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The Long-term Diffusion of Digital Platforms — An Agent-based Model

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Short Paper

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Abstract

In recent years, many industries have experienced the rise of digital platforms (e.g., eBay, Uber, or Takeaway.com). A common characteristic of these concepts is that they focus on fragmented markets populated by many small firms, which often show a high fluctuation. However, established diffusion models based on Bass (1969) do not account for fluctuation in the market potential, although the exit of adopters and the entry of new firms could change the diffusion curve significantly. Thus, we propose an extension of the Bass Model to account for the exit and entry of (potential) adopters and empirically test this framework in a real-world setting. Using two decades of adopter data of leading digital platforms and information on the complete market potential, we employ agent-based models to analyze the effects of fluctuation on the platform diffusion. Initial results confirm the existence of high fluctuation and indicate relevant impacts on the diffusion curve.

Keywords: Platform economy, agent-based modeling, diffusion models, market fluctuation

Introduction

Agile, innovative platforms accelerate the digitalization process and transform the economy from traditional industries to digital ecosystems. Seven out of the world's top 10 companies by market capitalization are platform ecosystems – Alibaba, Alphabet, Amazon, Apple, Facebook, Microsoft and Tencent (Financial Times 2015, updated 2019). Likewise, most of the so-called unicorn startup companies (valued > $1 bn) are indeed platform companies (Evans and Gawer 2016). According to projections by McKinsey & Company (2018), online platforms will account for 30 percent of global sales by 2025. Thus, digital platform businesses often disrupt traditional business models of established offline providers: Online sales cannibalize the stationary trade, so that profits shift to new market players that emerged outside the focal industry. On the other hand, platforms can lower transaction costs, attract a new audience, and introduce completely novel features into the value chain that add value for the customer.

Due to network effects and the inherent mechanisms of online media, platform economies often generate winner-takes-it-all settings with only one or a few companies dominating the market. Therefore, an understanding of how platforms spread among users from a start-up's perspective – right from the beginning – is essential. The most commonly used approach to track such diffusion processes is the Bass model (1969). While first being applied to the initial adoption of consumer durables on the category level, the model has been also used for sales predictions on the brand level and in new technology forecasting (Bass et al. 2001). The Bass model has not only paved the way for decades of academic studies on innovation diffusion but also has found wide attention in industry practice (Rogers 2003). However, as the Bass model has been validated and calibrated on sales of consumer durables decades before the rise of the World Wide Web, we put forward the question whether and how the model still holds in a world shaped by the unrelenting pace of digital innovations.

A particular aspect of digital platforms is that they focus on fragmented markets often populated by small (sometimes very small) and medium-sized firms and industries that traditionally show a high fluctuation among the market participants. For example, first-generation platforms like eBay or Amazon Marketplace are populated by many small retailers, second-generation platforms such as Airbnb, Uber, or Takeaway.com mostly aim for individual hosts, self-driving chauffeurs, or single-location restaurants. All of these industries share a high fluctuation, as a significant share of the (potential) adopters gives up their business and leaves the market, while an often similarly large number of new entrants fill their place. Statistics provide evidence that typical populations of business customers consist of up to 10 % new entrants. At the other side of the spectrum there are up to 10 % of the firms drop out of the market every year (Federal Statistical Office Germany (Destatis) 2019; US Census Bureau Center for Economic Studies 2018). Yet, in the fundamental Bass model, the market potential remains constant over time and such fluctuations are not captured. However, even if the sum of actual and potential adopters – on balance – remained constant, the observed high fluctuation leads to a different composition of the population. A population that differs in maturity and exposure to advertising and to adopting neighbors. We hypothesize that such fluctuation in the market potential affects the speed and pattern of adoption through three different mechanisms: a) if firms which have already adopted the innovative platform drop out of the market, the internal influence (e.g., through word-of-mouth, observation, or competition concern) is reduced; b) if firms which have (not yet) adopted the platform drop out of the market, the external influence is diminished (as the previous exposure of these firms to marketing activities is lost); c) new entrants into the market start with a significantly lower exposure to internal and external influences when compared to long-time market participants and, thus, require a higher initial investment to convert.

To account for the market fluctuations faced by digital platforms, we propose a modified version of the Bass model to empirically test our assumptions. Hence, we follow the call by Asadullah et al. (2018), who suggest broadening the methodological basis for studies on such digital platforms, especially by using simulations, that are still underrepresented in this area. To this end, we investigate the diffusion of two first-generation online platforms in the same market over a course of nearly two decades until this innovation has captured (nearly) the complete market potential. The firms that are subject to our study have established online platforms for the sale of (mostly used) cars online in a major European market.

