Communications of the Association for Information Systems

Accepted Manuscript

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Please cite this article as: Haurand, Michelle D.: Looking Beyond Membership: A Simulation Study of Market Entry Strategies for Two-Sided Platforms Under Competition, *Communications of the Association for Information Systems* (forthcoming), In Press.

Communications of the Association for Information Systems

Research Paper ISSN: 1529-3181

Looking Beyond Membership: A Simulation Study of Market Entry Strategies for Two-Sided Platforms Under Competition

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Abstract:

Implementing a proper market entry strategy is a necessity for successfully establishing a two-sided digital platform. Following the right strategy becomes even more crucial if a competing platform already exists in the targeted market: It is more difficult to reach critical mass because users flock to the already established, larger platform due to network effects, resulting in a potential winner-take-all situation. While previous research proposes strategies, it does not discuss how to find the right strategy. This paper introduces an agent-based market simulation for comprehensively evaluating alternative strategies under competition, that is, not only with regard to platform adoption for the entrant but also taking into account transactions, earnings, and weakening the incumbent. Through an example case parameterized with empirical data, it illustrates the application of the model. The findings suggest that a comprehensive evaluation of market entry strategies beyond just looking at membership figures is necessary because different strategies can be the most promising one with regard to platform growth of the entrant, weakening the incumbent, and for boosting the entrant's transactions and earnings.

Keywords: Two-Sided Platform, Market Entry Strategy, Competition, Agent-Based Simulation.

[Department statements, if appropriate, will be added by the editors. Teaching cases and panel reports will have a statement, which is also added by the editors.]

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This manuscript underwent [editorial/peer] review. It was received xx/xx/20xx and was with the authors for XX months for XX revisions. [firstname lastname] served as Associate Editor.] **or** The Associate Editor chose to remain anonymous.]

1 Introduction

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

A particular challenge during the initial phase of founding a new platform comes from cross-side (or indirect) network effects (i.e., user on one side of the platform having a benefit from the presence of more user on the other side of the platform), which are not in favor of gaining new members and which 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 the respective other side of the platform before joining it (dating sites constitute an illustrative example; see Evans, 2003).

Strong and positive network effects are also a reason for a winner-take-all scenario being common in platform markets, in which eventually, one large platform 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 this 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, was overtaken by Facebook (Press, 2018).

To be able to reach critical mass (i.e., acquire the number of users beyond which there are positive increasing returns; see Caillaud & Jullien, 2003; Casey & Töyli, 2012), the entrant needs a suitable market entry strategy. Existing research has discussed a variety of strategies, such as platform envelopment (Eisenmann, Parker, & Van Alstyne, 2011), opportunistic platform entry strategies (Karhu & Ritala, 2020), subsidizing one side (Armstrong, 2006; Caillaud & Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet & Tirole, 2006), focusing on a micromarket (Evans, 2003; Parker et al., 2016), harnessing the power of marquee users (Evans, 2009), and utilizing 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, Van Alstyne, & Choudary, 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 carried out a comparison of different market entry strategies with regard to their efficacy. While all of the papers on the different market entry strategies listed above describe these in detail, none of them contain empirical evaluations or simulation studies for a quantitative comparison of their effects, offering no insight specifically into how the choice of market entry strategy should be made. Those studies that do look at the early phase of establishing a two-sided platform from a quantitative perspective omit either a parameterization based on real (survey) data (Ruutu et al., 2017; Casey and Töyli, 2012), the inclusion of 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 only have one chance to establish their platform next to a competitor's. Furthermore, they have no means of evaluating ex ante whether the chosen market-entry strategy was the best. Thus, an enhanced understanding of how to establish a new platform gained through a method that does not rely on empirical evaluation is important not only for furthering research on platform strategies but also for practice.

This paper adopts an agent-based simulation (ABS; see Section 2.4) approach to close the research gaps and better understand how to establish a new two-sided digital platform if a competitor already exists. In particular, the output factors under consideration are the entrant's membership figures, number of transactions, and earnings (which should be as high as possible) as well as those same numbers for the incumbent (which should be lowered through the strategies) and how these are affected by different market entry strategies.

The concrete research questions is:

RQ: What are the effects of different market entry strategies for two-sided digital platforms on different output factors?

In the following, this paper provides the background necessary for the research carried out in this paper by describing network effects and reaching critical mass, market entry strategies, platform membership types, and the method of agent-based modeling. Next, it introduces the agent-based model and its sample application (a platform on which university students can buy and sell used textbooks), with regard to the model entities, the social network in which they are embedded, and the actions carried out by stakeholders (i.e., agents). This paper then elaborates on the parameterization of the model and the investigated market entry strategies. After presenting and examining the simulation results and their underlying causes, it concludes by outlining the contribution, followed by a discussion of the remaining shortcomings, and potential avenues for further research.

2 Background

2.1 Network Effects and Reaching Critical Mass

Once a critical mass has been reached, network effects have a positive influence on the speed of platform adoption (Arroyo-Barrigüete, Ernst, & López-Sánchez, 2010). These self-reinforcing effects, which can be direct and indirect (see below), are at least partly responsible for attracting users of two-sided platforms (Evans & Schmalensee, 2016).

An especially relevant issue when introducing a two-sided platform into the market are the cross-side (or indirect) network effects, that is, the number of users on one side of the platform influencing the number of users on the other side of the platform (Evans & Schmalensee, 2016; Katz & Shapiro, 1986). In contrast, same-side (or direct) network effects (i.e., the number of platform users affecting the number of users on the same side) were found not to have a significant effect for two-sided ecommerce platforms (Chu & Manchanda, 2016). Therefore, this study only focuses on cross-side network effects.

Cross-side network effects lead to the chicken-and-egg problem: a two-sided platform is only attractive if there is a sufficient number of users on the other side (Caillaud & Jullien, 2003; Evans & Schmalensee, 2016; Katz & Shapiro, 1986). While this always poses an obstacle in the establishment of a platform business model, it is even more crucial under competition because the incumbent has a head start and might thus reach critical mass, that is, 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, choosing a suitable market entry strategy is vital in the face of an already existing, and thus necessarily stronger, competitor.

