Modelling the Rise and Fall of Two-sided Markets

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ABSTRACT

Two-sided markets disrupted our economies, reshaping markets as diverse as tourism (airbnb), mobility (Uber) and food deliveries (UberEats). New market leaders arose leveraging on platform-based business model, questioning well-established paradigms. The underlying processes behind their growth are non-trivial, inherently microscopic, and leverage on complex human interactions. Platforms need to reach critical mass of both supply and demand to trigger the so-called cross-sided network effects.

To this end, platforms adopt a variety of strategies to first create the market, then expand it and finally successfully compete with others. Such a complex social system with many non-linear interactions and learning processes calls for a dedicated modelling approach. State-of-the-art methods well estimate the macroscopic equilibrium conditions, but struggle to reproduce the complex growth patterns and individual human behaviour behind.

To bridge this gap, we propose the microscopic S-shaped learning model where agents build their perception on the new service with time, affected by both endogenous (service quality) and exogenous (marketing and word-of-mouth) factors cumulated from experiences. We illustrate it with the case of two-sided mobility platform (Uber), where the platform applies a series of marketing actions leading to rise and then fall on the market where 200 drivers serve 2000 travellers on the complex urban network of Amsterdam.

Our model is the first to reproduce not only behaviourally sound, but also empirically observed growth trajectories, it remains sensitive to a variety of marketing strategies, allows reproducing the competition between platforms and is designed to be integrated with machine learning algorithms to identify the optimal market entry strategy.

KEYWORDS

Two-sided Platforms, Adaptive Multiagent Systems, Complex Social Systems, Learning Processes, Agent-Based Simulation

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1 INTRODUCTION

Two-sided platforms have reached significant market shares on a variety of markets (like eBay for online shopping, Netflix for streaming, Uber for transportation or airbnb for housing) in a short time through the two-sided platform business model. The reason underlying such a tremendous potential to grow in two-sided markets is the power of network. Two-sided markets are classically defined as the markets in which one or several platforms enable interactions between end-users and aim to onboard both supply and demand sides by implementing appropriate charges [27]. In essence, platforms associated with these markets rely on critical mass, i.e., the minimum market size necessary to trigger cross-side network effects and induce growth [3, 11]. This, in turn, forms a positive feedback loop, where the value created for one side of a network increases by adding users to another side [8]. These dynamics are taking place within the complex social system where suppliers and clients make individual, subjectively rational decisions to join the platform - here we aim to explicitly reproduce their long-term decision process in an agent-based model.

Platforms implement various market entry strategies in the early adaptation phase to pursue a desired growth pattern, typically comprised of different stages from launch to maturity [18, 22]. Albeit proven potential to grow rapidly, platforms face serious challenges to reach and sustain market shares sufficient to become profitable. First, platforms have no direct control on the supply and demand since both are decentralized. For instance, travellers on the mobility market can shift to alternative travel modes (public transport or competing platform) and drivers can opt for another occupation, benefiting from the flexibility of gig economy [15]. Second, the three involved parties have inherently conflicting interests: i) platforms aim to maximize their market shares and revenue, ii) clients wants high quality at low price, and iii) suppliers intend to earn enough to cover their costs, as well as to be at least on par with the so-called reservation wage, i.e., the minimum wage that workers require to join the labour market [33].

2 RELATED WORK

Platform revolution attracted a wide body of research addressing concerns on their viability, leading to a series of agent based models of two-sided markets [16, 17, 25, 32]. Yet only few studies focus explicitly on the system evolution, growth mechanisms and underlying process of learning the expected platform utility by both the clients and suppliers. Two-sided platforms are, by nature, complex and highly dynamic social systems, driven by non-linear interactions of involved parties to evolve [27]. Classic studies on the elements of two-sided markets and their interactions (with potential to affect system evolution) including qualitative, analytical, mathematical, or simulation methods were either equilibrium-based

