Communications of the Association for Information Systems

Volume 50 Paper

3-10-2022

Looking Beyond Membership: A Simulation Study of Market-entry Strategies for Two-sided Platforms under Competition

Michelle Désirée Haurand
Bielefeld University, m.haurand@uni-bielefeld.de

Recommended Citation

Haurand, M. D. (2022). Looking Beyond Membership: A Simulation Study of Market-entry Strategies for Two-sided Platforms under Competition. Communications of the Association for Information Systems, 50, pp-pp. https://doi.org/10.17705/1CAIS.05001

Communications of the Association for Information Systems

Research Article DOI: 10.17705/1CAIS.05001 ISSN: 1529-3181

Looking Beyond Membership: A Simulation Study of Market-entry Strategies for Two-sided Platforms under Competition

Michelle D. Haurand

Department of Business Administration and Economics, Bielefeld University

m.haurand@uni-bielefeld.de

Abstract:

Organizations need to implement a proper market-entry strategy to successfully establish a two-sided digital platform. Following the right strategy becomes even more crucial if a competing platform already exists in the targeted market. In this case, organizations will find it more difficult to reach critical mass because users flock to the already established, larger platform due to network effects, which will result in a potential winner-take-all situation. While previous research proposes strategies, it has not discussed how to find the right strategy. This paper introduces an agent-based market simulation to comprehensively evaluate alternative strategies under competition that accounts for not only platform adoption for the entrant but also for transactions, earnings, and the need to weaken the incumbent. Through an example case parameterized with empirical data, I illustrate how one can apply the model. The findings suggest that entrants need to comprehensively evaluate market-entry strategies beyond just looking at membership figures because different strategies can have the most promise with regard to growing the entrant's platform, weakening the incumbent, and boosting the entrant's transactions and earnings.

Keywords: Two-sided Platform, Market-entry Strategy, Competition, Agent-based Simulation.

This manuscript underwent peer review. It was received 6/23/2020 and was with the authors for 12 months for two revisions. Johan Sandberg served as Associate Editor.

1 Introduction

While two-sided markets have existed for a long time, the economic importance of two-sided digital platforms has increased dramatically as more and more platforms (including many high-value brands) have emerged (Dietl, Grütter, & Lutzenberger, 2009; Interbrand, 2020; Wan, Cenamor, Parker, & Van Alstyne, 2017). Naturally, multiple similar platforms intensify competition, and it becomes more difficult to enter the market and acquire the necessary number of users to survive.

A particular challenge when initially founding a new platform comes from cross-side (or indirect) network effects (i.e., users on one side of a platform benefitting from more users on the other side), which hinder the acquisition of new members and give rise to the so-called chicken-and-egg problem (Caillaud & Jullien, 2003). Without a chicken, there cannot be an egg and vice versa. Analogously, potential users demand existing users to be present on a platform's other side before joining it (dating sites constitute an illustrative example) (see Evans, 2003).

Strong and positive network effects also cause winner-take-all scenarios in which one large platform eventually dominates the market (Eisenmann, Parker, & Van Alstyne, 2006; Ruutu, Casey, & Kotovirta, 2017; Shapiro, Carl, & Varian, 1998). However, an entrant may still establish itself in the market and possibly even tear down an established competitor. While it seldom happens, it has occurred in the past, such as in the case of the social networking service Friendster losing out to MySpace, which, in turn, lost to Facebook (Press, 2018).

To reach critical mass (i.e., acquire the number of users beyond which positive increasing returns occur; see Caillaud & Jullien, 2003; Casey & Töyli, 2012), an entrant needs a suitable market-entry strategy. Existing research has discussed various strategies, such as platform envelopment (Eisenmann, Parker, & Van Alstyne, 2011), opportunistic platform entry strategies (Karhu & Ritala, 2020), the subsidization of one side (Armstrong, 2006; Caillaud & Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet & Tirole, 2006), a focus on a micromarket (Evans, 2003; Parker, Van Alstyne, & Choudary, 2016), the use of marquee users (Evans, 2009), and the provision of self-supply (Evans & Schmalensee, 2016; Hagiu & Spulber, 2013) if there is more demand than supply on the platform (for more details, see Section 2.2; for recent overviews on platform strategy, platform competition, and platform entry, see Cennamo, 2019; McIntyre & Srinivasan, 2017; Parker et al., 2016; Schirrmacher, Ondrus, & Kude, 2017; Stummer, Kundisch, & Decker, 2018; Wan et al., 2017).

However, no general guide to finding the most effective market-entry strategy for an entrant in a two-sided platform market exists, nor has any paper compared different market-entry strategies with regard to their efficacy. While all the papers on the different market-entry strategies above describe these strategies in detail, they do not conduct empirical evaluations or run simulations to quantitatively compare their effects. As such, they offer no insight specifically into how an organization should choose a market-entry strategy. The studies that have looked at the early phase of establishing a two-sided platform from a quantitative perspective either omitted a parameterization based on real (survey) data (Ruutu et al., 2017; Casey & Töyli, 2012), did not include already established competition in the market (Chu & Manchanda, 2016), or both (Haurand & Stummer, 2018b).

But this research gap is not only interesting from an academic point of view: platform operators usually have only one chance to establish their platform next to a competitor's. Furthermore, they have no means of evaluating ex ante whether the chose the best market-entry strategy. Thus, we need to better understand how to establish a new platform via a method that does not rely on empirical evaluation not only to further research on platform strategies but also for practice.

In this paper, I adopt an agent-based simulation (ABS)(see Section 2.4) approach to close the research gap and better understand how to establish a new two-sided digital platform if a competitor already exists. In particular, I consider the following output factors: the entrant's membership figures, number of transactions, and earnings (which the entrant wants to make as high as possible) and those same numbers for the incumbent (which the entrant wants to lower through the strategies). I also consider how different market-entry strategies affect them. Specifically, I examine the following research question (RQ):

> **RQ:** What effect do different market-entry strategies for two-sided digital platforms have on different output factors?

This paper proceeds as follows: in Section 2, I provide the background information on network effects and reaching critical mass, market-entry strategies, and platform membership types. In Section 3, I introduce the method of agent-based modeling. In Section 4, I describe the agent-based model and, in Section 5, its sample application (a platform on which university students can buy and sell used textbooks). Afterwards, in Section 6, I present results from the simulation and sensitivity analyses that I conducted. In Section 7, I outline the paper's contributions, its limitations, and potential avenues for further research. Finally, in Section 8, I conclude the paper.

2 Background

2.1 Network Effects and Reaching Critical Mass

Once a platform has reached a critical mass, network effects have a positive influence on the speed at which users adopt it (Arroyo-Barrigüete, Ernst, & López-Sánchez, 2010). These self-reinforcing effects, which can be direct and indirect (see below), play at least a partial role in attracting individuals to use two-sided platforms (Evans & Schmalensee, 2016).

Cross-side (or indirect) network effects (i.e., the number of users on one side of the platform who influence the number of users on the other side of the platform) constitute an especially relevant issue when introducing a two-sided platform into the market (Evans & Schmalensee, 2016; Katz & Shapiro, 1986). In contrast, researchers have found same-side (or direct) network effects (i.e., the number of platform users who affect the number of users on the same side) not to have a significant effect for two-sided ecommerce platforms (Chu & Manchanda, 2016). Therefore, I focus only on cross-side network effects in this study.

Cross-side network effects lead to the chicken-and-egg problem: users find a two-sided platform attractive only when the other side has a sufficient number of users (Caillaud & Jullien, 2003; Evans & Schmalensee, 2016; Katz & Shapiro, 1986). While this problem always poses an obstacle in establishing a platform business model, it becomes even more critical under competition because the incumbent has a head start and, thus, might reach critical mass (i.e., the positive self-reinforcement of user numbers through network effects) (Arroyo-Barrigüete et al., 2010) earlier. Due to the importance of quickly reaching critical mass, entrants need to choose a suitable market-entry strategy when faced with an already existing and, thus, necessarily stronger competitor.

2.2 Market-entry Strategies

At the beginning of the millennium when discussions about strategies for overcoming the market-entry problems for two-sided platforms began to emerge, researchers focused on pricing strategies (primarily subsidizing strategies) (Armstrong, 2006; Caillaud & Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet & Tirole, 2006). Since then, researchers have discussed further strategies, such as platform envelopment (Eisenmann et al., 2011), opportunistic platform entry strategies (Karhu & Ritala, 2020), the launch of the platform in a micromarket only at first (Evans, 2003; Parker et al., 2016), the employment of marquee users (Evans, 2009), and the use of a self-supply strategy (Evans & Schmalensee, 2016; Hagiu & Spulber, 2013). For recent overviews, see Parker et al. (2016), Stummer et al. (2018), or Wan et al. (2017).

Eisenmann et al. (2011) proposed a platform envelopment strategy whereby one offers a new platform's service through an already existing second platform with an identical user base to the new platform's target group. However, this strategy is only viable if a platform with compatible products already exists and if the entrant can access the platform. For example, Microsoft had the chance to give away its Windows Media player for free with its Windows operating system and, thereby, attack the incumbent RealNetworks (Rochet & Tirole, 2003). Because a suitable platform for carrying out the envelopment strategy does not always exist, entrants cannot always choose the envelopment strategy. Thus, I do not discuss it further in this paper.

If the incumbent platform remains open to attracting complementary innovation (Eisenmann, Parker, & Van Alstyne, 2009) or even focuses its business model on complementary innovation as an innovation platform (as opposed to a transaction platform, which connects, for example, buyers and sellers; see Cusumano, Yoffie, & Gawer, 2020), entrants can possibly adopt opportunistic platform entry strategies (Karhu & Ritala, 2020). These strategies come in three different forms: platform exploitation (e.g., copying elements of the application programming interface), platform pacing (copying and keeping up with the incumbent's boundary resources), and platform injection (establishing the new platform in the incumbent's ecosystem). For example, Amazon employed these strategies for Amazon Fire (Karhu & Ritala, 2020).