2.2 Market Entry Strategies

At the beginning of the millennium, when discussions of strategies for overcoming the market-entry problems for two-sided platforms began to emerge, pricing strategies—primarily subsidizing strategies—were the focus of research (Armstrong, 2006; Caillaud & Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet & Tirole, 2006). Since then, the literature has discussed further strategies, such as platform envelopment (Eisenmann et al., 2011), opportunistic platform entry strategies (Karhu & Ritala, 2020), at first launching the platform in a micromarket only (Evans, 2003; Parker et al., 2016), employing marquee users (Evans, 2009), and using 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. propose a platform envelopment strategy, whereby the service of a new platform is offered through an already existing second platform, the user base of which is identical to the target group of the new platform (Eisenmann et al., 2011). However, this strategy is only viable if there already exists a platform with compatible products and if this platform can be made accessible for the entrant. This was, for example the case for Microsoft, which had the chance to give away its Windows Media player for free with its operating system Windows, thereby attacking the incumbent RealNetworks (Rochet & Tirole, 2003). Because a suitable platform for carrying out the envelopment strategy is not always available, the option of choosing the envelopment strategy is not always existent. This is why it is left out from further analyses in this paper.

If the incumbent platform is rather open to attract complementary innovation (Eisenmann, Parker, & Van Alstyne, 2009) or even focuses its business model on this as an innovation platform (as opposed to a transaction platform, which connects, for example, buyers and sellers, see Cusumano, Yoffie, & Gawer, 2020), opportunistic platform entry strategies are possible (Karhu & Ritala, 2020). These can be executed 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 ecosystem of the incumbent), all of which were, for example, employed by Amazon Fire (Karhu & Ritala, 2020). However, as for the platform envelopment strategy, opportunistic platform entry strategies depend on the existence of other suitable (open) platforms, thereby building on aspects that are out of control of the entrant. Furthermore, this paper studies transaction platforms mediating the exchange of goods between its platform members, while the three strategies just mentioned apply to innovation platforms (Cusumano et al., 2020). Therefore, opportunistic platform entry strategies are omitted from further analyses in this paper, because they are not always achievable and apply to a different platform type that is not of concern for this study.

In the following, this paper focuses on strategies that are applicable to the sample case in a straightforward manner as described below. These four strategies are (i) subsidizing one side, (ii) focusing on a micromarket, (iii) harnessing the power of marquee users, and (iv) utilizing self supply if there is more demand than supply on the platform.

One can divide platforms into a "subsidy side", which is supported monetarily 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 is subsidized depends on the relative importance of the two sides (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 is different from a loss leader strategy, in which the prices of the products offered on a platform are decreased, leading 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 size of the critical mass and to make use of existing ties to gain new users and then expands once the necessary number of users has been reached (Parker et al., 2016; Schirrmacher et al., 2017). A popular example of this strategy is Facebook, which at the beginning was only open for Harvard students.

The strategy of using marquee users to further platform adoption is built 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). Especially influential students, for example, have been successfully used as marquee users to further the growth of a mobile payment platform (Schirrmacher et al., 2017).

In the self-supply strategy, for example 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, making the intervention of the platform increasingly superfluous. Amazon, for example, first sold books itself before opening up to other sellers. An added bonus of the self-supply strategy is control over the supply offered on the platform (Parker et al., 2016).

2.3 Platform Membership

An individual can be a user of several platforms (multi-homing) or just one platform (single-homing) of a given type (Armstrong, 2006; Caillaud & Jullien, 2003; Rochet & Tirole, 2006), such as, for instance, dating platforms. The possibility of multi-homing affects the number of possible platform users and the existence of a winner-take-all scenario, with higher rates of single-homing increasing the tendency toward monopolies, in which a single two-sided platform dominates the market (Sun & Tse, 2007).

In addition to the possibility of being a user on two platforms simultaneously, an individual might also be not only a buyer but also a seller, utilizing both sides of a two-sided platform, that is, they can perform side-switching, depending on whether the structure of the platform or the platform operators allow this 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 as a seller. Just like multi-homing, the possibility of side-switching can positively influence the number of users on either side of a platform.

Switching costs can be classified into transaction costs, learning costs, and artificial costs arising through the specifics of a contract a company chooses (Klemperer, 1987). According to Lam (2017), they are especially complex to analyze for two-sided markets because there exists an interaction between them and network effects. Thus, possibly unexpected consequences may arise from an increase or decrease of switching costs (Lam, 2017).

3 Method

This paper employs an agent-based simulation to study the market entry of a two-sided digital platform under existing competition. Using an agent-based simulation (ABS) can be considered a "third way of doing science" (Axelrod, 1997, p. 3) next to induction and deduction. It takes into account the various interactions of heterogeneous actors (agents), through which the behavior of complex markets emerges (Kiesling, Günther, Stummer, & Wakolbinger, 2012; Rand & Rust, 2011). Accordingly, ABS allows for including cross-side network effects, verbal recommendations (word of mouth), peer pressure through observation of usage (normative social influence), and so on, all of which might be influential in the process of becoming a user of a two-sided digital platform. Recent works in the field of information systems recommend the agent-based modeling to study two-sided platforms (Schalowski & Barrot, 2019; Torres Pena, Breidbach, & Turpin, 2019). For all of these reasons, an ABS is a good choice of method.

This paper examines which of the investigated market entry strategies are the most effective for a fictional application case parameterized with real (survey) data not only with regard to building a user base but also in terms of weakening the already present incumbent and boosting transactions and earnings. The results of this examination provide an answer to the research question of what effects different market entry strategies have when aiming at different output factors.

Please note, however, that 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 the model is correctly adapted and parameterized for a specific case, it can help to evaluate the efficiency of alternative market entry strategies for those specific markets. Then, the decision makers can choose a strategy based on individual preferences with regard to the different factors examined (i.e., number of users, transactions, and earnings).

In Appendix A: Model Evaluation, sensitivity analyses are used to evaluate the model and show that it produces logical as well as robust results in the face of changes in the assumed parameters. This strengthens the answer to the research question. The following section describes the agent-based model in more detail.

4 Agent-Based Model

4.1 Model Entities

The model in the fictional application case has two types of agents: 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 of agents, the students i, can buy and sell used textbooks. Students can both buy and sell books and can use both platforms, that is, side switching and multi-homing are possible.

4.2 Social Network

The students are connected in a social network, which is created upon simulation initialization and then remains static. The network is partially based on spatial proximity (people at the same university are more likely to have a social connection and thus be labeled "acquaintances" in the model). 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 are not spatially limited in the model. All students are assigned a certain number of acquaintances from their vicinity and randomly allocated a number of friends, as described in the Parameterization section below.