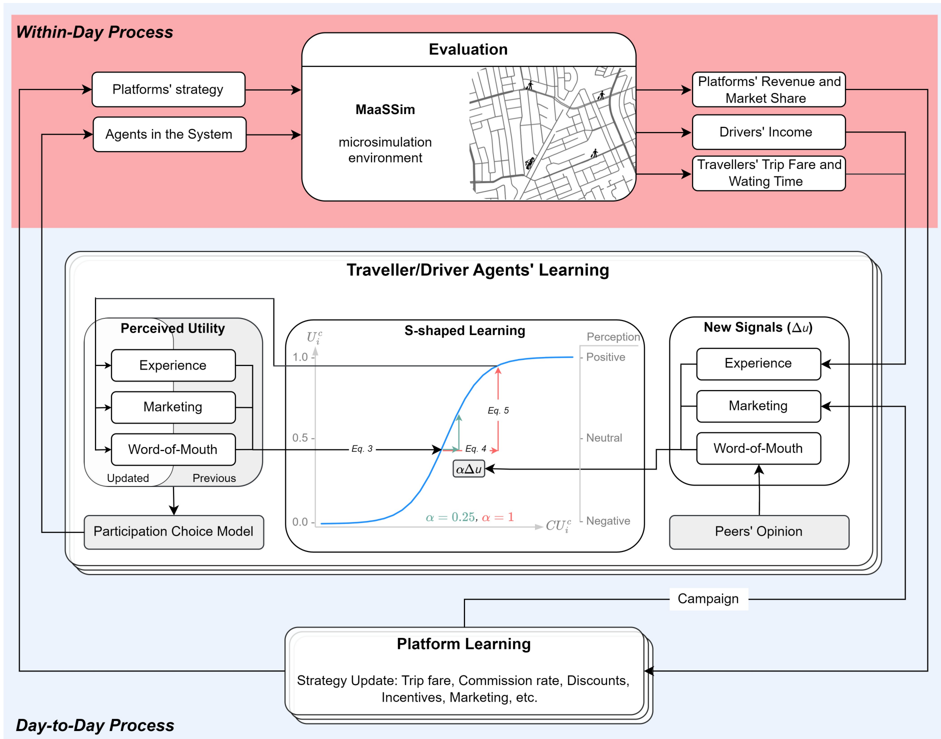

Figure 1: Methodology at glance: We use a microscopic simulator of two-sided mobility platform environment (top) and extend it with day-to-day S-shaped learning model (bottom) from [21]. In within-day simulations, drivers serve the trip requests made by travellers on a detailed urban road network. Accumulated within-day experiences together with other exogenous utility components (such as marketing and word-of-mouth) determine agent's (traveller/driver) choice on the next day. To reproduce how the experience is accumulated, we propose the S-shaped learning curves to update agent's perceived utility based on new signals. Perceived utility adjustment through signal rely on signal strength ΔU, learning sensitivity parameter α and, notably, the learning process depends also on the position on the S-shaped curve.The learning updates are low for both highly negative and positive utilities and high when the opinion is neutral.

or assumed fixed demand and/or supply [14, 20, 26, 36]. Which is insufficient to provide a complete image of the system evolution. Sun et al., [29] forecast ride-sourcing platforms' growth on the series of key performance indicators and the influence of various internal and external factors. They argue that ride-sourcing growth pattern is S-shaped (see fig. 2), which is inline with the empirical patterns . Yet, the fundamental element of growth mechanism - network effect is given as an input to the model rather than being generated from natural interaction of agents. This is because of macroscopic nature of their framework, which is not capable to reproduce the system interactions at individual level. This is, to some extent, addressed by Øverby et al., [24] who extended the compartmental model to multi-sided platforms. Agent-based modelling, with individual agents, is better suited for complex social interactions behind the platform growth [5, 28].

Djavadian and Chow [10] take an ABM approach to model the day-to-day dynamics of the urban mobility system. The proposed framework is adaptive at individual level due to learning process of agents based on past experiences, and system evolution depends on the actual interactions of travellers and drivers. Yet, the growth pattern produced by their framework is unalike empirical patterns (see fig. 2). First, because of the optimistic initial utility perceived by the agents for ride-sourcing platform, second, due to applying the model developed by Bogers at al., [4], which produces concave patterns, not inline with the platform growth patterns. In a similar study, de Ruijter et al., [9] focus on evolution in ride-sourcing labour supply with a day-to-day ABM to evaluate the effect of supply market properties and pricing strategies. They reach to reasonable equilibria, yet via unrealistic trajectories, with a very high participation at the beginning, damped to the convergence (see fig. 2). Similar agent-based models are available for housing (where airbnb market oscillations around stability are reproduced for Oslo [32] and Amsterdam [25]), food-deliveries ([17] where UberEats restaurants optimize their locations in mean-field space and customers do not opt out), or eBay ([16] where winner takes-it-all mechanism is explicitly simulated). Yet, up to our knowledge, the agents' participation choice model is typically simplified, and the behaviourally sound learning process of individual agents is not addressed explicitly. Making state-of-the-art models unsuitable for evaluating and optimizing platform policies.

Contribution: Understanding how platforms grow and what is their optimal growth pattern is of paramount importance not only to the platforms themselves, but also to the public, interested in predicting and controlling their potentially disruptive impact

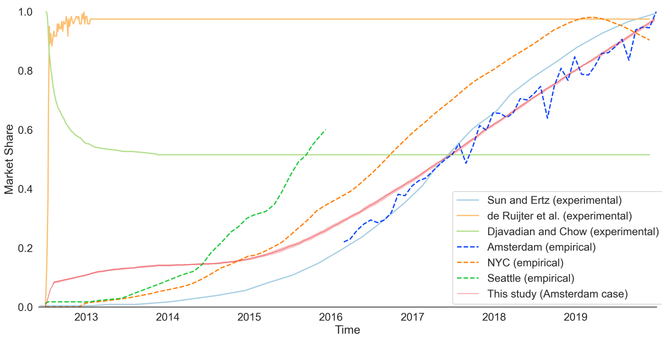

Figure 2: This study's research gap and contribution: Mobility platform growth trajectories empirically observed in NYC, Seattle and Amsterdam (dashed-lines), despite differences follow the similar patterns: start slowly in the early phase, reach the critical mass and steadily grow fuelled with cross-sided network effects. State-of-the-art microscopic models fail to reproduce those empirical patterns, consistent with theory of platform economies. Existing models either reach stability very fast without inducing network effects (Djavadian and Chow [10], green), or start with high market-share asymptotically damped to the equilibrium (de Ruijter et al. [9] - orange). Sun and Ertz [29] - blue, obtain a reasonable pattern with the macroscopic setting. Here, we propose the microscopic model to realistically reproduce platform growth patterns (red).

on the economy. Identifying the optimal strategy is far from trivial, as it requires realistic representation of the environment and its dynamics, which are missing in the literature. Consequently, strategies adopted by the platforms are likely to be suboptimal, as there is no framework where optimal strategies or adaptive policies could be learnt. We propose such a framework, capable to evaluate any predefined strategy and integrable with state-of-the-art deep learning methods.

Novelty lies in the realistic representation of adaptive learning of individual agents, capturing their sequential learning process while exposed to various signals (experience, word of mouth, marketing) and sensitive to the policies of the platform and its competitors. We propose a microscopic co-evolutionary model featured by the S-shaped learning curves to represent the day-to-day learning process of autonomous agents. Here, instead of memory-based learning [4], which lead to unrealistic growth patterns, we follow Murre [21] and propose a more adequate formulation, with the so-called S-shaped learning curve. Unlike machine learning approaches, which aim to optimize the actions, our model provides agents with a realistic behaviour adjustment. It stabilizes, and at the same time, remains sensitive to the system changes, naturally balancing between the memory (exploitation) and adaptation (exploration). In the proposed framework, agents are successively exposed to experiences of their own, their peers, and marketing image to gradually build their perceived utility of the platform (see fig. 1 for overview). This, thanks to reproducing the crucial platform-specific phenomena, gives rise to the desired emergent growth for the system at the aggregated level.