However, as for the platform envelopment strategy, opportunistic platform entry strategies depend on other suitable (open) existing platforms. In this way, they build on aspects that the entrant cannot control. Furthermore, in this paper, I study transaction platforms, while the three strategies above only apply to innovation platforms (Cusumano et al., 2020). Therefore, I do not further analyze opportunistic platform entry strategies because entrants cannot always achieve them and they apply to a different platform type that I do not focus on in this study.

I focus on strategies that pertain to the sample case in a straightforward manner as I describe below: 1) subsidizing one side, 2) focusing on a micromarket, 3) harnessing the power of marquee users, and 4) using self-supply if the platform has more demand than supply.

One can divide platforms into a “subsidy side”, which is supported with money, and a “money side”, which has to pay to join or use the platform: the subsidy side may get cheaper or free access to the platform or other monetary benefits or may even receive money to use it (Eisenmann et al., 2006; Evans, 2003). Which side becomes the subsidized one depends on the two sides’ relative importance (Eisenmann et al., 2006; Rochet & Tirole, 2006; Wan et al., 2017). Usually, in a shopping context, platform operators subsidize the demand side (for other examples of the typical division into the two sides, see Parker & Van Alstyne, 2005). Note that a subsidizing strategy differs from a loss leader strategy, in which a platform decreases the price of the products it offers, which leads to more transactions and, in turn, to more sellers entering a platform (Ryu, Choi, & Cho, 2019).

In the micromarket strategy, a platform first focuses on a geographical or social niche to minimize the critical mass’s size and to using existing ties to gain new users and then expands once it has obtained the necessary number of users (Parker et al., 2016; Schirrmacher et al., 2017). Facebook famously used this strategy in that only Harvard students could initially use it.

Using marquee users to further platform adoption relies on winning over influential users (through monetary or other incentives; see Parker et al., 2016) who will attract others. These marquee users can be opinion leaders, celebrities, or highly active users (Stummer et al., 2018). For example, a mobile payment platform used especially influential students as marquee users to further its growth (Schirrmacher et al., 2017).

In the self-supply strategy (e.g., for an ecommerce platform), the platform itself initially offers goods to attract the demand side (Hagiu & Spulber, 2013; Wan et al., 2017). More users on the demand side then attract more users on the supply side, which makes the platform’s intervention increasingly superfluous. Amazon, for example, first sold books itself before opening up to other sellers. As an added bonus, self-supply strategy allows a platform to control the supply that it offers (Parker et al., 2016).

2.3 Platform Membership

An individual can use several platforms (multi-homing) or just one platform (single homing) of a given type (Armstrong, 2006; Caillaud & Jullien, 2003; Rochet & Tirole, 2006), such as dating platforms. Multi-homing affects how many possibly users a platform may attract and can cause a winner-take-all scenario, while higher single-homing rates can lead to a tendency toward monopolies whereby a single two-sided platform dominates the market (Sun & Tse, 2007).

In addition to possibly being a user on two platforms simultaneously, an individual might also both buy and sell on a platform and, thus, use both sides of a two-sided platform; that is, they can switch sides depending on whether the platform’s structure or operators allow it or not (Schirrmacher et al., 2017). While side switching would normally not be possible for recruitment platforms (Haurand & Stummer, 2018b), platforms such as eBay allow participation on both sides by registering as a buyer and a seller. Just like multi-homing, side switching can positively influence how many users a platform attracts on either side.

One can classify switching costs into transaction costs, learning costs, and artificial costs that arise from specific clauses in a contract that a company chooses (Klemperer, 1987). According to Lam (2017), one faces particular difficulties in analyzing switching costs for two-sided markets because switching costs interact with network effects. Thus, possibly unexpected consequences may arise from an increase or decrease in switching costs (Lam, 2017).

3 Method

For this study, I employed an agent-based simulation to study a two-sided digital platform's entry into the market under existing competition. One can consider using an agent-based simulation (ABS) a "third way of doing science" (Axelrod, 1997, p. 3) next to induction and deduction. It considers the various interactions between heterogeneous actors (agents) through which the behavior of complex markets emerges (Kiesling, Günther, Stummer, & Wakolbinger, 2012; Rand & Rust, 2011). Accordingly, ABS allows one to include cross-side network effects, verbal recommendations (word of mouth), peer pressure through observing usage (normative social influence), and so on, which might all influence whether an individual becomes a two-sided digital platform user. Recent studies in the information systems (IS) field have recommended the agent-based modeling to study two-sided platforms (Schalowski & Barrot, 2019; Torres Pena, Breidbach, & Turpin, 2019). These reasons support ABS as a good methodological choice.

I examine which investigated market-entry strategies most effectively build a user base, weaken the incumbent, and boost transactions and earnings for a fictional application case parameterized with real (survey) data. The results provide an answer to what effects different market-entry strategies have on different output factors.

However, readers should not generalize the specific numbers of user, transactions, and earnings from the simulation experiment based on the fictional application case to other specific platforms. Nonetheless, practitioners might use the simulation as a starting point for a decision-support tool. If one correctly adapts and parameterizes the model for a specific case, it can help one to evaluate alternative market-entry strategies for those specific markets. Then, decision makers can choose a strategy based on individual preferences with regard to the different factors they examined (i.e., number of users, transactions, and earnings).

In the Appendix, I describe the sensitivity analyses I conducted to evaluate the model and show that it produced logical and robust results when exposed to changes in the assumed parameters. Accordingly, these analyses strengthen the answer to the research question. In Section 4, I describe the agent-based model in more detail.

4 Agent-based Model

4.1 Model Entities

The model in the fictional application case has two agent groups: platforms and students. It contains two two-sided digital platforms $k \in \{1; 2\}$: an incumbent and an entrant. On these two platforms, the second group, the students i, can buy and sell used textbooks. Students can both buy and sell books and can use both platforms (i.e., both side switching and multi-homing may exist).

4.2 Social Network

The students are connected in a social network, which the simulation creates on initialization and then remains static. The network partially builds on spatial proximity (people at the same university have a higher likelihood to have a social connection and, thus, for the model to label them as "acquaintances"). Students can also have a few closer connections, such as old friends from school. Because moving might sever one's looser social ties but not ties to one's closest friends, friendships do not have spatial limitations in the model. The model assigns all students a certain number of acquaintances from their vicinity and randomly allocates a number of friends to them as I describe in Section 5.

4.3 Actions

Three types of actions influence the process of choosing to become a platform member: word of mouth (WOM), normative social influence (SI), and marketing (M). Students talk to a randomly drawn friend at rate WOMRate. While WOMRate signifies how often a conversation takes place per period on average, note that the events in the simulation are not round-based but can happen randomly at any point in time. During such a conversation, students receive an influence WOM that depends on their own and their interlocutor's previous exposure to WOM (InterlocutorWOM). Analogously to the procedure in Haurand and Stummer (2018a), there is an S-shaped relation (see Figure 1) between the exposure to word-of-mouth information and WOM with more neutral students being more easily influenced than students whose previous experience strongly favored or opposed a certain platform.

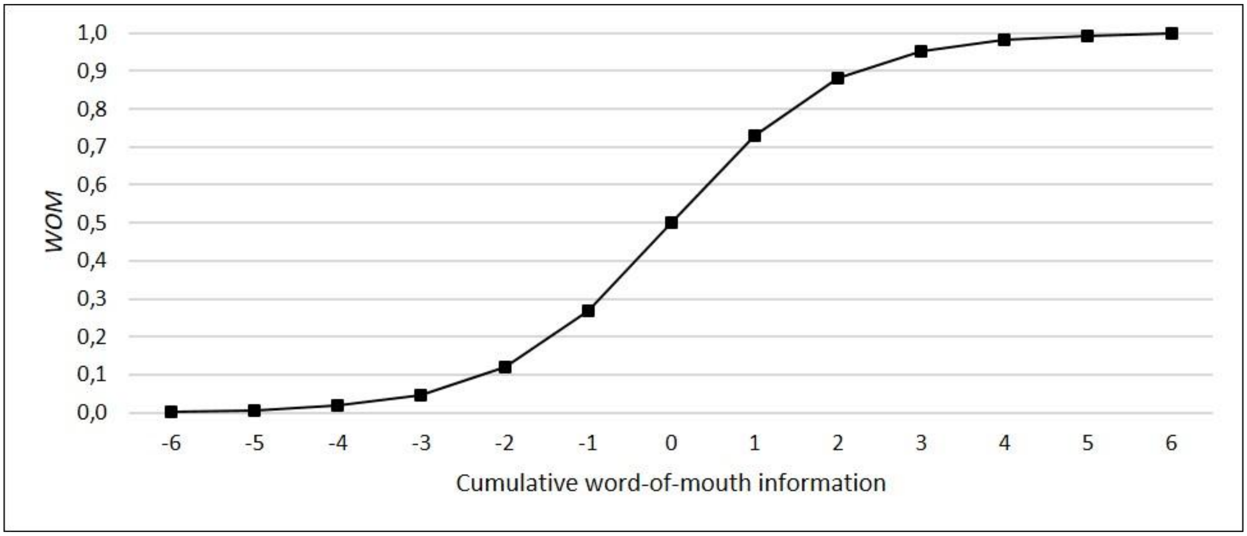

Figure 1. S-shaped Relation between Cumulative Word-of-mouth Information and WOM (Haurand & Stummer 2018a)

Thus,

$$WOM_{i,k,t} = \frac{1}{1 + e^{\ln\left(\frac{1}{WOM_{i,k,t-1}}-1\right)+ WOM_{i,k,t-1} - InterlocutorWOM_{i,k,t-1}}} \tag{1}$$

for a student i for platform k at time t with

$$\ln\left(\frac{1}{WOM_{i,k,t-1}} - 1\right) + WOM_{i,k,t-1} - InterlocutorWOM_{i,k,t-1} \tag{2}$$

being the cumulative word-of-mouth information for a student i for platform k at time t.

