the digital application growth rate. By setting the NPA parameter to 5%, the application growth rate reached its highest value, 422%, yielding 45,101 apps, compared to 8,644 without NPA. Even medium-high NPA values generated high growth rates. For instance, when setting the NPA to 10%, platforms with low openness achieved a 54% growth rate. Further, an NPA of 15%, led to a 29% growth rate. By setting the NPA to 20%, the function showed a decreased marginal growth rate (19%), which resulted in the lowest value, 9% (NPA = 40%). In sum, this NPA exerted the strongest positive influence of NPA on platform growth in situations of low platform openness.

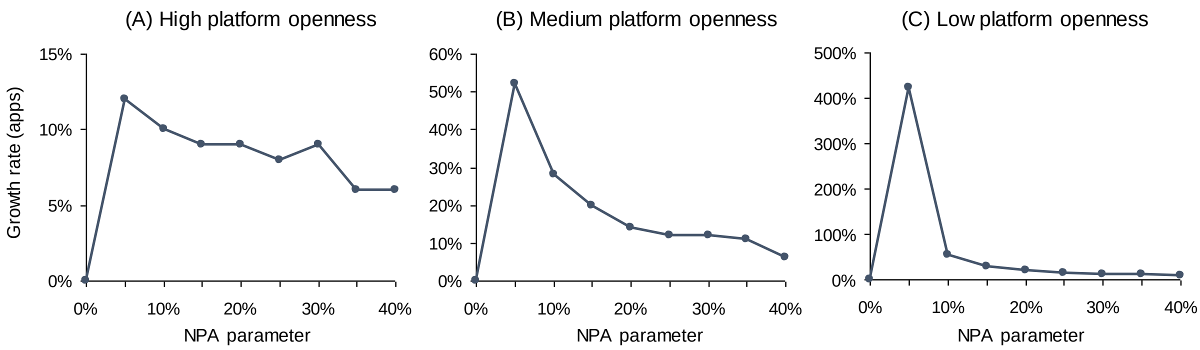

Figure 3. Effects of Platform Openness and NPA on the Growth of Digital Applications for High Openness (A), Medium Openness (B), and Low Openness (C).

Further, as illustrated in Figure 4, platforms with low openness and no NPA showed decreased *growth in attracting extension developers* (Figure 4C, without NPA), leading to platform failure caused by developer churn *(l)* over time. However, by setting NPA to 5%, platforms with low openness can mitigate this effect and can enable a 256% higher attraction of extension developers on average, as shown in Figure 4C. In the context of platforms with medium openness as shown in Figure 4B, where NPA was set to 5%, additional extension developers were attracted to participate on the platform. In this case, the NPA developers triggered network effects, which resulted in an increased growth rate for extension developers (plus 19%). In the absence of NPA, platforms with medium openness exhibited a decreased number of attracted extension developers. By contrast, platforms with high openness as shown in Figure 4A attracted on average just 4% more extension developers than without NPA among 100 discrete time-steps.

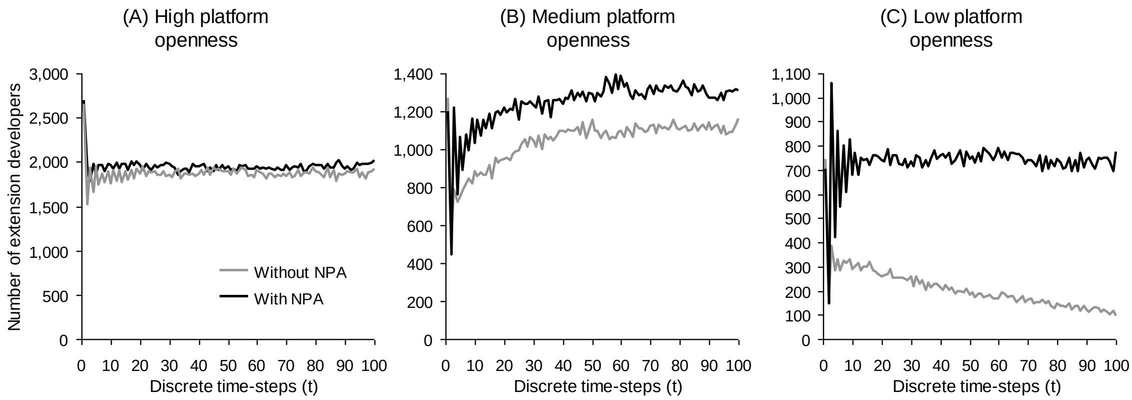

Figure 4. *Effects of 5% NPA on the Number of Platform's Extension Developers for High Openness (A), Medium Openness (B), and Low Openness (C).*