We propose a generic model applicable to the variety of platform models, which explicitly reproduces non-deterministic and suboptimal learning process of agents, who decide to join the platform and collectively create the desired critical mass, triggering non-linear cross-sided network effects and value creation effects as observed empirically (see fig. 2). With reproducible examples and open-source repository, this framework can evaluate any alternative platform entry strategy or learn the optimal one, when integrated within a reinforcement learning framework.

3 METHOD

In the proposed framework (synthesized on fig. 1), agents gradually learn the actual platform utility from multiple (endogenous and exogenous) signals. While the experience (income for the suppliers and performance/quality for clients) collected from the environment is the main component, the platform's marketing and peer's word-of-mouth are also included in the agent's decision making process. We argue that these three components are sufficient to cover the essence of agents' decision to participate in the two-sided mobility market. Here, we detail the method for the case of urban mobility, and discuss its applicability to other two-sided markets.

The learnt expectations of utility components are summed with respective weights and used to evaluate the participation probability of each agent in the new run of environment simulation. Here, we implement the binary logit choice model where each traveller and driver make daily choices between platform and alternative options. Remarkably, each agent (traveller/driver) undergoes a unique evolutionary path of the perceived platform utility. Thanks to the proposed S-shaped learning, unlike in the previous approaches, an agent with consecutive positive experiences/exposures rapidly adopts the platform, becomes loyal, and positively influence the other agents. Similarly, an unsatisfied agent hardly returns to the platform again, spreading the negative perception to her peers. Such framework explicitly reproduces both the positive and negative cross-sided network effects. Like in reality, signals differing from expectations may shift attitude at any moment - a critical modelling feature for the platform strategy evaluation. The open-source Python framework is available on the public repository [13] for reproducible experiments.

Environment simulator (MaaSSim): We apply the proposed model in the case of urban mobility by extending the MaaSSim [19] agent-based simulator for two-sided mobility platforms. MaaSSim simulates, on the dense urban road network, the detailed behaviour and interactions of two kind of agents: (i) travellers, requesting to travel from their origin to destination at a given time, and (ii) drivers supplying their travel needs by offering them rides. The spatiotemporal interactions between the two types of agents are mediated by the platform, linking demand to supply through the matching algorithm (we use the "first-dispatch" protocol for matching, which simply pairs the traveller with the nearest idle driver [34]). To model market growth, we propose daily participation rules for individual agents as detailed below. MaaSSim can be replaced with any microscopic simulator, as long as it outputs the individual performance for each supply and demand agent as well as the platform and its performance is sensitive to the platform strategy and other agents daily participation decisions. This allows to apply the proposed model to markets as diverse as streaming, house-sourcing or food deliveries by simply changing the simulation environment.

Agents' participation model: First, agents need to become aware of the new service by marketing (mainly) or word-of-mouth (sporadically), before they include the platform alternative in their choice-sets (represented with a binary variable $N_{i,t}$ in Eq. 2) and curiously start exploring it. Each notified traveller (client) r in our model on a day t selects among two alternatives from a binary choice set $C_r = \{rs, pt\}$ of public transport (pt) and a new ride-sourcing mode of transport offered by the mobility platform (rs). While, public transport utility is fixed (with constant cost based on the actual access/egress, waiting times, transfers, etc.), the expected ride-sourcing platform utility will vary along with the agents' learning process. Similarly, each notified driver (supplier) d selects between working for the platform rs or elsewhere rw from choice set $C_d = \{rs, rw\}$. Everyday driver may opt for the so-called reservation wage rw (expected wage on the market), instead of serving the platform.

For both sides' agents (denoted by i), we compose the platform utility with three components: experienced utility (U^E), word of mouth utility (U^{WOM}) and marketing utility (U^M):

$$U_{i,t} = \beta_i^E U_{i,t-1}^E + \beta_i^M U_{i,t-1}^M + \beta_i^{WOM} U_{i,t-1}^{WOM} + ASC + \epsilon_i \quad (1)$$

Experienced utility is endogenous and comes directly from the environment (simulation): drivers experience the actual income ($I_{d,t}$), travellers experience travel time, waiting time and trip fare. The marketing is exogenous and can express both positive (e.g., media campaign) and negative image (e.g., PR scandals) of the platform. Word-of-mouth represents the perceived utility of peer agents and is diffused between agents over underlying social network. When agents interact on a specific day, they exchange their perceived utilities $U_{j,t}^{rs}$ and diffuse opinions.

In Eq.1, the relative weights of respective utility components ensure that $\beta_i^E, \beta_i^E, \beta_i^{WOM} > 0$ and $\beta_i^E + \beta_i^E + \beta_i^{WOM} = 1$ while they can be user-specific. The alternative-specific constant (ASC) captures the effect of unobserved factors on the perceived utility of alternatives and ϵ_i is the error term. In such form, the utility is consistent with the discrete choice theory and can be applied e.g., in the logit model, to obtain participation probability $P_{i,t}^a$:

$$P_{i,t}^a = N_{i,t} \left(\exp\left(\mu U_{i,t}^a\right) / \left(\sum_{a' \in C_i} \exp\left(\mu U_{i,t}^{a'}\right)\right)\right. \quad (2)$$

S-shaped learning and adaptation: The key element of the proposed framework lies in the following adjustment mechanism, which allows us to realistically represent the agents' dynamics specific to the platform growth. Here, we adhere to Murre [21] and propose a behaviourally sound formulation of the so-called S-shaped learning curve in the context of two-sided platforms, illustrated in fig. 1. The adjustment process can be seen as moving along the S-shaped curve, where the incoming positive signal (from environment, marketing or peers) pushes perception to the right tail of the curve, while the negative signal to the lower tail. Notably, learning can go both directions at every state based on the relative signal value. The learning is slow at the tails when perceptions are strong and fast in the middle when perception is neutral. We assume all agents have the same and fixed learning rate α and we make a conservative assumption that agents start with negative perceptions of the new service: ($U_{t=0} = 0$ for all components), which may be easily extended to heterogeneous behaviours. With the proposed formulas, each agent may have a unique learning trajectory: first due to different alternatives (each traveller has unique public transport alternative quality) and second due to individual history of experienced and received signals.