To obtain normative social influence SI, students observe their friends and acquaintances using the platform at rate SIRate. From these observations, I computed the influence in favor of one platform over total influence following Delre, Jager, Bijmolt, and Janssen (2007). Thus, for example, the SI for platform k is:

$$SI_{i,k,t} = \frac{Observations_{i,k,t-1}}{\sum_{l=1}^{K} Observations_{i,l,t-1}} \tag{3}$$

If there is social influence for a platform, the students become aware of it (if they were not already before); that is, I set the binary variable awareness to 1.

Both platforms can engage in marketing measures. The more excess money they have after they deduct expenditures from the revenues they receive through costs for joining the platform and costs for platform usage (i.e., textbook sales), the more they can spend on marketing. Analogously to the influence through WOM, I computed the influence through based on previous exposure (see Haurand & Stummer, 2018a; for a discussion of the S-shaped relation between advertising effort and sales on a macro level, see Johansson, 1979) with the following equation:

$$M_{i,k,t} = \frac{1}{1 + e^{\ln\left(\frac{1}{M_{i,k,t-1}}-1\right)+ M_{i,k,t-1} - 1}} \tag{4}$$

Influenced by WOM, SI, and M, students decide which platform to join. The rate at which they consider joining a platform depends on the season: during the holidays, some students feel less inclined to deal with searching for ways to buy or sell used textbooks. This HolidayFactor influences their individual rate of considering joining a platform.

To determine which platform they choose, agents compare the two platforms' utilities. A platform's utility depends first on the cross-side network effect CNE. CNE is the change of estimated buyers with respect to the current number of buyers weighted by how much the number of sellers is supposed to change in relation to this according to previous studies (see Chu & Manchanda, 2016). I then multiplied it by an agent-specific (i.e., individual) scaling β^{CNE} of the cross-side network effect in relation to the importance of other factors, which expands on previous models (e.g., see Casey & Töyli, 2012; Ozer & Anderson, 2015).

Second, a student's utility depends on recommendations through WOM, observations that lead to SI, and exposure to marketing M as I describe above. Third, in line with Chu and Manchanda (2016), the price level on the platform L, the buyer quality Q (i.e., the number of books bought per buyer per year, which on the one hand depreciates over time because students who have already adopted the platform becomes less likely to buy a book when they have bought all the books they wanted but on the other hand increases as new, initially more active students, join the platform (which only sellers find important)), and the product variety V (which only buyers find important)) play a crucial role in a platform's utility.

Lastly, the cost of joining a platform on the buyer and seller side (CostsJoinB and CostsJoinS) and the cost per book bought or sold (CostsVariableB and CostsVariableS) influence platform utility. Note that, with regard to switching costs, only the cost of this one-time entry fee and no additional switching costs might possibly keep students from joining the platforms.

Further necessary conditions for joining a platform include awareness of the platform and willingness to interact on it on the specific side under consideration (i.e., the willingness to buy our sell a used textbook for the sample application; if students lacked the willingness to interact on it, I set the binary variable willingness to zero rather than one), whether the student already adopted it, and costs for joining on the buyer or seller side that do not exceed the maximum amount they would willingly spend (i.e., CostsJoinS ≤ CostsJoinSMax).

Given these factors, I compared the utility that an individual gained from joining a platform as seller S (which includes the individual weights β (which comprise the scaling of the different factors to euros (€) and their individual importance)), which I express as:

$$\begin{aligned} U^S_{i,k,t} = \beta_i^{CNE} \times CNE_{i,k,t} + \beta_i^{WOM} \times WOM_{i,k,t} + \beta_i^{SI} \times SI_{i,k,t} + \beta_i^{M} \times M_{i,k,t} + \beta_i^{L} \times L_{k,t} \\ + \beta_i^{Q} \times Q_{k,t} - \beta_i^{CostsJoinS} \times CostsJoinS_{k,t} - \beta_i^{CostsVariableS} \times CostsVariableS_{k,t} \end{aligned} \tag{5}$$

to the utility that an individual gains from joining the other platform as a seller. Thus, the individual becomes an active seller on whichever platform offers the most utility. The number of sellers (i.e., direct network effects) does not have a significant effect for ecommerce platforms (Chu & Manchanda, 2016). Therefore, I do not include it in the model.

5 Sample Application

5.1 Parameterization

I conducted parameterization with preexisting data from earlier research and publicly available statistics (i.e., data from the pre-existing knowledge base), data from a specifically conducted survey on 101 participants (50 males and 51 females with a mean age of 24.1 years), and through reasonable assumptions. Table 1 summarizes the (average) values of the parameters and their sources.

I parameterized each agent that represented a student with the data about one individual that I drew randomly from among the survey participants while keeping possible covariances between the parameter manifestations intact. Because the empirical study that I used to parameterize the simulation contained only German students and other countries use German textbooks less frequently, the model covers only the German market.

I based the number of agents on the number of students in Germany studying business administration and economics (i.e., 144,580 at the beginning of 2018) (Destatis, 2018), though I scaled it down by a factor of 10. The model allocates these agents to the federal states of Germany according to the number of students enrolled in each state. I set the number of students who already belonged to a platform for used textbooks as the number of the incumbent's users. I based whether they joined the platform as a buyer or seller or both on stated desire to buy or sell books in the survey. On average, I randomly assigned 100 of the 14,457 students as initial users of the new platform and allocated them to a side depending on their response in the survey.

Table 1. (Average) Values of Parameters and Their Sources

Parameter	Average value	Source	Parameter	Average value	Source
Number of agents	14,458	*	β^{L} for buyers/sellers	1.49/1.25	Survey
Change of buyers/sellers for a 1 percent change in the other (in %)	1.53/ 0.44	**	β^{Q}	0.23	
			β^{V}	0.29	
Users of incumbent (in %)	6	Survey	Average HolidayFactor (in %)	28	
Users on buyer/seller side (in %)	82/77		CostsJoinB (in €)	2.28	
Acquaintances at university	25.9		CostsJoinS (in €)	3.49	
Countrywide friends	13.3		Maximum distance between acquaintances (in km)	21	Assumptions
Max. number of acquaintances	320				
WOMRate (per month)	2.24		Number of users of entrant	100	
SIRate (per month)	2.94		Money incumbent/entrant (in €)	50,000/ 5,000	
β^{WOM}	0.99				
β^{SI}	0.31		ExpendituresRunning incumbent/entrant (in €)	1,000/ 100	
β^{M}	0.22				
CostsJoinBMax (in €)	2.28		CostsVariableB (in €)	1	
CostsJoinSMax (in €)	3.49		CostsVariableS (in €)	1	
$\beta^{CostsVariableB}$	1.42		L (in €)	10	
$\beta^{CostsVariableS}$	1.86		ExpendituresMarketing incumbent/entrant	0.08/ 0.12	
$\beta^{CostsJoinB}$	1.72				
$\beta^{CostsJoinS}$	1.41		MRate	{0, 3, 6, 9}	

* Destatis (2018)
** Chu and Manchanda (2016)

I also took the number of acquaintances at university and countrywide friends from the survey. The maximum number of acquaintances equaled the maximum number of acquaintances indicated among all respondents. I drew acquaintances from all students in a 21-kilometer radius, which mirrors attendance at the same university.

The strength of the cross-side network effect on both sides stems from Chu and Manchanda’s (2016) empirical research in a similar context; namely, on an online consumer-to-consumer platform. According to this study, the cross-side network effect leads to a ceteris paribus increase of buyers by 1.53 percent and sellers by 0.44 percent if the respective other side gains one percent more users.

I also took WOMRate and SIRate (i.e., the frequency of talking to others or observing others using the platform, which both influence the decision); the importance of WOM, SI, and M in making decisions; and how much a certain amount of WOM, SI, or M is worth in join costs (i.e., β^{WOM}, β^{SI}, and β^{M}) from the survey.

All parameterization settings regarding costs and prices for students originated from the survey. These settings affected the maximum amount students would willingly pay to sign up for the platform on the buyer side (CostsJoinBMax) or seller side (CostsJoinSMax) and the importance of variable costs for buyers ($\beta^{CostsVariableB}$) and sellers ($\beta^{CostsVariableS}$) and join costs for buyers ($\beta^{CostsJoinB}$) and sellers ($\beta^{CostsJoinS}$). Moreover, the model included the importance of the price level β^{L} on the platform (i.e., the average price at which users buy and sell books sold) for buyers and sellers.

I also took the influence that buyer quality Q (with an initial number of books bought per year per student of 0.025 * 30 (days) * 12 (months) = 9 when joining the platform) had on sellers and how much it was worth to them in variable costs (β^{Q}) and the influence that product variety V had on buyers and how much it was worth to them in join costs (β^{V}) from the survey. HolidayFactor influenced the rate at which the students considered joining a platform (four times a month during the semester). During the holidays (i.e., from the beginning of February until the end of March and from the beginning of August until the end of September), students considered joining a platform on average only 28 percent as often as during the semester. I also gathered this information from the survey data.

For the platforms, I used plausible start values for their stock of money (Money), their expenditures for running the platform (ExpendituresRunning), the costs of joining the platform as a buyer (CostsJoinB, which equals the mean CostsJoinBMax for both platforms) or as a seller (CostsJoinS, which equals the mean CostsJoinSMax for both platforms), the costs of buying (CostsVariableB) or selling (CostsVariableS) a book, the price level (L), how much income the platforms spend on marketing (ExpendituresMarketing), and how often they perform marketing measures with the money they spend (MRate < €40, €40-€80, €80-€120, > €120 spent on marketing).