5 Discussion

5.1 Theoretical propositions for platform openness and NPA

This study has generated rich insights into how to configure the developer base and platform openness in a way that fosters growth and innovation. Based on our findings, our proposed theoretical propositions have the potential to fuel digital platform theory-building and refinement (Davis, 2016). Our experimental findings support the importance of gaining a critical mass of extension developers to generate sustainable platform growth generated by positive network effects (Boudreau, 2011; Ruutu et al., 2017). Designating an appropriate degree of openness is a key decision for owners seeking to attract additional extension developers. However, the research has neglected to provide insights into how these developers are attracted under different degrees of openness. Our study results strongly suggest that low platform openness always leads to platform failures over longer periods if no countermeasures are taken. In these situations, failures are mainly caused by decreasing growth rates of extension developers. Also, it is accompanied by fewer digital applications, which – in turn – generate negative cross-side (i.e. end-users) and same-side (i.e. extension developers) network effects resulting in platform failure. In contrast, growth rates show positive developments over time as soon as the initial platform configuration is set to medium or high openness. Especially platforms with high openness outperform other settings' innovation capacities, since open platforms sustainably achieve the highest growth rates in digital applications. Thus, extension developers are more likely to adopt and participate in a given platform when owners set openness to medium or high. Based on our simulation results, we suggest:

P1a: *Low platform openness leads to decreasing growth rates of extension developers, which – in turn – trigger negative cross-side and same-side network effects. This effect results in platform failures.*

P1b: *Medium platform openness leads to increasing growth rates of extension developers, which – in turn – trigger positive cross-side and same-side network effects. This effect results in platform growth.*

The research indicates that platform owners increasingly enlist NPA developers to produce additional platform assets, which may attract both additional extension developers and end-users (Parker et al., 2017). We confirm that contracting NPA developers generates a positive effect on platform growth via network effects. However, there is an important caveat: NPA's effect on the growth rate is not equal across different degrees of openness. In fact, NPA becomes less important when the platform openness is high. In situations of high openness, NPA leads to moderate platform growth and has no significant influence on attracting additional extension developers. Having an open architecture with few NPA developers is found to be most efficient to boost platform growth. In contrast, in situations of low openness, findings indicate that platform owners benefit most from engaging NPA developers. When owners decide to choose low openness, where openness' impact on network effects and therefore platform growth is low, the simulation findings indicate that the engagement of NPA developers may yield higher growth rates than platform strategies without NPA. In other words, NPA allows platforms with low openness to reach a critical mass of extension developers. Further, NPA enables platforms with low and medium openness to achieve similar growth rates in digital applications than platforms with high openness. This effect enables owners to substitute a certain degree of openness with the engagement of NPA developers. Accordingly, owners can stay in control of the primary decisions relating to a platform's technological core while simultaneously generating sustainable platform growth. Based on the insights from our experiments, we suggest:

P2: *NPA is most efficient to achieve sustainable growth of digital applications and extension developers in platforms with low openness.*

5.2 Contributions and Implications for Research and Practice

We sought to increase our understanding of how to achieve a more sustainable platform growth by examining degrees of openness and NPA as determinants of platform growth. Specifically, this study has made several contributions to research. First, existing digital platforms research either take a technology-oriented perspective of a given platform by investigating openness' effects on development rates (e.g. Boudreau, 2010), or a market-oriented perspective by investigating distribution channels, platform pricing, or network effects (e.g. Ruutu et al., 2017). Further, past research has neglected an individual, developer-centric perspective on digital platform growth. However, to better understand platform growth and success, scholars have called for the integration of all perspectives, since they cannot be understood without each other (Benlian et al., 2015; Schreieck et al., 2016). To overcome these issues, we have expanded the digital platform literature by suggesting an underpinning theoretical framework that integrates all perspectives. Further, the insights obtained from our stochastic CA simulation experiments that operationalized our initial hypotheses shed light on how technology components (i.e. degree of openness) and market mechanisms (i.e. network effects and NPA) influenced by individual factors (i.e. dead application risk) synergistically contribute to platform growth. While simulating different levels of openness and NPA we broadened theoretical knowledge on initial conditions essential to achieve sustainable platform growth (de Reuver et al., 2018). Second, by suggesting theoretical propositions for platform openness and NPA based on our simulation results, we have reconciled previous studies' inconsistencies on platform growth and have offered building blocks for future theory development and testing. Third, we made a methodological contribution by applying a stochastic CA model to simulate the growth of synthetic and de facto digital platforms. While the potential of simulation approaches is often overlooked in our field (Za et al., 2018), we have proved their value for generating rich insights into digital platforms' growth patterns. By examining the under-explored relationships of NPA and openness and their mutual influence on platform growth, and deriving theoretical propositions grounded in our simulation results, our contributions may be considered significant, according to Colquitt and Zapata-Phelan's (2007) classification.