To compare our new approach to the fundamental Bass model, we employ a wide range of large-scale agent-based models to simulate diffusion processes with different levels of fluctuations (inflow/outflow) and different spatio-temporal patterns of fluctuations.

Literature

Our study relates to different streams of previous literature: technology adoption, diffusion models, and social influence. The adoption of electronic commerce channels in a business-to-consumer (B2C) context has been analyzed by Pavlou and Fygenson (2006). The study makes use of the theory of planned behavior as a model to understand the online information seeking and purchasing behavior by individuals. The authors found significant antecedents as trust, perceived usefulness, and perceived ease of use, to name a few. However, in the B2B context of this study additional or even different mechanisms driving the adoption behavior are likely to be at work. As we are focusing on business customers and not individuals signing up for the service, the process we are interested in belongs to the topic of organizational adoption.

The peer influence factors affecting the adoption behavior of firms can be ascribed to the forces of competition (competitive pressure to adopt) and legitimization (due to general acceptance of the technology, e.g. by distant non-competitors) (Rangaswamy et al. 2018). The importance of social networks in technology adoption, especially degree centrality and network clustering, has been established in the literature (Peng and Dey 2013).

In the diffusion literature, dynamic population models were introduced in the late 1970s to capture population growth trends (Mahajan et al. 1979; Mahajan and Peterson 1978). The dynamic market potential yielded a better fit to the actual diffusion curve than models assuming a constant ceiling of adopters ($.92 \leq r^2 \leq .99$). The analysis is based on population figures at the aggregate level and cannot account for flows on the individual level. Previous literature included the arrival of new customers through marketing measures, such as pricing and advertising (Dodson and Muller 1978; Horsky 1990; Horsky and Simon 1983), or electrification of households as a condition to use durables that require electricity (Kamakura and Balasubramanian 1988). Similar infrastructure related market potential expansions would be the increasing coverage of internet access (such as, ISDN, DSL, VDSL) or mobile telecommunication (such as, 3G or 5G). However, to our knowledge, no model extension exists so far that incorporates market fluctuations, i.e., in particular the constant drop-out of market participants.

Extending the Bass Model with a Dynamic Market Potential

Two mechanisms of influence act in the Bass model: one that is independent of others and one that is depending on the number of prior adopters. The influence that disregards the amount of previous adopters is represented by the coefficient of innovation p. The reason for adoption in this regard is external to the social system and can occur due to advertising, mere chance, or an intrinsic interest in the product utility or novelties in general. The coefficient of imitation q stands for social learning, word-of-mouth (WOM), and network effects. The fundamental Bass model can be formalized as

$$y_t = \left(p + q\frac{Q_{t-1}}{M}\right)(M - Q_{t-1}) \tag{1}$$

where

y_t: new adopters at time t

p: coefficient of innovation

q: coefficient of imitation

M: market potential

Q: cumulative adopters

M-Q: penetration gap

Q/M: market penetration

t: time

In this model, the market potential is assumed to be static. Every converted adopter adds to the internal influence, thus, constantly increasing the pressure to adopt, while the penetration gap closes as the cumulative adopters from previous periods are excluded from the remaining market potential. As repurchases are not accounted for in the fundamental Bass model, the number of adopters equals the number of adoptions. New adopters have to be gained from the penetration gap, and as the gap gets smaller, the diffusion process slows down in the later stages (S-shape of the diffusion curve).

However, the fundamental Bass model does not incorporate market fluctuations that are substantial in many real-life markets and which would impact particularly the internal influence. To account for the effects of market fluctuations, we extend the fundamental Bass model as follows:

$$y_t^* = \left(p + q\frac{Q_{t-1}^*}{M_{t-1}^*}\right)\left(M_0 - Q_{t-1} - \sum_t Exit_{t-1} + \sum_t Entry_{t-1}\right) \tag{2}$$

$$Q_t^* = Q_t - \sum_t Exit_{Adopter;t} \tag{3}$$

$$M_t^* = M_0 + \sum_t Entry_t - \sum_t \left(Exit_{Nonadopter;\,t} + Exit_{Adopter;t}\right) \tag{4}$$