We formalize the S-shaped adjustment model with a sigmoid function, and update respective perceived utility component ($U_{i,t}^c$, $c \in \{E,\ WOM,\ M\}$) day-to-day as follows (the procedure can be followed from fig. 1). First, we retrieve the cumulative utility on the previous day $CU_{i,t-1}$ by applying the inverse sigmoid function (Eq. 3) on the yesterday's utility $U_{i,t-1}$. Then, we update the cumulative utility CU based on the utility difference ΔU at the current day t (Eq. 4), with sensitivity parameter α determining the speed of learning. Eventually, we use the sigmoid function to obtain the updated utility for the day t (Eq. 5). Here, the learning depends on the previous position on the S-shaped curve.

$$CU_{i,t-1}^c = \ln(1/U_{i,t-1}^c - 1) \quad (3)$$

$$CU_{i,t}^c = CU_{i,t-1}^c + \alpha \cdot \Delta U_{i,t}^c \quad (4)$$

$$U_{i,t}^C = 1/(1 + \exp(CU_{i,t}^c)) \quad (5)$$

The above formulation is generic to represent various kinds of learning from new exogenous and endogenous signals. The specific formulas for three components of utility adjusted in our urban-mobility case are following: Experienced cumulative utility of driver d on day t is updated through the relative difference between her reservation wage (RW_d) and the most recently experienced income: $\Delta U_{d,t}^{E,rs} = (RW_d - I_{d,t})/RW_d$. Driver's income on day t ($I_{d,t}$) is the sum of trip fares of the served rides minus the platform commission fee (we assume flat commission rate) and operational costs. Similarly, traveller r adjusts its experienced cumulative utility on day t through the relative difference between the cost of the ride-sourcing platform (rs) and the public transport alternative (pt): $\Delta U_{r,t}^{E,rs} = (C_r^{pt} - C_{r,t})/C_r^{pt}$. The perceived cost of using the platform for a traveller $C_{r,t}$ is composed of the trip fare, travel time and waiting time where trip fare is controlled by the platform - can be subsidised, and the waiting time depends on the supply-demand balance in the system, i.e. indirectly on the number of drivers in the system, consistently with travel behaviour literature [35]. Note that the utilities of both reservation wage and public transport are fixed, while the experiences of the platform service will vary substantially day-to-day. Thanks to the S-shaped learning model, such fluctuations cumulate in the perceptions of the agents and are smoothed for a stable, yet sensitive behaviour.

For the sake of simplicity, here the marketing is an abstract unitless utility, spread uniformly among all the agents (target clients) and additively accumulated upon exposure in time over the period of the marketing campaign: $\Delta U_{i,t}^{M,rs} = p_i^M(1 - U_{i,t}^M)$. We assume that the marketing produces a positive effect on each exposure, upper bounded with 1. The exposure probability depends on the campaign intensity (p_i^M), controlled by the platform via the budget. Such naive formulation can be extended to cover negative or non-linear, non-additive models. Notably, marketing signal does not depend on the system performance but only its perception (which may be fake, like most of the marketing actions).

For the word-of-mouth, we assume random pairwise interactions among the agents, who share their perceived utility with each other bi-directionally. Analogically to the marketing, WOM intensity ($p_{i,j}^{WOM}$) determines the likelihood of the agent i to share his/her opinion with the agent j on the day t. Here, we used synthetic uniform social network for the sake of simplicity, which can be replaced with the actual topology and proper social diffusion models. Upon contact, agents exchange views and cumulative utility of word-of-mouth, with the signal strength proportional to difference between their perceive utilities: $\Delta U_{i,t}^{WOM,rs} = p_{i,j}^{WOM}(U_{i,t}^{WOM} - U_{j,t})$. Note that while agents diffuse opinions along the full simulation period, the marketing campaign runs only on predetermined days based on the platform strategy.

Evaluating platform's policy: Platforms aim to maximize long-term revenues, which typically requires a planning horizon longer than just immediate profits. They invest capital to grow, hoping for future returns, which may come only after the market is generated and said platform reaches critical mass at both the supply and demand and becomes profitable [7]. Notably, non-linear network effects may induce a harsh competition in this winner-takes-all market [12]. To win, platforms implement diverse market entry strategies, formalized for our case of urban-mobility as the sequence of actions: $A_t = \{f_t, c_t, d_t, m_t\}$, a tuple of trip fare f_t, commission rate c_t, discount d_t and marketing budget m_t for each day t of its operations.

Formally, our contribution can be seen as a function $\mathcal{R}$ which returns the platform reward (revenue) from the environment $\mathcal{E}$ as the consequence of exploiting some policy π, i.e. taking a sequence of actions A_t on each day of the simulated episode. In the experiments, we evaluate a fixed, pre-defined policy, i.e. assume the static environment on which we apply a sequence of predefined actions, hoping to maximise the cumulative reward.