5.2 Scenarios

In addition to the baseline scenario, I simulated four scenarios in which the entrant used one of the market-entry strategies: 1) subsidizing, 2) micromarket, 3) marquee users, or 4) self-supply (see Section 2). While I artificially cut-off the subsidizing, micromarket, and marquee user strategies after a one-year market-entry period, I left the self-supply strategy to taper off as more sellers entered the platform who could then handle the demand themselves. Because the incumbent has already surpassed the market-entry period, the market-entry strategies only take place for the entrant. Theoretically, however, the incumbent could react, which may pose an interesting avenue for further research based on this work.

As I state above, shopping platforms typically subsidize the demand side. Therefore, the supply side pays an additional CostsJoinB to join the new platform and an additional CostsVariableB per book sold on the new platform for the first year, while the demand side pays no costs during the same period. Afterwards, the entrant implements the same price structure as the incumbent.

In the micromarket scenario, the new platform focuses only on one spatially limited part of the whole market (namely, the most populous federal state, North Rhine-Westphalia). While the platform can have transactions for the first year only in this area, it can also focus all of its marketing activities there, which leads to a 3.51 times higher rate at which a student living in North Rhine-Westphalia experiences a marketing activity (as 28.45% of students live in North Rhine-Westphalia and 1/0.2845 = 3.51).

One can reasonably assume that, on average, the 106 universities in Germany that teach business administration and/or economics have one marquee user each. Thus, the probability that each student becomes a marquee equals 106/14,458. Marquees, who have 10 times the number of average and maximum acquaintances, receive €100 per month just to be on the new platform. If a student has been in contact with a marquee user, they consider joining the platform if their willingness to buy or sell a book is existent (i.e., willingness = 1), if they have not yet become a member on the platform on the specific side, and if the CostsJoinB and CostsJoinS do not exceed their CostsJoinBMax or CostsJoinSMax by more than €2, respectively. The last condition signifies that individuals subject to a marquee user's promotional effects will willingly pay a little more to join the platform.

In the self-supply scenario, the new platform holds up the other end of up to 200 transactions per period if it has less supply than demand. For these transactions, the platform foregoes the CostsVariableS it would have gained from a regular transaction but otherwise has no monetary consequences.

6 Simulation Results

Because I focus on market-entry strategies in this paper, I ran the market simulation for 84 periods (i.e., seven years) after the entrant entered the market and stopped it in the first year the entrant exceeded 16 percent market share (signifying 2.5% innovators plus 13.5% early adopters according to Rogers (2003)) in terms of total adoption in the baseline scenario. All results are averages over 200 simulation runs. Thus, simulating the five scenarios (the baseline scenario without market-entry measures plus the four strategy scenarios) amounts to 1,000 simulation runs, which took about 47 hours in a regular desktop environment with a 2.13 GHz processor and 8 GB RAM. Additionally, I conducted extensive sensitivity analyses.

6.1 Platform Membership

Figure 2 shows the resulting number of platform members for the demand and supply side of the entrant since its market entry. On both platform sides, the user base's growth followed the shape of the first half of the typical diffusion S-curve (Bass, 1969) in the baseline scenario. As Figure 2 indicates, the entrant reached critical mass (beyond which positive network effects occur) only with the most effective strategy (i.e., marquee users) and only for the buyers after six-and-a-half years (Arroyo-Barrigüete et al., 2010).

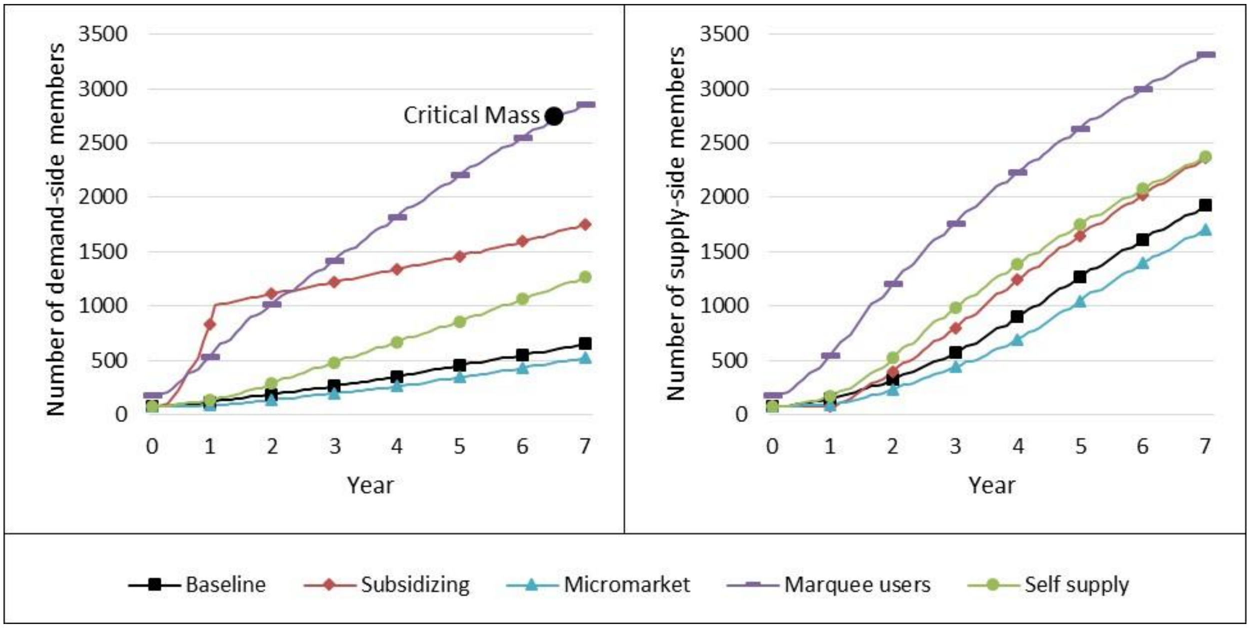

Figure 2. Demand- and Supply-side Members of the Entrant over a Seven-year Period Starting at Market Introduction

If the entrant subsidized the buyer side for the first 12 months, the buyer side grew much more quickly while the seller side stagnated (at least while the subsidization lasts). Focusing on a micromarket for the first 12 months, however, led to an initial reduction in growth that an entrant could not compensate for. While the self-supply strategy had a marginal effect on the supply side, the final number of demand-side members was about one quarter higher than in the baseline scenario.

Paying marquee users for the first year yielded the best results. However, while the other scenarios exhibited a growth pattern analogous to the first half of the typical S-curve, in the marquee user scenario, the growth already began to slow toward the end of the simulation horizon and to mirror the second half of the S-curve that led up to saturation as the effect tapered off. While having contact with a marquee user could have directly influenced a student to join the platform (see Section 5.2), this effect did not even lead to a fifth of the total membership figures in the marquee user scenario as Figure 3 shows. Note that the total number figures correspond to the marquee user scenario in Figure 2.

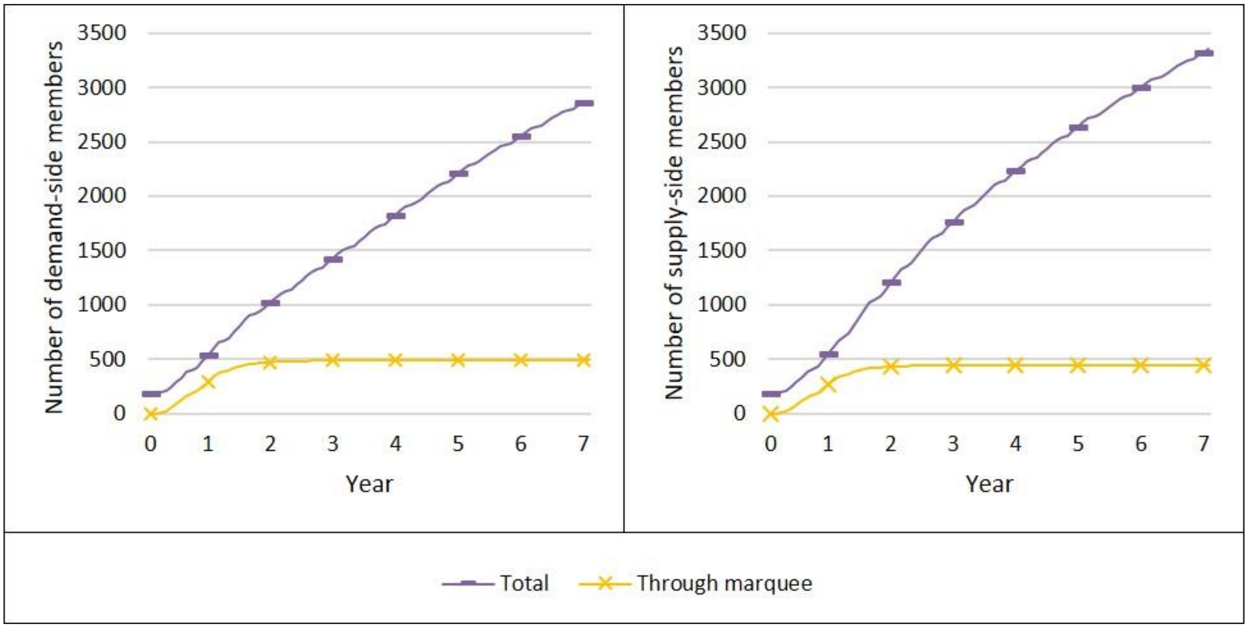

Figure 3. Demand- and Supply-side Members of the Entrant Split into Total Members and Members Coming Directly through a Contact with a Marquee for the Marquee User Scenario

Furthermore, this direct marquee user effect faded out once the entrant no longer paid them after a year. The number of members coming through it reached 490 for the demand side and 446 for the supply side.

Figure 4 shows the incumbent's membership situation since the entrant entered the market. Note that the legend refers to the strategies that the entrant used in the different scenarios, while the incumbent did not change its strategy.