Entry: number of new firms entering the market

Exit: number of firms exiting the market

We adjust the remaining penetration gap for each period by subtracting all market exits of active firms in the previous periods and adding all new market entrants. While the penetration gap (M-Q), from which new adopters can be drawn, is monotonously falling in the fundamental Bass model (1), our model is able to capture growth trends as well as a decimation of the remaining market potential (2). The market exit of an adopter is a phenomenon that would have been overlooked had we applied traditional diffusion models. With any such exit, the competitive pressure in the local area decreases. Moreover, the "death" of a firm implies that it ceases to be a source for word-of-mouth (WOM). Yet, such peer influence associated with WOM is the driving force of the diffusion process, once an initial group of innovators and early adopters has adopted (Rogers 2003). The factor peer influence becomes more important when the penetration proceeds; this is reflected in the product of q and the corrected penetration rate (Q^*/M^*). As a consequence, any diffusion process facing a market with significant fluctuation becomes less efficient. Converted adopters drop out instead of spreading word-of-mouth, promising leads with high exposure to the innovation may exit, while new firms which require a complete restart of the conversion efforts enter. Due to the constant inflow of new entrants, the penetration gap closes more slowly and the pressure to adopt builds up more slowly. Therefore, in such a setting, we would expect a) a longer time to take-off, b) a flatter and more prolonged shape of the S-curve, and c) a longer time period to complete the diffusion process, i.e., to completely convert to complete market potential.

Data and Technology

Actual Adopters

Our study includes data on adoption for two major European ecommerce firms who operate online platforms for the sale of new and used cars, motorcycles and commercial vehicles. Each platform offers hosting, search capabilities, and a dealer rating system for their business customers (professional car dealers). The platform's purpose is lead generation: Customers can contact the car dealer via the platform and arrange test drives and the purchase of the vehicle. Note that the platforms do not act as intermediaries in the actual transactions. Both firms have established a specific platform for each country where they are active. These platforms are operated under different domain names (.de/.it/.co.uk/etc.) and sometimes even under a different brand name (due to M&A activities). The reason for keeping these platforms separate on the national level is that B2C car trading is nearly exclusively limited to national markets – due to language barriers and, particularly, to legal complications of cross-border transactions for cars even within the EU. As Germany is by far the largest market for used cars in Europe and both leading platforms have started in Germany, we have chosen this market for our empirical study.

Available Adopter Data		
	Company A	Company B
Address, geocode	✓	✓
Telephone numbers	✓	✓
Number of page visits on dealer's platform page	$\bar{X}_1 = 78{,}904$ $s_1 = 151{,}580$	×
Adoption date	Year, month, day	Year, month, day
Car brands	✓	✓
Dealer rating on 5 star scale	$\bar{X}_{2,A} = 4.49$ $s_{2,A} = 0.62$	$\bar{X}_{2,B} = 4.36$ $s_{2,B} = 0.64$
Number of reviews per dealer	$\bar{X}_{3,A} = 12.2$ $s_{3,A} = 24.0$	$\bar{X}_{3,B} = 8.9$ $s_{3,B} = 23.3$
Registered car dealers (2017)	38,496	25,870

Table 1. Description of Adopter Population (German Market)

Company A is the first mover in the market of listing vehicles on an online marketplace and started its operations in Germany in late 1997. Currently, more than 1.5 million cars are listed on the platform. For this company, all car dealer registrations from the launch of the platform in 1997 until the end of 2017 are recorded. This enables us to describe a diffusion process retrospectively for a time span of almost two decades. Company B followed as a competitor in mid-1999 and lists currently more than 1 million cars online. Adoption data are available for all business customers until 2017. Both companies charge a basic fee plus a variable price component depending on the number of listed cars for business clients. On average, the second mover charges 40% lower prices than the first mover. However, the number of page visits for company A is 86 % higher than that for company B (IVW 2019). Key metrics of both focal online platforms are described in Table 1.

Potential Adopters

For the purpose of our study, knowledge of the complete market potential is required, in our case all professional car dealers in Germany. The population of potential adopters indicates the market potential for every period (stock) and serves to derive the number of market entries and exits (flows). To that end, data from nationwide digital directories (1998 – 2017) were collected and validated across different providers. All entries are curated by regional publishing houses and assigned to at least one industry. Geographical data are accurate to the street number level. Car dealers were identified both through the pre-classifications of the data providers as well as additional queries of the data bases using search terms often found in the firm names of car dealers (such as, car brands, or identifiers, such as "Autohaus", "Fahrzeughandel", "Gebrauchtwagenhandel"). Geo-location data as well as a two-stage manual check were used to validate the data and to exclude redundancies. Our final data set consists of all active car dealerships in the German market between 1998 and 2017 (i.e., more than 50,000 dealers in any year).