Yet, our framework allows for more complex settings with an adaptive policy, which takes optimal actions in a given state of the environment ($\pi_t^*(s|a)$). The state s may be the actual market share, possibly enhanced with the utilities of individual agents (potential clients) to better tailor actions for the actual position on the growth trajectory. In the multi-platform scenario, the state may include actions of competitors (historical or predicted), which yields an intriguing game-theoretical setting. Both settings require applying some algorithms to learn an efficient policy, presumably with deep reinforcement learning (which is out of scope of this study, here we introduce the sound framework, an inevitable prerequisite to evaluate and train such policies). Which can be easily integrated in the classical RL training framework in the future, within the *Algorithm 1*.

Algorithm 1: `Platform policy` - pseudo-code

```
MarketEntryStrategy
    inputs :
        Q                 # agents' of supply and demand
        β's, params, G           # behavioural & control
    parameters, environment setting
    output:
        R       # rewards (profit and /or market size)
    Env.init(params, Q, G)         # initialise environment
    for each day t in D do
        for each platform do
            make action A_t
        end
                    # policy evaluation or exploitation
        Env.simulate(S_t)             # simulate single day
        for each agent do
                                         # agents' learning
            update U_t^E, U_t^WOM, U_t^M,utility components (Eq. 3-5)
            update total utility U_{i,t} (Eq. 1)
            update participation probability P_{i,t} (Eq. 2)
        end
        store single day results R_d
    end
Result: R, KPI
```

4 RESULTS

Experimental setting: We run an Uber experiment in Amsterdam, the Netherlands, where 2000 travellers and 200 drivers adapt over 400 days to the time-varying platform strategy. Each traveller every day chooses between public transport and ride-sourcing platform service to travel from her origin to destination. We sample these 2000 trips from the real-world Albatross tripset [1]. For each trip request, we query for the public transport alternative and obtain the detailed trip utility with OpenTripPlanner. Each of 200 drivers choose between working as a platform driver and alternative occupations with reservation wage of 10.63[€/hour] (based on the minimum daily wage in the Netherlands [23]). We simulate a four-hour period (8:00-12:00) of each day, during which we reproduce ride-sourcing service operations: travellers request rides, and the platform matches them with the vehicles. The speed of ride-sourcing vehicle is set to the flat 36 [km/h]. We assume the trip requests do not change day-to-day (travellers have fixed origins, destinations and departure times) and drivers start their shifts from the same positions every day (drawn randomly at day one). A single day of the simulation is simulated in around 30s and a complete 400 day experiment took 3h on the standard laptop.

In our experiment, for all the agents we fixed the corresponding utility components' weight to $\beta_i^E = 0.8$ for the weight of experience, $\beta_i^{WOM} = 0.18$ for word-of-mouth and $\beta_i^M = 0.02$ for marketing. This is in-line with the findings on the actual platform-growth trajectories, which are fuelled first with marketing, secondly with WOM, yet mainly with a positive experience in a cross-side network effects at the later stages [6]. We arbitrarily assume the probability of being exposed to the marketing information during a single day of the campaign $p_i^M = 10\%$. Similarly, each agent has 10% probability to exchange views with some other agent every day $p_{i,j}^{WOM}$. We do this by simply sampling 10% of agents every day and randomly assigning them in pairs among which they exchange views (which can be enhanced with the more adequate social diffusion models and social network topologies). The patience threshold of travellers to be matched is set to 10 minutes, after which they leave unsatisfied (if no driver is available to supply their demand). Such unfulfilled requests yield extra disutility for the platform (lost revenues) and for the travellers (strongly negative experience in $\Delta U_{i,t}^E$). The trip fare

Table 1: The predetermined platform strategy for the 400 days of operations used in the experiments.

Day t	Stage number	Stage name	Marketing [€/agent/day]	Comm. c_t	Disc. d_t
0 - 25	I	Kick-off	–	10%	–
25 - 50	II	Discount	–	10%	40%
50 - 100	III	Launch	5	10%	40%
100- 200	IV	Growth	–	10%	40%
200 - 300	V	Maturity	–	10%	–
300 - 400	VI	Greed	–	50%	–

is 1.2 [€/km] with a minimum fare of 2 [€] (based on the Uber price estimator for Amsterdam [31]). The revenue of drivers working for the platform equals the fares of all trips served, minus the platform commission fee (varying). The drivers operational costs (0.25 [€/km] for fuel, depreciation costs, etc. [30]) are deducted from revenues to obtain the profit.

After each day of the simulation, we record the actual experience of each agent, from which we update their expectations for future days. We store both individual performance of agents and system-wide indicators. We report the results first by showing individual learning trajectories of the selected agents at fig. 3, followed with a system-wide supply and demand evolutions at fig. 4. On fig. 5 we report the system-wide performance for both travellers and drivers. Finally, on fig. 6 we show sensitivity of resulting growth patterns to various strategies and stability across replications.

Platform strategy: We hand-craft a reasonable and complex market entry strategy with six consecutive stages for the 400 days of simulation (summarized in Table 1). Platform starts with 10% commission at the kick-off stage, which is followed by a 40% discount on trip fares in the discount stage. The discounting scheme is a specific one, at the platform's expense not the suppliers: the platform reduces the trip fare only for the travellers and the drivers receive the full fare minus commission. Moreover, we offer the discount only for those travellers who are not yet loyal to the platform (i.e. their probability to use platform is below 50%). Initially, agents are not notified about the new mode of transport and the market shares are null (fig. 4). This changes in the *launch stage*, the 50-day marketing campaign (costing 5[€/recipient/day]) triggers the user acquisition by notifying them ($N_{r,t}$ in Eq. 2 becomes one) and creating a positive image of the platform. After 50 days of marketing, when the majority of agents are notified, platform reaches a desired fast growth pace and quits the campaign in the *growth stage*. When sufficient market size is reached, the platform quits discounting on the day 200 and enters the *maturity stage* when it stabilizes profits, market shares and agent behaviour. For illustrative purposes, in the last 100 days of the proposed scenario, the platform opts for a greedy move via increasing the commission rate to 50 to maximize the profit during the *greed stage*, which has catastrophic consequences (such reverse trend would not be reproduced in state-of-the-art methods).