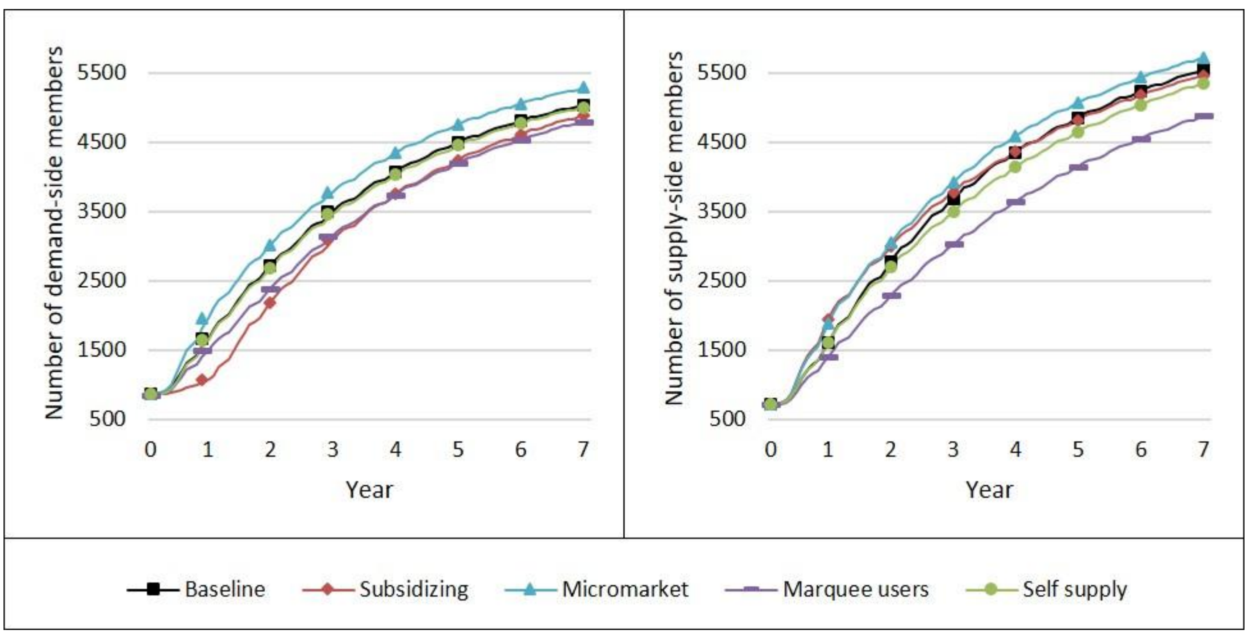

Figure 4. Demand- and Supply-side Members of the Incumbent over a Seven-year Period Starting at Market Introduction of the Entrant

While the already least favorable path—the micromarket strategy—strengthened the incumbent on both sides, only the most effective strategy with regard to the entrant's members—the marquee users strategy—had a substantial negative effect on platform membership for the incumbent.

6.2 Number of Transactions

Figure 5 shows the total number of transactions for both the entrant and the incumbent since the former entered the market. Note that the curve's shape, which also looks like the beginning of the S-curve for the incumbent, stemmed from the aggregation only. The curve for transactions per period showed the typical flattening toward the end of an S-curve for the incumbent as one would expect. However, the way in which I present the data (in the form of total numbers) makes the total gains and losses in transactions more intuitive.

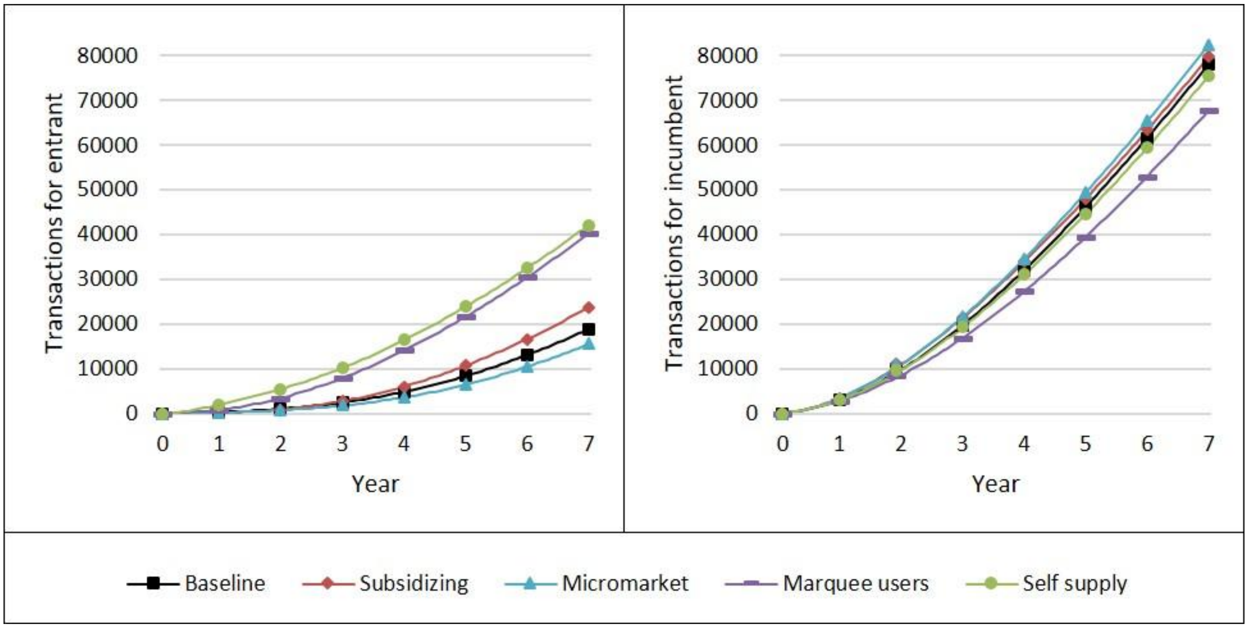

Figure 5. Total Transactions for the Entrant and the Incumbent over a Seven-Year Period Starting at Market Introduction of the Entrant

Even though the marquee user strategy proved more successful in garnering members for the entrant and kept them from joining the incumbent, the self-supply strategy proved the most effective in stimulating transactions for the entrant, though the marquee user strategy followed closely behind in this regard. Using marquees again weakens the incumbent the most by a margin.

6.3 Earnings

Figure 6 shows both the entrant's and the incumbent's financial gains for the seven-year period since the former entered the market. Note that, as above for the transactions, the aggregated form of the curves, which I chose to illustrate the magnitude of the total gains and losses, does not reflect the typical curve flattening towards the end of an S-curve for the incumbent, which would be visible on a per-period basis.

While the marquee user strategy managed to weaken the incumbent the most, it also led to substantial losses for the entrant at first and led to worse results in the long run than in the self-supply scenario, which benefitted the entrant's earnings the most.

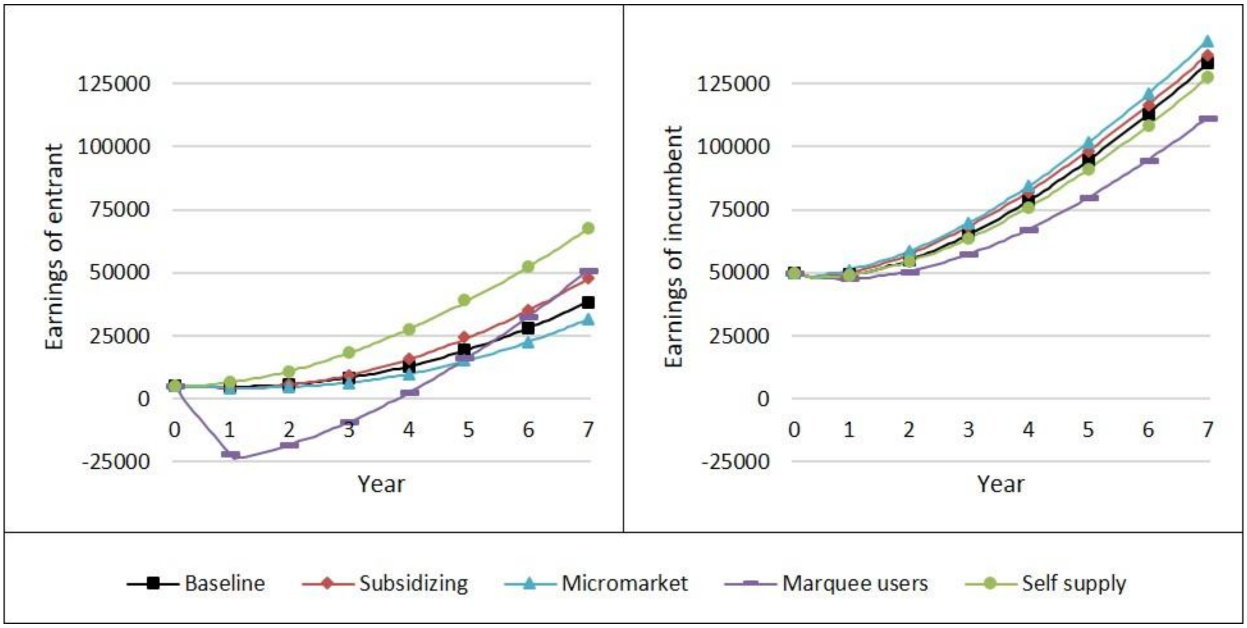

Figure 6. Earnings of the Entrant and Incumbent over a Seven-year Period Starting at Market Introduction of the Entrant

6.4 Sensitivity Analyses

In order to prove simulation results' soundness, one must carefully evaluate a simulation. In the Appendix, I describe the sensitivity analyses I conducted to evaluate the model and show that it produced logical and robust results when exposed to changes in the assumed parameters.