Determining Fluctuation

In the first step of our empirical study, we analyze the scope of fluctuation in our focal market. For this purpose, we compare the listed car dealerships for each available year of data. In addition, we crawled all official publications from the local company registers on exiting and entering firms. Again, these publicly available data were filtered in a multi-step process. For example, we match the data with the *Python Record Linkage Toolkit* that supports to arrange possible matching pairs into blocks and allows for exact (e.g., zip code) and approximate (e.g., Levenshtein distance of names) variable comparisons (Christen 2012). Firm entries for all years are stored in a database, and a deduplication process reveals the first and the last occurrence for each firm. Furthermore, an analysis of the official trade register reveals which firms entered and left the market. Here, we observe a ten-year period from the beginning of the electronic trade register in 2007 until 2017.

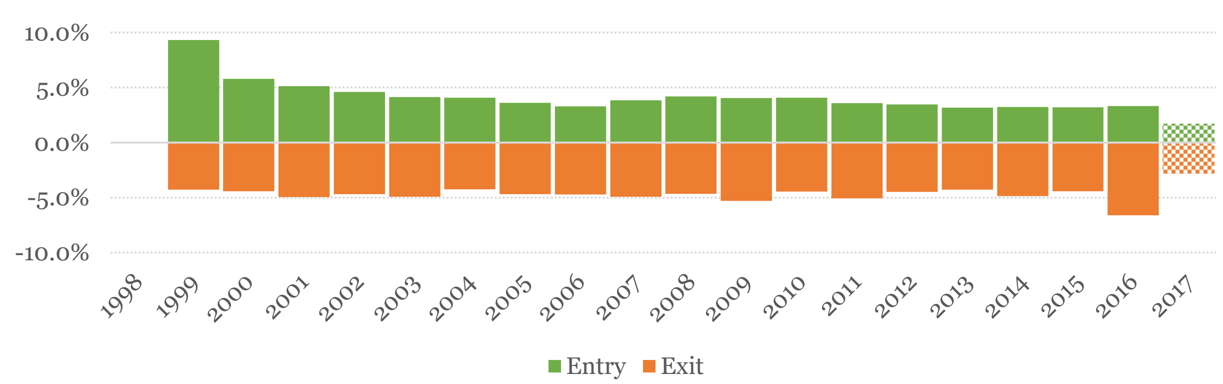


Figure 1. Share of New Entrants and Exiting Car Dealerships per Year 1998 – 2017

Interestingly, the absolute number of active car dealers did not change drastically across the observation period. Starting with 57,088 dealers in 1998, the market increased to a peak of 61,206 dealerships in 2001 and continuously shrinked afterwards to 51,364 in the beginning of 2017. The average number of car dealers is at 57,475 very close to the starting value, i.e., it seems as if the Bass model assumption of a constant market potential would be confirmed, at least on the aggregate level.

However, a deeper analysis on the micro-level reveals a totally different picture: Figure 1 describes the fluctuation among the total population of professional car dealerships in Germany. On average, we observe a yearly inflow of new entrants equivalent to 4.2 % of the active car dealers while 4.7 % of the active car dealers leave the market each year. Thus, while the absolute numbers remain rather stable, the actual composition of the market participants constantly changes.