Resulting agents' adaptive behaviour and system performance: While the strategies outlined in Table 1 are implemented

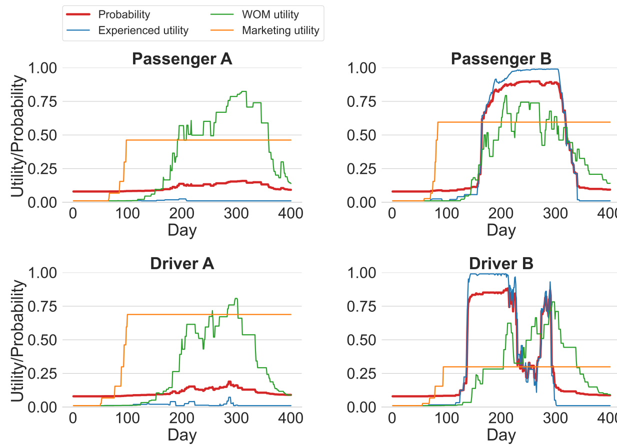

Figure 3: Temporal evolution of choice probability (red) and three components of utility for four sampled agents with various temporal trajectories.

globally on the market, each agent follows a distinct, unique evolution path depending on her exposition to the marketing, word of mouth received from her peers and, most notably, her own experiences gained while participating in the platform. On fig. 3 we illustrate participation probability of selected four agents and the 400-day evolution of their perceived utility components. Passenger A is initially exposed to positive marketing (orange) and later to positive WOM (green) effects. Despite positive peers' WOM opinion, she does not cumulate positive experiences (blue), and her probability of using the platform remains low. Passenger B, instead, accumulates considerable positive experiences with the platform, and her participation probability stabilizes around 0.9 before it drops to 0.1 at the greed stage. For driver A, despite the positive WOM and marketing, the actual experience is negative and probabilities remain low. Driver B has an early positive experiences with using the platform and her participation probabilities are high, despite lower WOM and marketing effects. Nonetheless, she opts out from the system already in its maturity stage, due to series of bad experiences. Consequently, we obtain a rich and diverse population of agents with unique learning trajectories.

Growth trajectory: The most important result is how these individual experiences and trajectories of the agents' evolution translate into the rise and fall of the platform, fig. 4 provides system-wide averages. For the six stages of market entry strategy, it illustrates the three components of perceived utility (system-wide means) and the resulting market share. Notably, the demand and supply are naturally balancing each other, thanks to our model structure, they produce very similar trends. Agents with no experience remain inattentive to the new mode until getting notified (stage III). By adding the ride-sourcing to their mode choice set, they curiously start to explore it and build their experience (due to long tails of the logit choice model, the probability remains positive (Eq. 2)). Later (stage IV), the value creation through the positive cross-side network effect, fuelled by discounts, speeds up the platform growth.

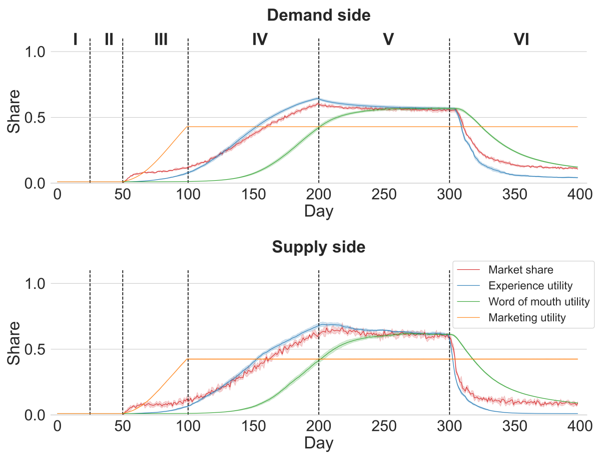

Figure 4: Six stages depicting the 400-day evolution of the market entry strategy in Amsterdam, replicated five times with varying origins and destinations of agents. The market share (red) results from individual agents' decisions, based on utility, composed of three components: marketing (orange), word of mouth (green) and experience (blue). In the first two stages, despite offering discounts from 25th day, the platform fails to launch. Marketing campaign (*III*) launched on day 50 attracts both supply and demand, which allows the platform to reach 20% market share before the campaign ends on day 100. Nonetheless, the strong word of mouth effect sustains the steady growth (*IV*) until the stabilization before the 200th day. When stabilized, the platform stops offering discounts (*V*), which only slightly affects its stable market shares. The greed (*VI*), however, leads to a significant drop in market share from day 300, when the platform recklessly decides to collect 50% from the drivers as the commission fee.

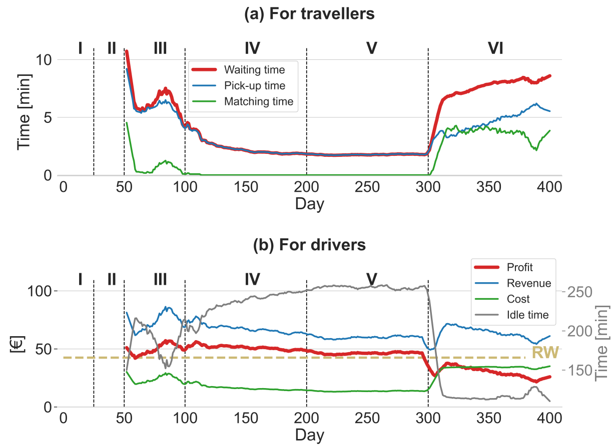

Figure 5: Evolution of key performance indicators for the supply (top) and demand (bottom). Travellers' waiting times (top) steadily drop to two minutes per traveller after 200 days, fuelling the value creation. The drivers' profits remain (red on the bottom) above the reservation wage (dashed) – showing self-equilibration of supply and demand – until it drops when the platform opts for 50% commission rate.