Our findings also have implications for practice. Since swiftly gaining a substantial user base is paramount for owners of early-stage platforms, we suggest three growth strategies. First, to achieve *fast and efficient platform growth*, owners should choose high platform openness and aim for 0-5% of vertically-integrated NPA developers. This strategy also allows owners to harness extension developers' expertise, which has been found to be key to high innovation capacity (Parker et al., 2017). However, this may reduce owners' platform profits owing to lower platform exclusivity and asset quality. Second, in situations where owners seek to absorb higher platform profits, we suggest a *moderate and profit-oriented platform growth strategy*. This growth strategy is characterized by medium openness aim for 10% to 20% of vertically-integrated NPA developers. Platforms with this strategy can achieve higher growth rates than platforms that utilize high openness as their single growth factor. However, this strategy's growth rate is lower compared to platforms with high openness and high NPA. Owing to lower platform growth, this strategy leads to a moderate innovation capacity in terms of digital applications. On the other hand, owners can absorb higher profit shares owing to higher exclusivity and platforms' digital applications' quality. In the long term, the increased exclusivity could also lead to higher value, which – in turn – further increases platform profits (Eisenmann et al., 2011). However, these profits are mitigated by higher costs for NPA developers compared to the first growth strategy. Third, we suggest utilizing a *highly profit-oriented platform growth strategy* in situations where low openness is inevitable. Similar to previous strategy, owners should aim for 10% to 20% of vertically-integrated NPA developers when openness is low to achieve a continuous platform growth rather than mitigate platform failures (see Figure 4B and 4C). However, this configuration is not particularly cost-efficient and is limited in harnessing extension developers' innovation capacity. While this strategy requires high investments in engaging NPA developers, owners are able to absorb a high share of platform profits. Owners may later decide to adjust efficiency and trigger further platform growth by progressively increasing the degree of openness.

6 Conclusion

Strategies to drive platform growth are of particular interest so as to attract a critical mass of developers and end-users, which may lead to platform sustainability. In this regard, owners can tweak two primary properties of their platforms: contracting developers and designating a platform as open. We have responded to recent calls for integrating the technology-level (i.e. openness), the market-level (i.e. network effects, NPA), and the individual-level perspectives (i.e. developer churn and dead application risk) to explore platform growth patterns (de Reuver et al., 2018; Schreieck et al., 2016). By applying a stochastic CA, we have provided a novel methodological account on these criteria's effects on platform growth. Our experiments revealed that platforms with low openness lead to failures owing to decreased attraction of extension developers, if not mitigated. In contrast, platforms with medium openness generate moderate platform growth, while platforms with high openness achieved the highest platform growth. Further, we have demonstrated engaging NPA developers mitigate the negative effects in situations with low openness and enhance the effects of medium and high openness on platform growth. Based on our simulation results, we derived theoretical propositions to inform theory-building in the digital platforms field and have outlined platform growth strategies for practice. There are limitations, some of which may provide thrusts for future research. First, we based the parameters on platform openness' influence on path coefficients with moderate effect size provided by research (Benlian et al., 2015). By utilizing more fine-grained openness parameters, researchers may further increase our proposed stochastic CA's predictive validity. Second, additional parameters that affect developers' adoption rate could be considered in future stochastic simulations. For instance, researchers can integrate factors such as trust in the platform (Hurni and Huber, 2014), the platform's standalone value (Eisenmann et al., 2011), and others to increase our proposed stochastic CA's prediction capability. Third, while the risk of developers' technical failure is well accepted as impeding platform growth (Tiwana, 2015b), there is no empirical data for NPA developers' application risk in the literature. However, the empirical literature indicates that the group of extension developers also contains a considerable share of individualists and private developers with little experience and no commercial interests (David and Shapiro, 2008), as opposed to NPA developers with a professional background contracted to develop pre-specified outcomes. Thus, we assumed that NPA developers' dead application risk is lower than for extension developers. Future research may empirically scrutinize NPA developers' dead application risk and may update the simulation parameters accordingly. Fourth, our simulation focused on the developers' roles in increasing platforms' growth and outputs, excluding deceitful or harmful digital applications and assuming that every additional digital resource may attract new end-users, eventually contributing to overall platform sustainability (Tuunainen et al., 2011). Thus, it may be valuable to empirically investigate how quantity and quality of digital application portfolios influence end-user adoption. Overall, this study can be understood as a starting point to further explore platform ecosystem dynamics and growth, relevant for both theory and practice.

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