4.3 Actions

Three types of actions influence the process of choosing to become a member of a platform: word of mouth (*WOM*), normative social influence (*SI*), and marketing (*M*). Students talk to a randomly drawn friend of theirs at rate *WOMRate*. While *WOMRate* signifies how often per period a conversation takes place on average, it must be noted 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* dependent on their own and their interlocutor's previous exposure to *WOM* (*InterlocutorWOM*). Analogously to the procedure described by Haurand and Stummer (2018a), the influence of their own previous exposure to *WOM* leads to an S-shaped curve (Figure 1), with more neutral students being more easily influenced than students whose previous experience is strongly biased in favor of or against a certain platform.

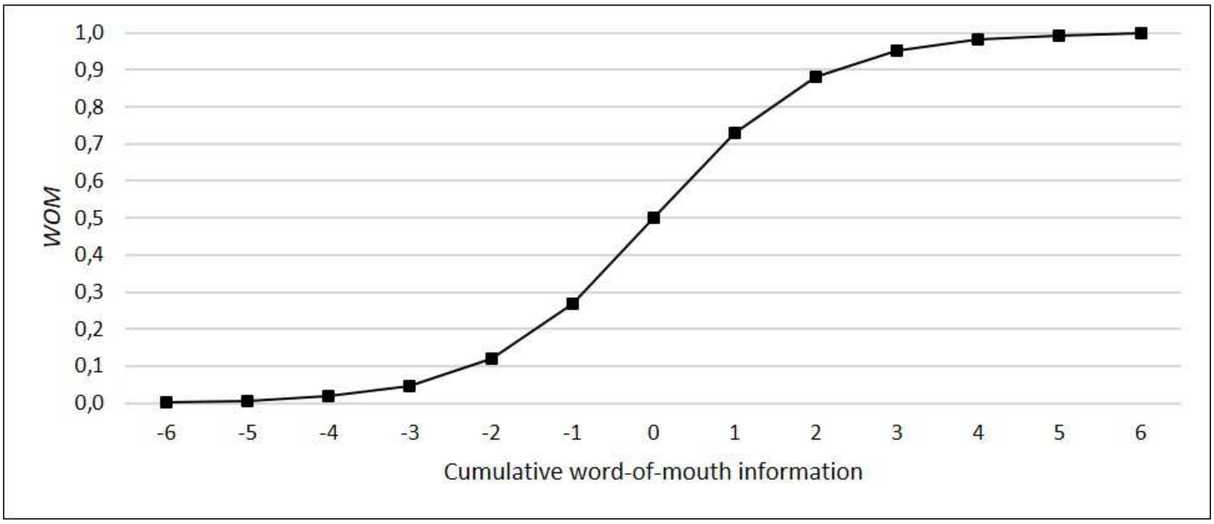

Figure 1. S-Shaped Relation between Cumulative Word-Of-Mouth Information and WOM (cf. Haurand and Stummer 2018a)

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, the influence in favor of one platform over total influence is computed, as proposed by by Delre, Jager, Bijmolt, & 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 so before), that is, the binary variable *Awareness* is set to 1.

Both platforms can engage in marketing measures. The more excess money they have after they deducted the expenditures from revenues received 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*, the influence through marketing is computed 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

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

Influenced by *WOM*, *SI*, and *M*, students decide which of the two platforms to join. The rate at which they consider joining a platform depends on the season: during the holidays, some students are 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 utilities of the two platforms. 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). It is multiplied by an agent-specific that is, individual, scaling β^{CNE} of the cross-side network effect in relation to the importance of other factors. This is an expansion of previous models (see, e.g., Casey & Töyli, 2012; Ozer & Anderson, 2015).

Second, a student's utility depends on recommendations through *WOM*, observations leading to *SI*, and exposure to marketing *M*, as described above. Third, in line with another study, the price level on the platform *L*, the buyer quality *Q*, that is, the number of books bought per buyer per year, which on the one hand depreciates over time because each student who is already an adopter of 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 is only important to sellers), and the product variety *V* (which is only important to buyers) are crucial to a platform's utility (Chu & Manchanda, 2016).

Lastly, the cost of joining a platform on the buyer and seller side (*CostsJoinB* and *CostsJoin*S) 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 are *Awareness* of the platform and *Willingness* to interact on it on the specific side under consideration (i.e., for the sample application, this would be the willingness to buy our sell a used textbook—if this is not present, i.e., the binary variable *Willingness* is set to zero instead of one, the student understandably would not consider joining any platform at all), whether the student has already adopted it, and costs for joining on the buyer or seller side that do not exceed the maximum amount they are willing to spend (i.e., *CostsJoinS* ≤ *CostsJoinSMax*).

Given these factors, the utility of a platform when joining as a seller *S* including the individual weights *β* (which comprise the scaling of the different factors to euros (€) as well as their individual importance),

$$\begin{aligned} U^{S}_{i,k,t} = {} & \beta^{CNE}_{i} \times CNE_{i,k,t} + \beta^{WOM}_{i} \times WOM_{i,k,t} + \beta^{SI}_{i} \times SI_{i,k,t} + \beta^{M}_{i} \times M_{i,k,t} + \beta^{L}_{i} \times L_{k,t} \\ & + \beta^{Q}_{i} \times Q_{k,t} - \beta^{CostsJoinS}_{i} \times CostsJoinS_{k,t} - \beta^{CostsVariableS}_{i} \times CostsVariableS_{k,t} \end{aligned} \quad (5)$$

is compared to the utility of joining the other platform as a seller, and if this is larger, the agent becomes an active seller on the platform. The number of sellers (i.e., direct network effects) does not have a significant effect for ecommerce platforms (Chu & Manchanda, 2016). It therefore does not occur in the model.

5 Sample Application

5.1 Parameterization

Parameterization is carried out 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 of 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 as well as their sources.

Each agent representing a student is parameterized with the data of one individual drawn randomly from among the participants of the survey, keeping possible covariances between the manifestations of parameters intact. Because the empirical study with which the simulation is parameterized contains only

German students and German textbooks are less frequently used in other countries, the model only covers the German market.

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	As-sump-tions
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)

The number of agents was based on the number of students in Germany studying Business Administration and Economics, which totaled 144,580 at the beginning of 2018 (Destatis, 2018), scaled 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. The number of students already belonging to a platform for used textbooks is set as the number of users of the incumbent. Whether they have joined the platform as a buyer or seller or both is based on stated desire to buy or sell books in the survey. On average, 100 of the 14,457 students are randomly assigned as initial users of the new platform (which side of the platform they choose depends on their response in the survey).