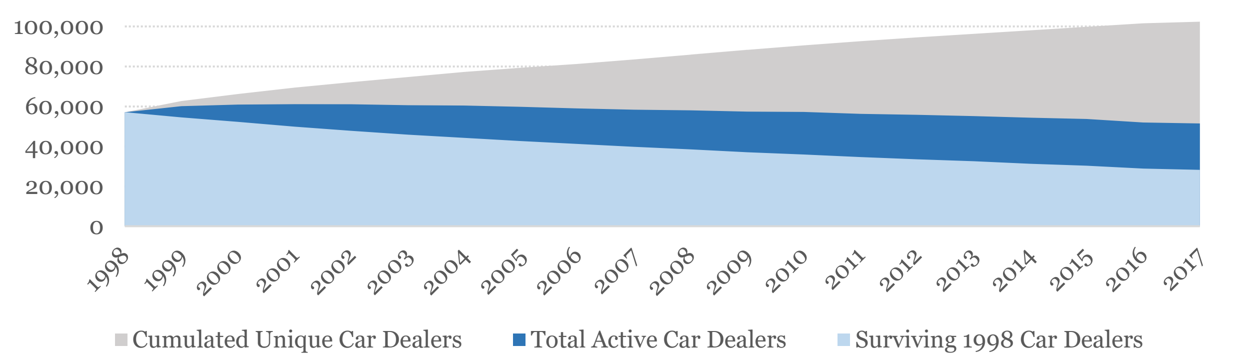


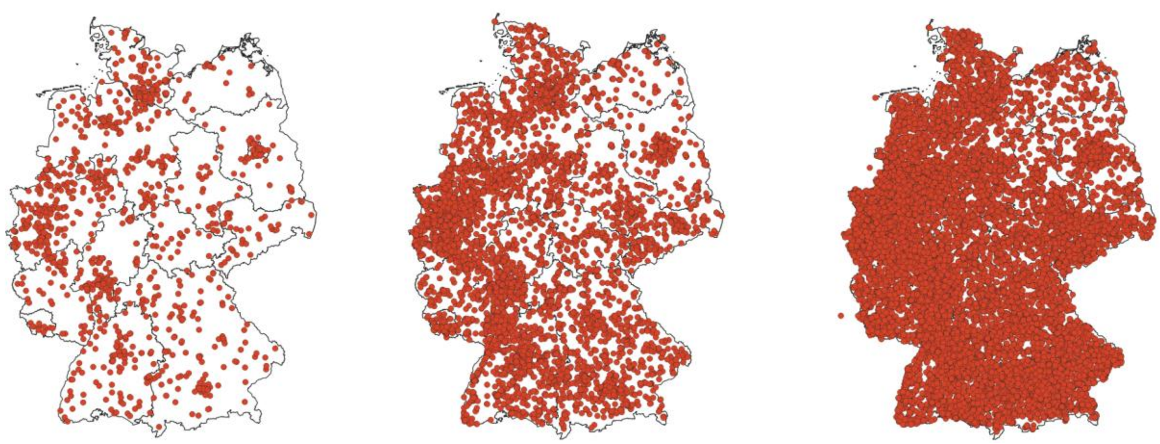
Figure 2. Active Car Dealers vs. Cumulated Unique Car Dealers per Year 1998 – 2017

This fact is visualized in Figure 2: Out of the original active car dealers in 1998, when the novel digital car trading platform was introduced to the wider German market, more than 20% ceased to exist within the first five years. In 2017, at the end of the diffusion process, less than 50% of the original car dealers were still active. At the same time, the constant inflow and outflow of new car dealers results in a totally different setting for the innovating firm: During the course of the diffusion process, they were faced with a cumulated number of more than 102,000 unique car dealers, i.e., twice the number of the active market potential in 2017. Obviously, it is a drastically different challenge for an innovator to propagate a new platform model among a moving target of more than 100,000 car dealers, when compared to a stable market potential of about 50,000 potential adopters, as it would be modelled in the traditional Bass framework. While the Bass model assumes that the penetration gap constantly closes over time and the effect of the internal influence increases in parallel, the market reality is that 51,000 firms (among them many adopters or advanced leads close to conversion) exit, and the innovator has to re-start its efforts with more than 45,000 new entrants, which have not been exposed to contagion effects or prior marketing efforts. These inefficiencies lead to a significantly slower diffusion process as compared to a Bass model prediction. To determine the degree of this effect, we need to employ a micro-level model, as any approach on the aggregate level would fail to properly account for the effect of market fluctuations.

A Whole Market in an Agent-based Model

In the second step of our analysis, we establish an agent-based model capable of capturing diffusion processes at the individual level with variable characteristics. Our aim is to identify the specific effect of varying levels of market fluctuations on the platform diffusion and to describe the deviations from a standard Bass model specification. For this purpose, we use our real-world data on the market for used cars in Germany. Hence, we incorporate approximately 60,000 agents based on the original locations and characteristics of the real-world dealerships and also account for the annual fluctuations in our model.