Apart from such analyses, Table 2 shows the interesting results I obtained from comparing scenarios under a decrease and increase in L for the incumbent (results for the entrant are always the other way around concerning the decrease and increase; see Table A1).

Table 2. Number of Buyers/Sellers for the Incumbent/Entrant by Scenario and Change in L for the Incumbent

Scenario	Change in L in percent	Number of buyers/sellers on the incumbent/entrant platform			
		Buyers		Sellers	
		Incumbent	Entrant	Incumbent	Entrant
Baseline	- 10	5125	1886	3888	3854
	+ 10	4486	1613	5850	1265
Subsidizing	- 10	5023	2526	4136	3991
	+ 10	4300	2620	5840	1398
Micromarket	- 10	5361	1219	4483	3475
	+ 10	4887	1326	5977	1100
Marque users	- 10	4659	3474	3072	4829
	+ 10	4244	2591	5612	1984
Self-supply	- 10	5038	2563	3669	4128
	+ 10	4386	2001	5774	1476

While changes in numbers were significant and at times large, the number of users on both platforms still proved the most beneficial the entrant for the marquee user scenario and least beneficial in the micromarket scenario with the other scenarios in between except for one instance. For an increase in L, the subsidizing scenario even slightly overtook the marquee user scenario for the number of buyers for the entrant (2620 versus 2591). However, employing marquee users still remained the second best option by far.

7 Discussion

In this section, I discuss the effects of the different strategies. While no research had quantitatively compared market-entry strategies for two-sided digital platforms under competition parameterized with survey data before this study, I can nonetheless compare the results to partial finding from other papers.

7.1 Platform Membership

Because a two-sided platform needs to gain members to become established, we need to look at the influence that market-entry strategies have on the entrant's membership situation. The incumbent's existence can explain the entrant's generally slow growth. The incumbent also plays a role in whether the entrant reaches critical mass, which only happens for the buyer side when employing a marquee user strategy. This study goes beyond the work of Evans and Schmalensee (2010) who already recommended expanding their analysis by including an incumbent platform. Furthermore, it confirms the difficulties of reaching critical mass as an entrant if an incumbent in the platform market that acts as a gatekeeper already exists as Ruutu et al. (2017) have pointed out. However, Ruutu et al. did not study this issue with real (survey) data.

While subsidization benefits only the buyer side at first because sellers have to pay significantly more to join, both sides profit from this strategy over time. The boost from cross-side network effects through growth in the demand side may explain why. In studying the total sum of the cross-side network effect over time, I found that the subsidization strategy produced the highest values for both sides—they even surpassed the cross-side network effects in the marquee user scenario. The positive influence that strategically distributing (joining or variable) costs between both market sides had on total market size is concurs with Parker and Van Alstyne's (2005) reasoning.

The micromarket strategy cannot compensate the lag in growth from focusing on a smaller number of possible users at first because the condition that makes the micromarket strategy most effective—local interactions (Schirrmacher et al., 2017)—does not exist in our application case of an ecommerce platform. However, note that this finding may differ for other markets. Facebook, for example, successfully employed the micromarket strategy and, thus, lowered the required critical mass (Parker et al., 2016).

We can attribute the marquee user strategy's success not only to the head start that marquee users provide and the subsequent cross-side network effects (as Parker at al. (2016) have alluded to) but also to the sustainable positive influence that marquee users have on WOM and SI, which continue to spread through the network. Even though the marquee users no longer received compensation to promote the platform after one year and the number of user recruited through their efforts was relatively small (as discussed in Section 6.1), employing them leads to long-lasting effects by influencing a particularly well-connected part of the network. First, because the marquees users continued to use the platform, even though they did not actively recruit for it anymore, they lastingly strengthened its visibility, which led to a higher overall awareness, and individuals who choose the entrant platform in times after the direct marquee promotion also had a higher average SI value for it. While individuals who joined the entrant platform had a higher average WOM for the subsidizing strategy at the beginning, the marquee user strategy overtook it in the long run (not even counting individuals who joined due to the marquees' direct efforts during their actively paid promotion phase). Thus, this study expands on Parker et al.'s (2016) research by demonstrating that a self-enhancing influence also on the same side of the platform (through higher awareness, WOM, and SI values) can occur, though users do not value the presence of users on the same side as would occur, for example, with same-side network effects on social media platforms such as Facebook (Haucap & Heimeshoff, 2014). As a counterexample to a successful marquee user strategy, we might consider the music-streaming platform Tidal that Jay Z launched: even though some of the biggest stars advocated their membership on the supply side, Tidal did not thoroughly communicate its unique selling propositions and, thus, did not launch successfully (Connelly, 2015). In this context, it would be interesting to study whether marquee users might have been more effective if they had been on the demand side rather than on the supply side.

Supply does not directly but only indirectly positively affect the supply side (as Parker and Van Alstyne (2005) already noted; that is, ecommerce platforms lack direct network effects (Chu & Manchanda, 2016). However, the self-supply strategy still has an effect on the supply side. This effect results from a cross-side network effect on the demand side, which then leads to a cross-side network effect on the supply side: more supply leads to more buyers, which, in turn, leads to more sellers. On the one hand, the self-supply strategy does not profit the platform as much as the baseline scenario with the same number of users would because it has to generate some of the supply itself, which means it foregoes income on the supply side. On the other hand, it is associated with lower costs than the more effective marquee user strategy and a lower risk than the likewise more effective subsidization strategy, which may create irreparable damage to the membership situation on the supply side. Thus, depending on how strongly the entrant desires safety (i.e., low risk of going bankrupt or losing potential users in comparison to the baseline scenario), profits, and growth, one might recommend that it adopt different strategies based solely on its membership figures.

However, while establishing membership growth provides a good sign that the entrant will survive in the long term, the incumbent has a considerable head start and, thus, the entrant needs to weak it in order to survive in a likely winner-take-all scenario (see Ruutu et al., 2017). In this regard, only the marquee user strategy weakens the incumbent by diminishing its user numbers. Thus, because platform markets tend toward a winner-take-all situation (Eisenmann et al., 2006; Shapiro et al., 1998), the marquee user strategy might be the only viable strategy for long-term survival because it might cause the incumbent to lack the ability to regain its previous monopoly.

7.2 Number of Transactions

Nonetheless, high(er) membership rates alone cannot fully explain long-term platform success. Transactions that occur both sides of a platform fuel positive cross-side network effects, which explains why platforms need to ensure that members remain active (for a recent study on how to nudge platform members to remain active users, see Von Briel & Davidsson, 2019).

Both increasing the number of transactions for the entrant and weakening the incumbent by reducing its number of transactions play an important role in winning the battle for the market. While I found the self-supply and marquee user strategies the most effective with regard to transactions, the former more successfully strengthened the entrant (which Evans and Schmalensee (2005 have already noted), while the latter weakened the incumbent the most. Thus, this study goes beyond existing literature by looking at the effect that different strategies have on the transactions of both the entrant and the incumbent. Specifically, I found that, based on transactions alone, the results do not allow for a clear recommendation to favor either the self-supply or the marquee user strategy.

7.3 Earnings

Lastly, establishing a large and active platform (i.e., increasing membership and the number of transactions) does not represent a worthwhile endeavor in its own right because, ultimately, a platform must be financially successful as well.

The results show that the marquee user strategy involves many risks financially speaking. On the one hand, I found that it hurts the incumbent more than any other strategy. Thus, it at least slightly diminishes the market's appeal and keeps the incumbent from investing as much in promotional strategies. On the other hand, it also damages the entrant in the long run next to creating losses for the first four years (through having to pay the marquee users, a potentially costly affair according to Eisenmann et al. (2006)), which happens under no other strategy. To the best of my knowledge, no other study has discussed financial risk in the marquee user or other strategies.

7.4 Overall Evaluation of Strategies

In this paper, I examine the best strategies with regard to the outcome measures demand-side users, supply-side users, transaction, and earnings for both platforms in a duopoly from the entrant's perspective. The marquee user strategy helps the entrant to gain many members and successfully weakens the incumbent in all regards due to a long-lasting effect on awareness, WOM, and SI that goes beyond the marquee users' direct recruiting efforts by creating lasting positive effects in particularly well-connected parts of the social network. However, the self-supply strategy performs best with regard to transactions and earnings for the entrant. Thus, even though the marquee user strategy might look superior at first glance, one needs to remember that transactions fuel cross-side network effects more effectively than pure membership numbers, and entrants require earnings to conduct further promotional measures to boost platform growth. As such, the self-supply strategy, which also involves less financial risk, might represent the more desirable option in the long term. Going beyond existing research on market-entry strategies for two-side platforms under competition in comparing several strategies that one can apply to various platforms, I show the value in comprehensively examining not only membership figures but also transactions and earnings and how much the entrant weakens the incumbent.

I gathered data only from one specific application case: if a platform had no monetary transactions between its two sides (as it is the case for dating or social media platforms), factors such as the price level L for the products bought and sold on the platform would not play a role in the utility considerations.

Factors such as the HolidayEffect in their current form apply only to similar platforms (namely, platforms that target people attending or teaching at university or school and that offer service that people need mostly outside the holidays). However, seasonality per se can be an issue also for wildly different platforms—from travel booking platforms such as AirBnB to platforms that sell decorations or clothes and dating platforms (Markey and Markey (2013) found dating to underlie seasonal effects). Thus, researchers only need to parameterize even the HolidayEffect from the current model correctly to fit each case; they could even set it to a value that eliminates most or all seasonal effects.

Other factors, such as WOM, SI, and M nearly universally apply to all platform markets because others talk about or can observe most platforms' usage (even though people may only communicate their usage behavior only on the Internet or with very close friends if the platform touches a taboo topic) and most platforms would resort to marketing to boost their membership. Likewise, at least one side of a platform market needs to pay for the services, which makes CostsJoin and/or CostsVariable generally applicable. For an overview on which side of a platform usually has to pay money, see Parker and Van Alstyne (2005).