The number of acquaintances at university and countrywide friends are also taken from the survey, with the maximum number of acquaintances equaling the maximum number of acquaintances indicated among all respondents. Acquaintances are drawn from all students within a 21 km radius, which mirrors attendance at the same university.

The strength of the cross-side network effect on both sides stems from previous 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 1 percent more users (Chu & Manchanda, 2016).

The *WOMRate* and *SIRate*, that is, 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, that is, β^{WOM}, β^{SI}, and β^{M}, are again taken from the survey.

All parameterization settings regarding costs and prices for students originate from the survey. This affects the maximum amount students are willing to pay to sign up for the platform on the buyer side (*CostsJoinBMax*) or seller side (*CostsJoinSMax*) as well as 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 includes the importance of the price level β^{L} on the platform (i.e., the average price at which books are bought and sold) for buyers and sellers.

The influence of 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) on sellers and how much this is worth to them in variable costs (β^{Q}) and the influence of product variety *V* on buyers and how much this is worth to them in join costs (β^V) are also taken from the survey. The *HolidayFactor* influences the rate at which the students consider joining a platform (which is four times a month during the semester). During the holidays, which are from the beginning of February until the end of March and from the beginning of August until the end of September, students consider joining a platform on average only 28 percent as often as during the semester. This information is likewise gathered from the survey data.

For the platforms, their stock of *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 level of price (*L*), and the part of their 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) take on plausible start values.

5.2 Scenarios

In addition to the baseline scenario, four scenarios in which the entrant uses one of the market entry strategies are simulated: (i) subsidizing, (ii) micromarket, (iii) marquee users, or (iv) self supply (see Section 2). While the subsidizing, micromarket, and marquee-user strategies are artificially cut off after a one-year market entry period, the self-supply strategy is left to taper off as more sellers enter the platform, who can then handle the demand themselves. Because the incumbent is already beyond the market entry period, the market entry strategies only take place for the entrant. Theoretically, a reaction of the incumbent would be possible, though, and might be an interesting avenue of further research based on this work.

As stated above, for the present type of platform, typically, the demand side is subsidized. 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 for the demand side, there are 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, leading 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).

It is reasonable to assume that there is on average one marquee user per one of the 106 universities in Germany at which the subject of business administration and/or economics is taught. Thus, each student becomes a marquee with a probability of 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 are not yet a member of the platform on the specific side, and if the *CostsJoinB* and *CostsJoinS* do not exceed their *CostsJoinBMax* or *CostsJoinSMax* by more than €2, respectively. This signifies that those subject to the promotional efforts of a marquee user are willing to 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 there is 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 the focus of this paper is on market entry strategies, the simulation of the market runs for 84 periods (i.e., seven years) after market introduction of the entrant, stopping in the first year the entrant has 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, extensive sensitivity analyses were run.

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.

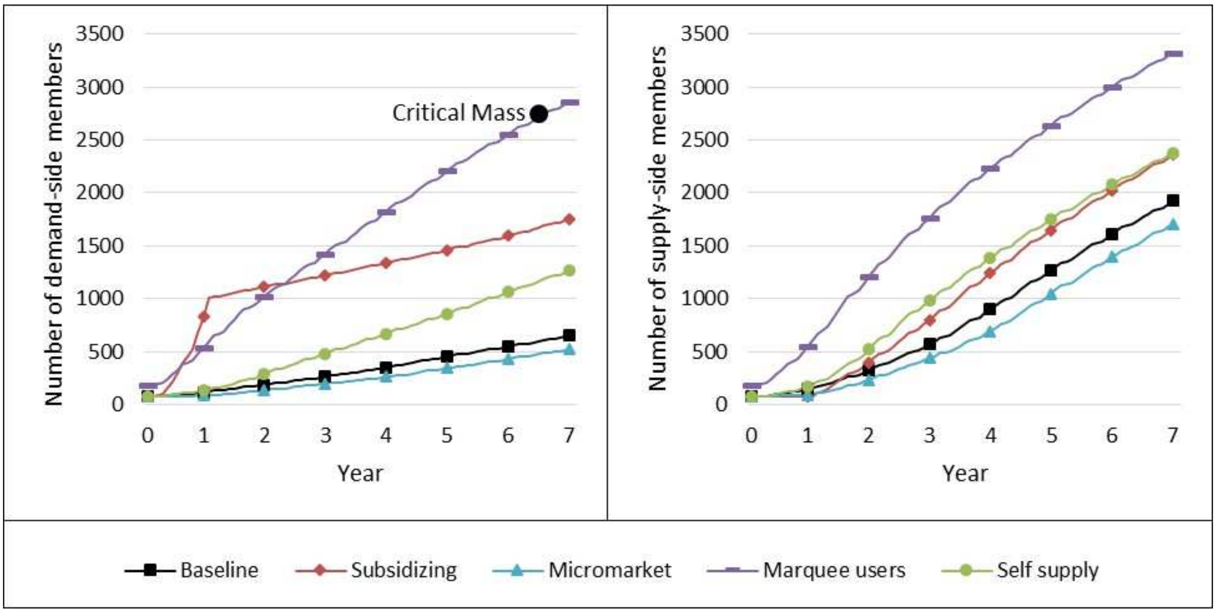

Figure 2. Demand- and Supply-Side Members of the Entrant over a Seven-Year Period Starting at Market Introduction

On both sides of the platform, the growth of the user base follows the shape of the first half of the typical S-curve of diffusion (Bass, 1969) in the *baseline* scenario.

As is indicated in Figure 2, only with the most effective strategy, *marquee users*, and only for the buyers, *critical mass*, that is, the number of adopters beyond which the network effects are positive (Arroyo-Barrigüete et al., 2010), is reached after six and a half years.

If the buyer side is *subsidized* for the first twelve months, growth is much faster on the buyer side, while the seller side stagnates, at least while subsidization lasts. Focusing on a *micromarket* for the first twelve months, however, leads to an initial reduction in growth that cannot be compensated. While the effect of the *self-supply* strategy on the supply side is marginal, the final number of demand-side members is about one quarter higher than in the *baseline* scenario.

Paying *marquee users* for the first year yields the best results. However, while the other scenarios exhibit a growth pattern that is analogous to the first half of the typical S-curve, in the *marquee user* scenario, the growth already begins to slow toward the end of the simulation horizon, beginning to mirror the second half of the S-curve leading up to saturation, as this effect tapers off. While having contact with a marquee user may directly influence a student to join the platform (see Section 5.2), this effect does not even lead to a fifth of the total membership figures in the marquee-user scenario, as can be seen in Figure 3. Note that the graphs of the total numbers corresponds to the ones of the marquee-user scenario in Figure 2.