The agent-based model intends to cover the whole car dealer market in Germany on the adopter side. On the innovator side, we include the first mover in Germany and its main competitor. Based on the number of adopters, both platforms have today a nearly complete coverage (>97 %) of all professional car dealers registered in Germany. The code for the diffusion process in the agent-based model is adapted from Netlogo's *simple viral marketing* model (Rand and Wilensky 2012; Stonedahl et al. 2010). The transition rule for agents to change their status from non-adopter to adopter is in accordance with the Bass model: There is a small probability for the agents to adopt due to external influence and a larger probability to adopt the innovation contingent on the number of adopters in the neighborhood of the focal agent that have already adopted. As the model for our study consists of a vast number of agents that interact with each other and as the environment is based on geographical data, we opt for GAMA (Taillandier et al. 2018) as our modeling platform. GAMA, being also open source, can handle large models comprising up to millions of agents and is specialized on operating with GIS data. The idea is to enrich the Bass model with social networks that are based on the geographic distance between any two agents. Spatial proximity increases the probability for social interaction, observation and learning between local car dealers (Rangaswamy et al. 2018). Due to zoning laws, car dealerships are often geographically clustered, for example along major roads (so called "Automeile" or auto malls). These are often located in industrial areas with a limited number of catering outlets. Indeed, many restaurants in the neighborhood of auto malls are hotspots for social interactions and technical discussions. In many cities, local dealers form an advertising association, a joint committee to coordinate events (for example special sales weeks, street festivals, or car fairs) and to discuss business matters (Rangaswamy et al. 2018). Consequently, after-sales-service surveys, in which new platform adopters were called one month after signing up for the service, confirm such social contagion effects: asked how they became aware of the platform and why they signed up for the service, 54.3% of the adopting car dealers named referrals from other car dealers, customers, or suppliers as key sources (Rangaswamy et al. 2018). Thus, the adoption process is significantly driven by word-of-mouth, facilitated by the (professional) social network of a car dealer.



3a. Diffusion 1999 **3b. Diffusion 2001** **3c. Diffusion 2017**

Figure 3. Observed Spatial Diffusion (First Mover)

A network that is based merely on geographic distance is highly clustered, and the characteristic path length is high and information needs to be passed through local subsets of nodes. The speed of information dissemination is inversely correlated with the characteristic path length, which would lead to a slower diffusion process, and some distant nodes, especially in sparsely populated areas in Eastern Germany, would never be affected by social contagion at all. Following the more realistic idea of small world networks (Watts and Strogatz 1998), we include short cuts between distant agents, either randomly, or based on observable criteria, such as the affiliation with a certain car brand. These distant links decrease the characteristic path length while preserving a large amount of clustering. In the model, we instantiate all car dealers at their actual geographical location and, depending on the actual entry respectively exit date, agents are activated or deactivated at the according time step.

In a first stage, we model the empirical diffusion process to assess the occurrence of peer effects and adopter clusters. Figure 3 visually confirms one of the key factors to choose agent-based models for the simulation of the diffusion processes in our study. When plotting the actual adoption data (originally in much finer resolutions), we clearly observe a distinct pattern of adopter clusters, very similar to the phenomenon described by Garber et al. (2004). These clusters can be confirmed also analytically with divergence measures (here, we use the cross-entropy), while controlling for aspects such as population density or distribution of car dealerships. The existence of clusters in the adoption process signals the influence of contagion effects (word-of-mouth) among nearby car dealers. Thus, it is critical for the individual adoption process where a car dealer is located and whether a drop-out or market-entry occurs in proximity. This can only be captured in individual-level simulations and not in aggregate models.

Next Steps

In the next stage of the agent-based model development, we will implement scenarios of different degrees of fluctuation in the adopter population, simulate the resulting diffusion processes, and evaluate the effects of ongoing changes in the market population. We argue that market entry and exit does not only alter the population quantitatively, but also qualitatively with regard to the mixture of young and old firms. Depending on the firm age, different degrees of exposure to marketing measures, e.g., advertising stock, will hold in the population. To refine the modeling of the adoption process, we will include an awareness stage that separates the spread of information via observation or direct communication from the actual adoption of the innovation.

We aim to quantify the effects of fluctuation in terms of change in adoption probabilities (as used as a dependent variable by Bollinger and Gillingham 2012) or time between starting up a car dealership until the adoption event. A core focus will be if and to what extend fluctuations within the potential market alter the diffusion curve of a digital platform, thereby testing the hypotheses that higher levels of fluctuation lead to a longer time to take-off, a flatter and more prolonged shape of the S-curve, and a longer time period to complete the diffusion process.

Furthermore, we aim to have a closer look at local sub-clusters of adopters, auto malls, to study the mechanisms of social influence on a meso-level as an intermediate between individual adoptions (micro-level) and economy-wide diffusion (macro-level). Finally, we strive to quantify the value of a “lost” adopter due to market exit.

These findings will be relevant for existing and future online platforms with a focus on markets with significant levels of fluctuation (for example, the current generation of innovative payment services), and may also provide insights for businesses marketing to customers that enter a cohort only for a limited time, associated likewise with constant inflows and outflows (e.g., students).

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