This results in many agents who preferably opt for ride-sourcing and find the new mode valuable. When platform ends the discounts (stage V) it reaches stability with 60% of market share. Intending to maximize its profit in short while, the platform recklessly raises the commission rate (stage VI), which turns to a tragedy and a great market share loses on both demand and supply side.

System performance: We investigate the performance of the platform for the six stages of the market entry strategy through the selected key performance indicators (KPIs). On the fig. 5, we report the average waiting time for travellers (composed of the average pick-up time and the matching time). We see the positive network effect: when the market grows, its performance improves. While in the early stages the waiting time is composed mostly with pick-up time (since the number of drivers is low), significantly increased matching time plays a substantial role at the greed stage. The profit (5, bottom) remains above the reservation wage (RW) for the whole period when the platform grows, asymptotically approaching it (equilibrium) - showing that our model well reproduces supply-demand interactions. We argue that stage V is optimal, with a good performance for travellers, drivers and the platform. Crucially, our simulated system self-equilibrates while growing: drivers' wages remain above the reservation wage from 100th to 300th day. In parallel, the value creation improves the system performance (waiting time) while the system grows from 20 to 60% market share.

Finally, we illustrate the key feature of the model: its sensitivity to the platform strategy. On fig. 6 we report the evolution curves over 400-day periods in alternative scenarios and show how it impacts market shares and platform revenues (rewards). We play with the commission rate (30%, 20% and 10%), trip fare (1.8, 1.2, 0.6€/km) and discounting/incentives campaigns. Our model reasonably reacts to a variety of strategies, providing strong signals for algorithms to learn the optimal policies. Here, we also report stability of the proposed model, surprisingly, the trajectories on fig. 6 result from 5 independent replications, but the confidence intervals are too small to be read from the figure. Apparently, individual agent-dependent learning trajectories cumulate into a stable market shares.

5 DISCUSSION AND CONCLUSION

In this research, we propose a novel agents' learning framework, suitable to reproduce complex interactions between supply, demand and a platform for the two-sided economies. We develop an empirically valid co-evolutionary model to represent the day-to-day dynamics of the two-sided market with individually learning agents of both supply and demand sides. Agents are rational decision-makers, maximizing their perceived, excepted utility. To properly reproduce the learning process, we formulate the utility composed of the endogenous experience, and exogenous word of mouth and marketing. We argue that such formulation allows to cover the key phenomena behind the platform growth: critical mass, band-wagon effect, network effects, cross-sided network effects, tragedy

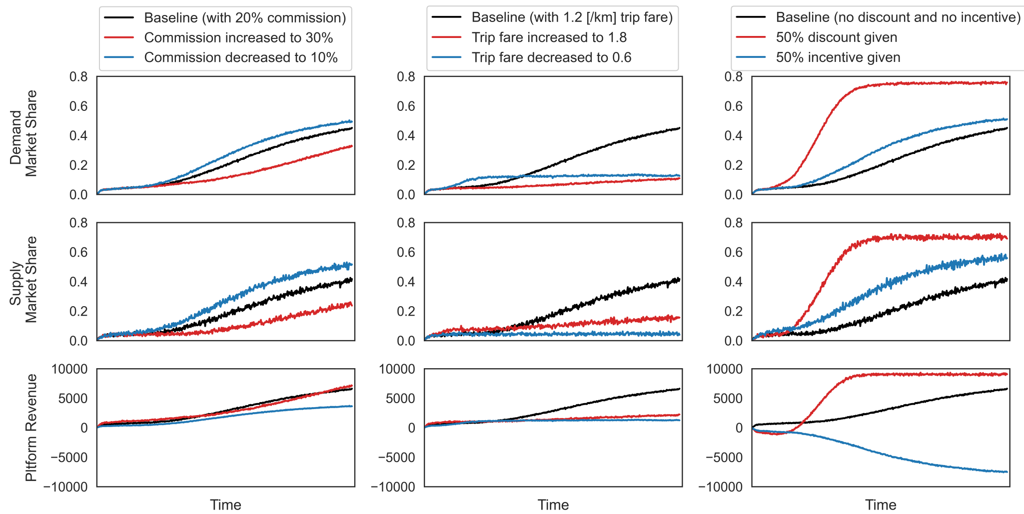

Figure 6: Sensitivity analysis of the proposed model. Market shares and platform revenues in three alternative scenarios for three selected control variables.

of commons, value creation and economies of scale. We apply it for the mobility platforms, like Uber, presumably the most complex of all the markets, where on top of platform-related challenges, the operator needs to address the complex spatiotemporal interactions of drivers and travellers on dense urban networks.

The proposed model reproduced a strong positive cross-side network effect at the microscopic level, crucial for the platform growth. At the beginning of the simulation, the number of agents is insufficient to reach the high service performance. Travellers experience long waiting times and there is a low number of trips to be supplied by the drivers. However, as some travellers and drivers decide to remain in the platform (due to own positive experiences or platform marketing and/or subsidy campaigns, as seen on fig. 3), the value creation begins, feeding the positive cross-side network effect (as demonstrated on fig. 5). Indeed, along with the market growth, the travellers' waiting time decrease and even more of them join the platform, which affects cross-side as more trips, in turn, attracts new drivers to join the platform. Which is in line with theoretical models [2, 8, 18] and empirical observations (fig. 2)

To steer those supply-demand interactions toward the profitability, the mobility platform controls: trip fare, commission rate, discounts and launches marketing campaigns. We run a 400-day simulation with a predefined six-stage market entry strategy of the ride-sourcing platform. Agents, notified about the new platform service, start reluctant, but explore it, building their own experience and sharing views with peers. In the maturity stage, the marketing campaign and discounts are no longer needed: the market share remains high without them (fig. 4), as value created for the platform through network effect does not disappear. This can be interpreted as the main rationale behind the large subsidies that platforms (including Uber) apply at the early adaptation phase. Importantly, platforms can also collapse as a result of inappropriate strategies or harsh competition, which is also covered with our model. In the greed stage of our experiment, the platform raises the commission rate to a reckless 50%. Unlike in the existing methods, this triggers the downward trend via the negative cross-side network effect, and the market-share falls in short time. This is possible thanks to S-shaped learning, where stable positive perceptions can be reversed after receiving a sufficient number of bad inputs.