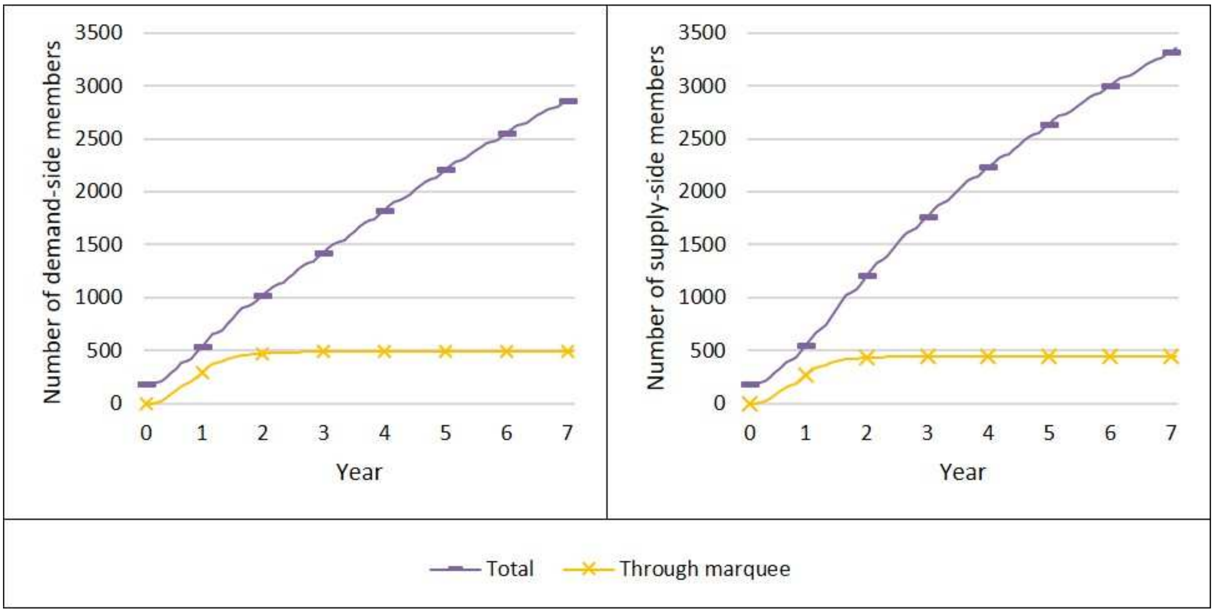

Figure 3. Demand- and Supply-Side Members of the Entrant Split into Total Members and Members Coming Directly through a Contact with a Marquee for the Marquee-User Scenario

Furthermore, this direct effect of the marquee users fades out once they are no longer paid after a year. The number of members coming through it reaches 490 for the demand side and 446 for the supply side.

Figure 4 shows the membership situation of the incumbent since market entry of the entrant. Please note that the strategies referred to in the legend are those employed by the entrant in the different scenarios while the incumbent does not change its strategy.

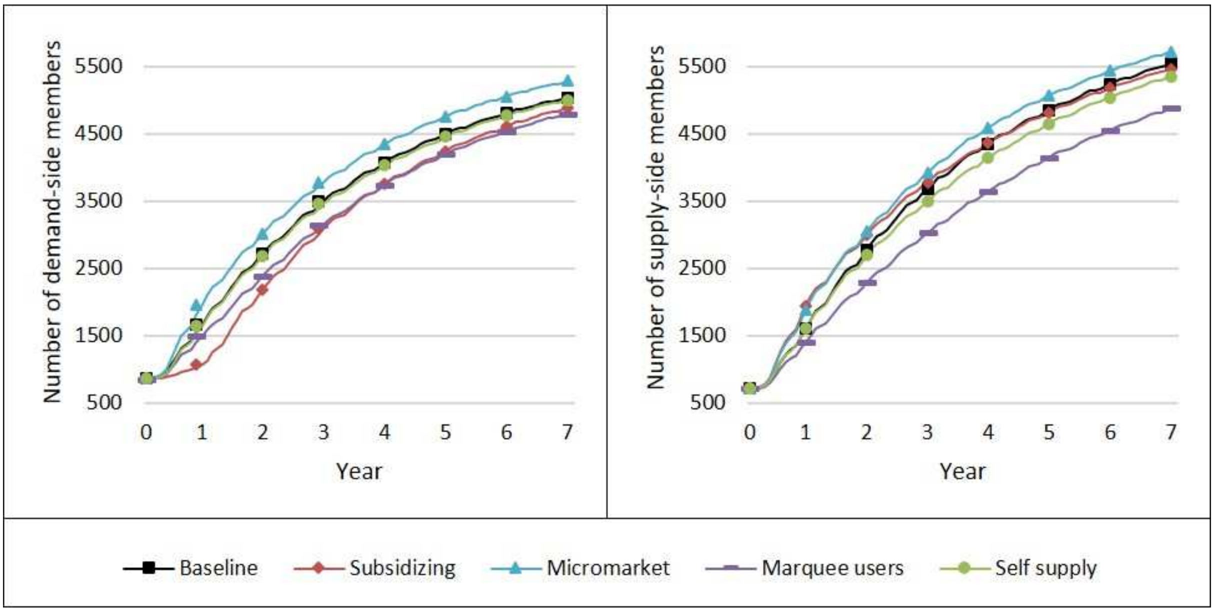

Figure 4. Demand- and Supply-Side Members of the Incumbent over a Seven-Year Period Starting at Market Introduction of the Entrant

While the already least favorable path—the *micromarket* strategy—strengthens the incumbent on both sides, only the most effective strategy with regard to members of the entrant—*marquee users*—has 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 market entry of the former. Please note that the shape of the curve, which also looks like the beginning of the S-curve for the incumbent, stems from the aggregation only. The curve for transactions per period shows the typical flattening toward the end of an S-curve for the incumbent, as is to be expected. However, the chosen form of presentation (in the form of total numbers) makes the total gains and losses in transactions more intuitive.