Even though one cannot generalize the results above about platform growth to all platform markets, they exemplify how different measures for platform success can benefit from different market-entry strategies. The different effects that the strategies have on different measures for platform success explain why researchers and platform operators should take a comprehensive approach to analyzing market-entry strategies for digital two-sided platforms that considers account several factors. It might help platform operators to succeed in establishing a platform despite the threat that a potential winner-take-all situation poses in favor of an already established incumbent.

7.5 Sensitivity Analyses

I discuss the results from the sensitivity analyses in Appendix A. However, the effect that decreasing/increasing the price level L on one platform has on the number of users on the two sides of both platforms (see Table A1) might appear a bit confusing at first and, thus, warrants attention. To understand the effect, one must keep two things in mind: on the one hand, a higher L on one platform makes it more attractive to the sellers because it means that they receive more money for their books while buyers favor a platform with low prices because they can buy books for cheaper. The increased L for the incumbent, which leads to more sellers and fewer buyers (and the opposite for the entrant, which now has a lower level of prices), exemplifies this effect.

On the other hand, the cross-side network effect makes dramatic increases on the number of users on one side of a platform lead to an increase also on the other side of a platform. This effect explains why lowering L for the incumbent does not only have a positive effect on the number of sellers for the entrant (as it deters sellers from joining the ceteris paribus less attractive incumbent) but also on the buyer side. The cross-side network effect that comes from the dramatic increase in the number of sellers (plus 97.23 percent) overcompensates for the negative effect through having to pay a higher price for the goods when being a member of the entrant. As I mention in Section 5.1, a one percent increase in sellers leads to a 1.53 percent increase in buyers (Chu & Manchanda, 2016).

The results from the sensitivity analyses in Section 6.4 indicate that, even though I uncovered some large and potentially initially complicated-to-understand effects (as with changing the price level L for the incumbent and the entrant), these effects are not only logical but also do not affect the overall conclusions that pertain to beneficial strategies. The marquee user strategy remained the most favorable since it outperformed all other strategies by a large margin except for the one instance when it became the second best to the subsidy strategy. The marquee user strategy may have succeeded because, even though users on the seller side of the entrant decreased by the largest percent, the remaining absolute number of users remained comparably high. Through the cross-side network effects, the marquee user scenario also affected buyers more negatively than the other scenarios. However, while we found a large difference in buyer numbers between the marquee user scenario and the other three scenarios (which were still inferior), the two best strategies only differed by 29 users (i.e., (2620 - 2591) on average.

Furthermore, lower or higher prices on one platform will not likely remain over years in a duopoly market without any compensation (e.g., through goods' quality). Thus, the overall results remain robust concerning uncertainties in the assumed input parameters.

8 Conclusion

While establishing a two-sided platform constitutes a difficult endeavor, it becomes even more difficult when an established competitor already profits from its advanced position in the race to gain critical mass and, thus, harness positive self-reinforcing effects on user numbers. In this study, I examine alternative strategies that two-sided digital platforms can pursue to enter a market with an already established competitor. Specifically, I describe how I created an agent-based simulation and used it in an illustrative application case to comprehensively evaluate several market-entry strategies while considering platform membership, transactions, and earnings for both the entrant and the incumbent. Accordingly, the study not only furthers the theoretical literature on two-sided platforms but also contributes to practice. .

In the illustrative application case, i found using marquee users the most promising market-entry strategy to boost network effects and reach critical mass and to weaken an already established competitor because it generated lasting positive effects on awareness, WOM, and SI in particularly well-connected parts of the social network. The strategy also continued to produce benefits after the first year the platform entered the market when direct promotions through the marquee users ended. Furthermore, only the marquee user strategy helped the incumbent reach critical mass in less than seven years. However, the self-supply strategy performed the best with regard to the entrant's transactions and earnings. Considering the important role that transactions play in long-term success and the high risk connected with founding a platform (i.e., the possibility that the entrant will decide to leave the market before even reaching the break-even point around the fourth year), it might even be the more recommendable strategy. However, this recommendation may not apply to all platform markets (see below) as different circumstances might favor different strategies.

Even so, with this study, I show the need for entrants to comprehensively examine more factors other than their platform membership numbers to make a well-informed decision about market-entry strategies because I found different strategies to differ in how well they boosted different output parameters. As such, I address how different market-entry strategies for two-sided digital platforms in the face of competition affect different output factors. In creating and evaluating the simulation model, I also took a first step in helping entrant platform operators to find a suitable market-entry strategy under competition, though they would have to modify the model to fit their own markets in order to gain specific insights.

Accordingly, this study has multiple general implications: platform operators should not only examine potential membership numbers when choosing a market-entry strategy and might benefit from creating an adapted version of the model that I created for this study. Researchers should also assess transactions and earnings for both the entrant and the incumbent next to membership figures when evaluating market-entry strategies for two-sided platforms.

Specific implications for platform operators on which strategy they should employ have certain limitations: one can generalize the strategic recommendations only to other platform markets that closely resemble the application case (i.e., transaction platforms mediating the exchange of standardized goods between their (possibly side switching and multi-homing) platform members that do not lead to local interactions as Schirrmacher et al. (2017) have described). Furthermore, in reality, the incumbent platform might be so technologically superior that no strategy proves successful, or the new platform might have such advanced technological attributes that it could replace the incumbent even with an unsuitable market-entry strategy. Therefore, the specific results about which strategy an entrant should use to reach certain goals may generalize only to markets that do not exhibit a large technological gap between the rivaling platforms.

Establishing a novel platform means accepting a high risk and possibly substantial costs. In this case, Gonzalez (2009) recommends using simulations to gain insights and conducting evaluations first and then waiting for someone to use the model in practice. Should platform operators employ the model as a decision-support tool, it would be a worthwhile step to analyze strategies in different combinations over time because such combinations might be more effective than implementing just a single strategy. Beyond that, the model currently reflects only one specific case—a consumer-to-consumer ecommerce platform that allows side switching and multi-homing. To advance insights into different markets, researchers may apply it to further cases, which may lead to some generalizable recommendations. On a similar note, integrating real case studies to demonstrate the model's validity based on real data represents another promising direction for further research. In this vein, researchers could examine the continued growth for a marquee user strategy as opposed to the sudden decline in growth for the subsidization strategy. Maybe it would even be possible to empirically evaluate how large the effect of the direct contact with a marquee is as opposed to the lingering effects once an entrant no longer employs them (analogous to the breakdown in Figure 3). Finally, researchers could examine potential counterstrategies that the incumbent could employ.

References

Armstrong, M. (2006). Competition in two-sided markets. *RAND Journal of Economics*, *37*(3), 668-691.

Arroyo-Barrigüete, J. L., Ernst, R., López-Sánchez, J. I., & Orero-Giménez, A. (2010). On the identification of critical mass in Internet-based services subject to network effects. *Service Industries Journal*, *30*(5), 643-654.

Axelrod R. M. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*. Princeton, NJ: Princeton University Press.

Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science*, *15*(5), 215-227.

Caillaud, B., & Jullien, B. (2003). Chicken & egg: Competition among intermediation service providers. *RAND Journal of Economics*, *34*(2), 309-328.

Casey, T. R., & Töyli, J. (2012). Dynamics of two-sided platform success and failure: An analysis of public wireless local area access. *Technovation*, *32*(12), 703-716.

Chu, J., & Manchanda, P. (2016). Quantifying cross and direct network effects in online consumer-to-consumer platforms. *Marketing Science*, *35*(6), 870-893.

Connelly, J. (2015). Jay Z's faltering streaming service is a case study in failure-to-launch syndrome. *Entrepreneur*. Retrieved from https://www.entrepreneur.com/article/247587

Cennamo, C. (2019). Competing in digital markets: A platform-based perspective. *Academy of Management Perspectives*, *35*(2).

Cusumano, M. A., Yoffie, D. B., & Gawer, A. (2020). The future of platforms. *MIT Sloan Management Review*, *61*(3), 46-54.

Delre, S. A., Jager, W., Bijmolt, T. H., & Janssen, M. A. (2007). Targeting and timing promotional activities: An agent-based model for the takeoff of new products. *Journal of Business Research*, *60*(8), 826-835.

Destatis. (2018). *Bildung und Kultur: Studierende an Hochschulen 11*. Wiesbaden: Statistisches Bundesamt.

Dietl, H. M., Grütter, A., & Lutzenberger, M. (2009). Defensive competitive strategies in two-sided markets: The example of the mail industry. *Competition and Regulation in Network Industries*, *10*(1), 3-15.

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard Business Review*, *84*(10), 92-101.

Eisenmann, T. R., Parker, G., & Van Alstyne, M. (2009). Opening platforms: How, when and why? In A. Gawer (Ed.), *Platforms, markets and innovation* (pp. 131-162). London, UK: Edward Elgar.

Eisenmann, T., Parker, G., & Van Alstyne, M. (2011). Platform envelopment. *Strategic Management Journal*, *32*(12), 1270-1285.

Evans, D. S. (2003). The antitrust economics of multi-sided platform markets. *Yale Journal on Regulation*, *20*(2), 325-382.

Evans, D. S. (2009). How catalysts ignite: The economics of platform-based start-ups. In A. Gawer (Ed.), *Platforms, markets and innovation* (pp. 99-130). London, UK: Edward Elgar.

Evans, D. S., & Schmalensee, R. (2005). *The industrial organization of markets with two-sided platforms.* Retrieved from https://www.nber.org/papers/w11603

Evans, D. S., & Schmalensee, R. (2010). Failure to launch: Critical mass in platform businesses. *Review of Network Economics*, *9*(4).

Evans, D. S., & Schmalensee, R. (2016). *Platforms: The new economics of multisided platforms*. Boston, MA: Harvard Business Review Press.