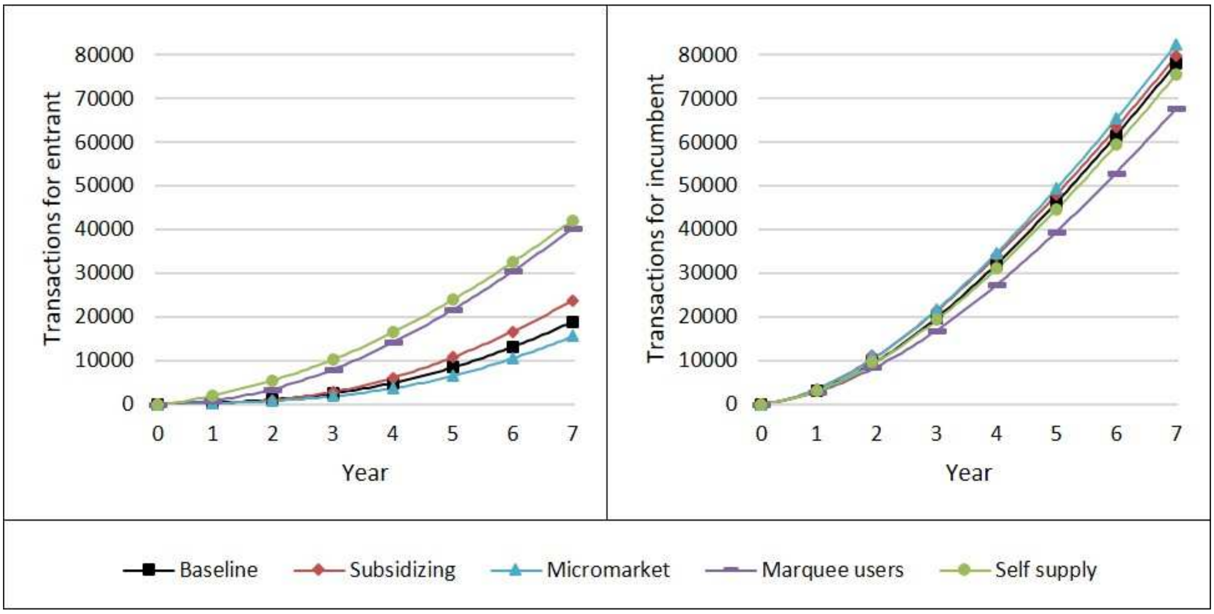

Figure 5. Total Transactions for the Entrant and the Incumbent over a Seven-Year Period Starting at Market Introduction of the Entrant

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

6.3 Earnings

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

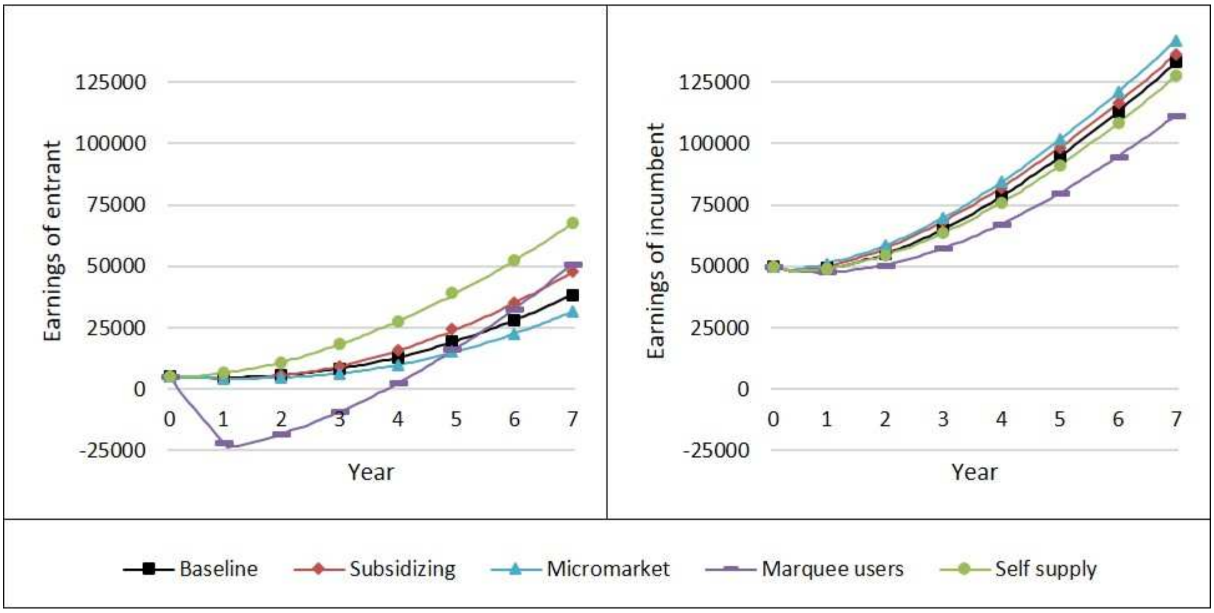

Figure 6. Earnings of the Entrant and Incumbent over a Seven-Year Period Starting at Market Introduction of the Entrant

While the *marquee-user* strategy manages to weaken the incumbent the most, it also leads to substantial losses for the entrant at first, and leads to worse results in the long run than in the *self-supply* scenario, which benefits the earnings of the entrant the most.

6.4 Sensitivity Analyses

In order to prove the soundness of the results, a simulation must be carefully evaluated. For details on the use of sensitivity analyses for this as well as their results, see Appendix A: Model Evaluation.

Apart from this, Table 2 shows the interesting results of the comparison of 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…on the…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 are significant and at times large, the number of users on both platforms are still most beneficial for 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 overtakes the marquee user scenario for the number of buyers for the entrant (2620 versus 2591). However, employing marquee users still remains the second best option by far.

7 Discussion

In the following, using the different strategies shall be discussed, also taking into account already existing literature in the field. While no quantitative comparison of market-entry strategies for two-sided digital platforms under competition parameterized with survey data yet existed before this study, the results can nonetheless be compared to partial finding from other papers.

7.1 Platform Membership

Because gaining members is crucial for establishing a two-sided platform, it is important to look at the influence of market entry strategies on the membership situation of the entrant. The generally slow growth for the entrant can be explained by the existence of the incumbent. The incumbent also plays a role in the reaching of critical mass by the entrant, which only happens for the buyer side when employing a marquee-user strategy. This study goes beyond the work of Evans & Schmalensee (2010), who already recommend expanding their analysis by including an incumbent platform. Furthermore, it confirms the difficulties of reaching critical mass as an entrant if there is already an incumbent in the platform market acting as a gatekeeper, as pointed out by Ruutu et al. (2017), who, however, did not study this issue with the help of real (survey) data.

While at first, only the buyer side profits from *subsidization* while growth of the seller side is even harmed because sellers have to pay significantly more to join, over time, however, both sides profit from this strategy. This may be attributed to the boost from cross-side network effects through the growth of the demand side. Studying the total sum of the cross-side network effect over time, it turns out that for the *subsidization* strategy, it is indeed the highest for both sides, even surpassing the cross-side network effects in the *marquee-user* scenario. The positive influence of the strategic distribution of (joining or variable) costs between both sides of the market on total market size is in line with the reasoning by Parker and Van Alstyne (2005).

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

The success of the *marquee-user* strategy may not only be attributed to the head start the marquee users provide and the subsequent cross-side network effects (as alluded to by Parker at al., 2016) but also to the sustainable positive influence of the marquee users on *WOM* and *SI*, which continue to spread through the network. Even though the marquee users are no longer paid to promote the platform after one year and the number of user recruited through efforts on the side of the marquee user is 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. Firstly, because the marquees continue using the platform, even though they are not actively recruiting for it anymore, its visibility is lastingly strengthened, which leads to a higher overall *Awareness* and those choosing the entrant platform outside of the direct marquee promotion also have a higher average *SI* value for it. While at the beginning, the average *WOM* of those joining the entrant platform is higher for the *subsidizing* strategy, the *marquee-user* strategy overtakes it in the long run (not even counting those who joined through direct efforts on part of the marquees during their actively paid promotion phase). Thus, this study expands on the research by Parker et al. (2016) by demonstrating the possibility of a self-enhancing influence also on the same side of the platform (through higher *Awareness*, *WOM*, and *SI* values), though users do not value the presence of users on the same side, as would, for example, be the case with same-side network effects on social media platforms such as Facebook (Haucap & Heimeshoff, 2014). The launch of the music-streaming platform Tidal by Jay Z may serve as a counterexample to a successful *marquee-user* strategy: Even though some of the biggest stars were advocating 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 already noted by Parker and Van Alstyne, 2005), that is, there is an absence of direct network effects for ecommerce platforms (Chu & Manchanda, 2016). However, there still exists an effect of the *self-supply* strategy on the supply side. This 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, thus foregoing 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 comes with the possibility of creating irreparable damage to the membership situation on the supply side. Thus, depending on the strength of the desire for safety (i.e., low risk of going bankrupt or losing potential users in comparison to the *baseline* scenario), profits, and growth, different strategies might already be deemed recommendable solely based on membership figures for the entrant.

However, while establishing membership growth is a good sign for the long-term existence of the entrant, the incumbent has a considerable head start and thus it is imperative to also weaken it in order for the entrant to survive in a very likely winner-take-all scenario (cf. Ruutu et al., 2017). In this regard, only the already proven to be effective *marquee-user* strategy weakens the incumbent by diminishing its user numbers. Because platform markets tend toward a winner-take-all situation (Eisenmann, et al., 2006; Shapiro et al., 1998), the *marquee-user* strategy might thus be the only viable strategy for long-term survival because it might avert that the incumbent defends its previous monopoly.

7.2 Number of Transactions

Nonetheless, high(er) membership rates alone cannot fully explain long-term platform success. Positive cross-side network effects are fueled by transactions taking place between the two sides of a platform, which is why it is important to maintain the activity on the platform (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 their number of transactions play an important role in winning the battle for the market. While the *self-supply* and *marquee-user* strategies are the most effective with regard to transactions, the former is most successful in strengthening the entrant (and was already recommended for doing so by Evans & Schmalensee, 2005), while the latter weakens the incumbent the most. Thus, this study goes beyond existing literature by looking at the effect of different strategies on transaction on both the entrant and the incumbent, finding that based on transactions alone, the results do not allow for a clear recommendation in favor of either of the *self-supply* or the *marquee-user* strategy.

7.3 Earnings

Lastly, establishing a large and active platform, that is, increasing membership as well as the number of transactions, is not a worthwhile endeavor in its own right, because ultimately, a platform must be financially successful, too.

The results show how risky the *marquee-user* strategy is, financially. On the one hand, it is the strategy that hurts the incumbent the most. Thus it at least slightly diminishes the appeal of the market 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, which can be very costly, according to Eisenmann et al., 2006), which happens under no other strategy. To the best of my knowledge, the aspect of financial risk through the *marquee-user* or other strategies is discussed nowhere in the existing literature.

7.4 Overall Evaluation of Strategies

This paper examines 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 perspective of the entrant. The *marquee-user* strategy helps the entrant to gain many members and successfully weakens the incumbent in all regards. This is fueled by a long-lasting effect on *Awareness*, *WOM*, and *SI* that goes beyond the direct recruiting efforts of the marquee users by making use of 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, it is important to remember that transactions fuel cross-side network effects more effectively than pure membership numbers and earnings are very important for further promotional measures to boost platform growth. This might make the *self-supply* strategy for market entry, which is also less financially risky, more desirable in the long term. Going beyond existing research on market-entry strategies for two-side platforms under competition, this paper shows the value of a comprehensive examination not only of membership figures, but also on transactions and earnings and how much the incumbent is weakened by quantitatively comparing several strategies that can be applied to a variety of platforms.

All of the data gathered naturally only comes from one specific application case. If there are no monetary transactions taking place between the two sides of a platform (as is the case for dating or social media platforms, for example), factors such as the price level *L* for the products bought and sold on the platform do not play a role in the utility considerations.

Factors such as the *HolidayEffect*, are in the current form only applicable to similar platforms, namely those aiming, for example, at people attending or teaching at university or school and offering a service that is mostly needed outside of the holidays. However, seasonality per se can be an issue also for wildly different platforms, from travel booking platforms like AirBnB to platforms selling decorations or clothes up to dating platforms (with dating being found to underlie seasonal effects, see Markey & Markey, 2013). Thus, even the *HolidayEffect* from the current model only needs to be parameterized correctly to fit each case and could even be set to a value that eliminates most or all seasonal effects.

Other factors, such as *WOM*, *SI*, and *M* are nearly universally applicable to all platform markets because there is an exchange about most platforms (even though this might happen 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, making *CostsJoin* and/or *CostsVariable* generally applicable. For an overview on which side of a platform usually has to pay money, see Parker & Van Alstyne (2005).

Even though the results above are not generalizable for all platform markets concerning the exact figure of platform growth, they exemplify how different measures for platform success can benefit from different market entry strategies. This is why a comprehensive approach to analyzing market entry strategies for digital two-sided platforms taking into account several factors is recommendable. It might help platform operators to succeed in the challenging task of establishing it despite the threat of a potential winner-take-all situation in favor of an incumbent that is already established in the market.