Gonzalez, R. A. (2009). Validation of crisis response simulation within the design science framework. In *Proceedings of the 30th International Conference on Information Systems*.

Hagiu, A. (2006). Pricing and commitment by two-sided platforms. *RAND Journal of Economics*, *37*(3), 720-737.

Hagiu, A., & Spulber, D. (2013). First-party content and coordination in two-sided markets. *Management Science*, *59*(4), 933-949.

Haucap, J., & Heimeshoff, U. (2014). Google, Facebook, Amazon, eBay: Is the Internet driving competition or market monopolization? *International Economics and Economic Policy*, *11*(1-2), 49-61.

Haurand, M. D., & Stummer, C. (2018a). Stakes or garlic? Studying the emergence of dominant designs through an agent-based model of a vampire economy. *Central European Journal of Operations Research*, *26*(2), 373-394.

Haurand, M. D., & Stummer C. (2018b). The early-stage development of two-sided digital platforms: A simulation approach. In *Proceedings of the 26th European Conference on Information Systems*.

Interbrand. (2020). *Best global brands 2019 rankings*. Retrieved from https://www.rankingthebrands.com/The-Brand-Rankings.aspx?rankingID=37&year=1273

Johansson, J. K. (1979). Advertising and the s-curve: A new approach. *Journal of Marketing Research*, *16*(3), 346-354.

Katz, M. L., & Shapiro, C. (1986). Technology adoption in the presence of network externalities. *Journal of Political Economy*, *94*(4), 822-841.

Karhu, K., & Ritala, P. (2020). Slicing the cake without baking it: Opportunistic platform entry strategies in digital markets. *Long Range Planning*, *54*(5).

Kiesling, E., Günther, M., Stummer, C., & Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: A review. *Central European Journal of Operations Research*, *20*(2), 183-230.

Klemperer, P. (1987). Markets with consumer switching costs. *Quarterly Journal of Economics*, *102*(2), 375-394.

Lam, W. M. W. (2017). Switching costs in two-sided markets. *Journal of Industrial Economics*, *65*(1), 136-182.

Markey, P. M., & Markey, C. N. (2013). Seasonal variation in internet keyword searches: A proxy assessment of sex mating behaviors. *Archives of Sexual Behavior*, *42*(4), 515-521.

McIntyre, D. P., & Srinivasan, A. (2017). Networks, platforms, and strategy: Emerging views and next steps. *Strategic Management Journal*, *38*(1), 141-160.

Ozer, G., & Anderson, E. (2015). Innovation and breaching strategies in multi-sided platform markets: Insights from a simulation study. In *Proceedings of the 36th International Conference on Information Systems*.

Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management Science*, *51*(10), 1494-1504.

Parker, G. G., Van Alstyne, M. W., & Choudary, S. P. (2016). *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. New York, NY: Norton Publishing.

Press, G. (2018). Why Facebook triumphed over all other social networks. *Forbes*. Retrieved from https://www.forbes.com/sites/gilpress/2018/04/08/why-facebook-triumphed-over-all-other-social-networks/#6d127e5c6e91

Rand, W., & Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, *28*(3), 181-193.

Rochet, J. C., & Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the European Economic Association*, *1*(4), 990-1029.

Rochet, J.-C., & Tirole, J. (2006). Two-sided markets: A progress report. *RAND Journal of Economics*, *37*(3), 645-667.

Rogers, E. M. (2003). *Diffusion of innovations*. New York, NY: The Free Press.

Ruutu, S., Casey, T., & Kotovirta, V. (2017). Development and competition of digital service platforms: A system dynamics approach. *Technological Forecasting and Social Change*, *117*, 119-130.

Ryu, S., Choi, K., & Cho, D. (2019). A stirring effect of the loss leader strategy in a two-sided online platform. In *Proceedings of the 40th International Conference on Information Systems*.

Schalowski, J., & Barrot, C. (2019). The long-term diffusion of digital platforms—an agent-based model. In *Proceedings of the 40th International Conference on Information Systems*.

Schirrmacher, N.-B., Ondrus, J., & Kude, T. (2017). Launch strategies of digital platforms: Platforms with switching and non-switching users. In *Proceedings of the 25th European Conference on Information Systems*.

Shapiro, C., Carl, S., & Varian, H. R. (1998). *Information rules: A strategic guide to the network economy*. Boston, MA: Harvard Business School Press.

Stummer, C., Kundisch, D., & Decker, R. (2018). Platform launch strategies. *Business and Information Systems Engineering*, *60*(2), 167-173.

Sun, M., & Tse, E. (2007). When does the winner take all in two-sided markets? *Review of Network Economics*, *6*(1), 16-40.

Thiele, J. C., Kurth, W., & Grimm, V. (2014). Facilitating parameter estimation and sensitivity analysis of agent-based models: A cookbook using NetLogo and R. *Journal of Artificial Societies and Social Simulation*, *17*(3).

Torres Pena, M., Breidbach, C., & Turpin, A. (2019). Crafting agent-based models to analyze service platforms. In *Proceedings of the 40th International Conference on Information Systems*.

Von Briel, F., & Davidsson, P. (2019). Digital platforms and network effects: Using digital nudges for growth hacking. In *Proceedings of the 40th International Conference on Information Systems*.

Wan, X., Cenamor, J., Parker, G., & Van Alstyne, M. (2017). Unraveling platform strategies: A review from an organizational ambidexterity perspective. *Sustainability*, *9*(5), 734-752.

Appendix: Model Evaluation

In addition to assessing simulations' face validity, Gonzalez (2009) recommends that researchers conduct sensitivity analyses to evaluate simulation models. He also points to the fact that, because simulations answer "what-if" questions, "model validity can no longer simply be understood as how close the computed behavior is to the 'real' answer, because there is no 'real' answer when we are dealing with 'what-if' analysis" (Gonzalez, 2009, pp. 5-6). I performed extensive sensitivity analyses to determine the robustness of the conclusions regarding possible uncertainties in the assumed input parameters. Table A1 shows the results.

Table A1. Results of Sensitivity Analysis

Parameter	Change in percent	Effect on buyers/sellers in percent change compared to baseline			
		Buyers		Sellers	
		Incumbent	Entrant	Incumbent	Entrant
Maximum distance between Acquaintances	- 10	-0.03	-0.48	0.05	-0.53
	+ 10	0.01	-1.42	0.07	-1.41
Number of users of entrant	- 10	-0.07	**-5.51**	0.27	**-2.96**
	+ 10	-0.08	**3.45**	0.01	1.32
Money incumbent	- 10	-0.03	-0.73	0.08	-0.29
	+ 10	-0.03	-0.73	0.08	-0.29
Money entrant	- 10	-0.03	-0.73	0.08	-0.29
	+ 10	-0.03	-0.73	0.08	-0.29
ExpendituresRunning incumbent	- 10	0.05	-1.02	0.08	-1.35
	+ 10	-0.04	-0.13	-0.02	0.12
ExpendituresRunning entrant	- 10	0.00	0.77	-0.07	0.69
	+ 10	-0.06	-1.98	0.16	-1.38
CostsVariableB incumbent	- 10	0.20	**-9.61**	0.29	**-2.02**
	+ 10	-0.21	**9.38**	-0.24	1.22
CostsVariableB entrant	- 10	-0.22	**7.37**	0.00	0.19
	+ 10	0.16	**-8.58**	0.24	**-1.60**
CostsVariableS incumbent	- 10	0.17	**-14.38**	**3.05**	**-17.68**
	+ 10	-0.25	**24.38**	**-3.65**	**17.48**
CostsVariableS entrant	- 10	-0.19	**21.52**	**-3.47**	**16.65**
	+ 10	0.20	**-12.71**	**2.92**	**-16.45**
L incumbent	- 10	**1.35**	**184.84**	**-30.17**	**97.23**
	+ 10	**-11.28**	**143.59**	**5.06**	**-35.27**
L entrant	- 10	**-11.28**	**143.59**	**5.06**	**-35.27**
	+ 10	**1.35**	**184.84**	**-30.17**	**97.23**
ExpendituresMarketing incumbent	- 10	-0.05	-0.39	0.04	-0.54
	+ 10	0.01	-0.76	0.01	-0.88
ExpendituresMarketing entrant	- 10	-0.02	-3.55	0.31	-2.20
	+ 10	0.02	2.11	-0.20	1.01
MRate incumbent	- 10	-0.01	0.46	-0.01	-0.25
	+ 10	-0.03	-2.49	0.22	-1.60
MRate entrant	- 10	0.00	-1.13	0.07	-0.61
	+ 10	0.00	0.24	0.00	-0.08

I bold significant values at α = 1% in bold.

I both decreased and increased the parameters that stemmed only from assumptions (see Table 1) by 10 percent and compared the average values at the end of the simulation runs (e.g., see Thiele, Kurth, & Grimm, 2014). Table A1 displays the results. Thus, for example, a 10 percent decline in the maximum distance between acquaintances led to a 0.03 percent decline in the number of buyers for the incumbent at the end of the simulation horizon.

The findings indicate that all changes in platform membership due to parameter variation occurred in a logical direction. For example, decreasing/increasing the number of initial users for the entrant hurts/benefits the number of users of the entrant at the end of the simulation horizon, which evidences the soundness of the model structure, which I based on the existing literature on market-entry strategies for two-sided platforms.

About the Authors

Michelle D. Haurand is a Postdoctoral Researcher at the Chair of Innovation and Technology Management in the Department of Business Administration and Economics at Bielefeld University. Her research focuses on the diffusion of innovations in (digital) networks exhibiting complex interactions and has been published in outlets such as *International Journal of Innovation Management*, *Central European Journal of Operations Research*, *Proceedings of the International Conference on Information Systems*, *Proceedings of the European Conference on Information Systems*, and *Operations Research Proceedings*.