7.5 Sensitivity Analyses

A general discussion of the results of the sensitivity analyses underlining the soundness of the model structure can already be found in Appendix A: Model Evaluation. However, the effect of decreasing/increasing the price level *L* on one platform on the number of users on the two sides of both platforms (see Table A1) might appear a bit confusing at first and is thus of special interest. This is why an explanation of the underlying mechanisms shall be discussed in this section. To understand the effect of decreasing/increasing the price level *L* on one platform, 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 a low level of prices because there, they can buy the books cheaper. The case of the increased *L* for the incumbent, which leads to more sellers and fewer buyer (and the opposite for the entrant, which now has a lower level of prices), exemplifies this.

On the other hand, there is the cross-side network effect, which 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 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 negative effect through having to pay a higher price for the goods when being a member of the entrant is overcompensated by the cross-side network effect coming from the dramatic increase in the number of sellers (plus 97.23 percent). As was already mentioned before, a 1 percent increase in sellers leads to a 1.53 percent increase in buyers (Chu & Manchanda, 2016).

The results of the sensitivity analyses presented in Section 6.4 indicate that even though there are some large and maybe initially complicated to understand effects, as is the case for changing the price level *L* for the incumbent and the entrant, these are not only logical but also do not affect the overall conclusions pertaining to beneficial strategies. The marquee user strategy remains the most favorable, except for in the one instance when it becomes the second best to the subsidy strategy, outperforming all other strategies, however, by a large margin. The reason for this could be that on the seller side of the entrant, which diminishes by about 35 to 40 percent for each scenario, the absolute decrease in users is the largest for the marquee user scenario because it started out with the highest number of users. Through the cross-side network effects, the buyers are also the most negatively affected in the marquee user scenario. However, while the difference to the other three scenarios is large, the two best strategies only differ by (2620 - 2591 =) 29 users on average and the usual order is kept for all other cases. Furthermore, a lower or higher level of prices on one platform is not very likely to remain over years in a duopoly market without any compensation, for example through the quality of the goods. Thus, the overall results are robust concerning uncertainties in the assumed input parameters.

8 Conclusion

Establishing a two-sided platform is in itself already a difficult endeavor but it becomes even more difficult when there already is an established competitor profiting from its advanced position in the race to gain critical mass and thus harness positive self-reinforcing effects on user numbers. This is why the thorough comparison of potential market entry strategies does not only further the theoretical literature on two-sided platforms, as it fills a research gap, but is also important for practice. This paper is concerned with alternative strategies to be pursued by a novel two-sided digital platform that is about to enter a market with an already established competitor. To this end, it describes the creation of an agent-based simulation and its use in an illustrative application case for a comprehensive evaluation of several market-entry strategies (i.e., taking into account platform membership, transactions, and earnings for both the entrant and the incumbent).

In the illustrative application case, employing marquee users is the most promising market entry strategy to boost network effects and reach critical mass and to weaken an already established competitor. This can be attributed to generating lasting positive effects on *Awareness*, *WOM*, and *SI* in particularly well-connected parts of the social network with the effect of the marquee-user strategy going beyond the influence of direct promotions through the marquees during the first year after platform introduction of the entrant. The marquee-user strategy is also the only strategy that helps to reach critical mass in less than seven years. However, the self-supply strategy performs best with regard to transactions and earnings of the entrant. Taking into account the importance of transactions for long-term success and the high risk connected with founding a platform, that is, the high possibility of deciding to leave the market before the break-even point is reached around the fourth year, it might even be the more recommendable strategy. However, this must not be the case for all platform markets (see below), as different circumstances might favor different strategies.

Despite this, the exemplary application demonstrates the importance of a comprehensive examination of more factors than just platform membership numbers of the entrant in order to make a well-informed decision on market entry strategies because different strategies turned out to be the most effective in boosting different output parameters. It thereby answers the research question of how different market entry strategies for two-sided digital platforms in the face of competition affect different output factors. The creation and evaluation of the simulation model also constitute a first step in helping platform operators of entrants to find a suitable market entry strategy under competition, who, of course, need to modify the model to fit their own markets in order to gain specific insights.

This study therefore 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 created for this paper to study this. 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. Beyond that, they might look into the prospective further research outlined below to expand the understanding of establishing two-sided platforms.

Specific implications for platform operators on which strategy they should employ have certain limitations: The strategic recommendations can only be generalized for other platform markets that are very similar to the application case, that is, 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 described by Schirrmacher et al. (2017). Furthermore, in reality, the incumbent platform might be so technologically superior that none of the strategies are 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 pertaining to which strategy should be used to reach certain goals can only be generalized to markets that do not exhibit a large technological gap between the rivalling platforms.

As already mentioned, establishing a novel platform means accepting a high risk and possibly substantial costs. In this case, Gonzalez (2009) recommends using the simulation for gaining insights and for evaluation first and then waiting for the usage of the model in practice. Should platform operators employ the model as a decision support tool, it would be a worthwhile step to analyze combinations of strategies over time because such combinations might be more effective than implementing just a single strategy. Beyond this, the model is currently reflecting only one specific case, namely 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, perhaps leading to some generalizable recommendations. On a similar note, integrating real case studies for demonstrating the validity of the model based on real data is another promising direction for further research. In this vein, it might be of particular interest to 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 they are no longer employed (analogously to the breakdown in Figure 3). Finally, the investigation of potential counterstrategies employed by the incumbent might be an interesting avenue for further research

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Appendix A: Model Evaluation

Next to assessing the face validity of the simulation, Gonzalez (2009) recommends sensitivity analysis 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 volatility of the results for changes to the specific scenario, that is, I thoroughly examined 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…in percental change compared to baseline			
		Buyers		Sellers	
		Incumbent	Entrant	Incumbent	Entrant
Maximum distance betw. 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
Significant values at α = 1 % are in bold.					

I both decreased and increased the parameters stemming only from assumptions (see Table 1) by 10 percent and compared the average values at the end of the simulation runs (see, e.g., Thiele, Kurth, & Grimm, 2014). Table A1 displays the results with significant values at $\alpha = 1$ % written in bold. Thus, for example, a 10 percent decline in the maximum distance between acquaintances leads 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, if there are significant changes in platform membership due to this, these are 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. This underlines the soundness of the model structure, which is based on the existing literature on market-entry strategies for two-sided platforms.

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