In our approach, each agent follows a distinct, unique evolution path depending on its exposition to the marketing, word-of-mouth received from the peers and, most notably, own experiences gained while participating in the platform (as illustrated on fig. 3). The participation model is probabilistic and allows incorporating heterogeneity e.g. in learning speed, reservation wage or utility components weights.

We believe that the proposed modelling framework offers a richer and more solid representation of the underlying complexity behind platform growth and paves the path towards the realistic evaluation of the market entry strategies. With the proposed framework, we can evaluate multiple strategies and identify the optimal one. Moreover, now we can further propose the dynamic, adaptive policies, adjusting the actions every day. This allows to formulate this complex optimization problem as a (deep) reinforcement learning problem. In an even more complex scenario, the two or more competing platforms may concurrently adjust their strategies and compete for the market shares in an even more intriguing game-theoretic setting. The case observable on the platform-dominated markets, yet with no reliable agent-based representations so-far.

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REFERENCES

[1] Arentze Theo A and Harry J.P Timmermans. 2004. A learning-based transportation oriented simulation system. *Transportation Research Part B: Methodological* 38, 7 (2004), 613–633.

[2] Mark Armstrong. 2006. Competition in Two-Sided Markets. *The RAND Journal of Economics* 37, 3 (2006), 668–691.

[3] Paul Belleflamme and Martin Peitz. 2018. 11. Platforms and network effects. *Handbook of game theory and industrial organization* 2 (2018), 286.

[4] Enide A. I. Bogers, Michel Bierlaire, and Serge P. Hoogendoorn. 2007. Modeling Learning in Route Choice. *Transportation Research Record* 2014, 1 (2007), 1–8. https://doi.org/doi:10.3141/2014-01

[5] Eric Bonabeau. 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the national academy of sciences* 99, suppl_3 (2002), 7280–7287.

[6] Jacques Bughin, Jonathan Doogan, and Ole Jørgen Vetvik. 2010. A new way to measure word-of-mouth marketing. *McKinsey & Company* (2010).

[7] Carmelo Cennamo and Juan Santalo. 2013. Platform competition: Strategic trade-offs in platform markets. *Strategic management journal* 34, 11 (2013), 1331–1350.

[8] James Currier. 2019. The Network Effects Bible. NFX. Retrieved Jul. 30, 2022 from https://www.nfx.com/post/network-effects-bible

[9] Arjan de Ruijter, Oded Cats, Rafal Kucharski, and Hans van Lint. 2022. Evolution of labour supply in ridesourcing. *Transportmetrica B: Transport Dynamics* 10, 1 (2022), 599–626.

[10] Shadi Djavadian and Joseph YJ Chow. 2017. An agent-based day-to-day adjustment process for modeling 'Mobility as a Service'with a two-sided flexible transport market. *Transportation research part B: methodological* 104 (2017), 36–57.

[11] David S. Evans and Richard Schmalensee. 2010. Failure to Launch: Critical Mass in Platform Businesses. *Review of Network Economics* 9, 4 (2010). https://doi.org/doi:10.2202/1446-9022.1256

[12] Tom Evens, Karen Donders, Tom Evens, and Karen Donders. 2018. *Winner Takes All*. Springer.

[13] Farnoud Ghasemi and Rafał Kucharski. 2024. Two-sided Mobility Marketplace Modelling Framework. https://doi.org/10.5281/zenodo.10639039

[14] Ren-Yong Guo and Hai-Jun Huang. 2022. Day-to-day dynamics in a duopoly ride-sourcing market. *Transportation Research Part C: Emerging Technologies* 135 (2022), 103528.

[15] Jonathan V Hall and Alan B Krueger. 2018. An analysis of the labor market for Uber's driver-partners in the United States. *Ilr Review* 71, 3 (2018), 705–732.

[16] Michelle D. Haurand and Christian Stummer. 2020. Go Big or Go Home? Simulating the Effect of Publishing Adopter Numbers for Two-Sided Platforms. In *Advances in Social Simulation*, Harko Verhagen, Melania Borit, Giangiacomo Bravo, and Nanda Wijermans (Eds.). Springer International Publishing, Cham, 195–199.

[17] Zhou He, Guanghua Han, TCE Cheng, Bo Fan, and Jichang Dong. 2019. Evolutionary food quality and location strategies for restaurants in competitive online-to-offline food ordering and delivery markets: An agent-based approach. *International Journal of Production Economics* 215 (2019), 61–72.

[18] Junic Kim and Jaewook Yoo. 2019. Platform growth model: The four stages of growth model. *Sustainability* 11, 20 (2019), 5562.

[19] Rafał Kucharski and Oded Cats. 2022. Simulating two-sided mobility platforms with MaaSSim. *PLOS ONE* 17, 6 (2022), 1–20.

[20] Iliya Markov, Rafael Guglielmetti, Marco Laumanns, Anna Fernandez-Antolin, and Ravin de Souza. 2021. Simulation-based design and analysis of on-demand mobility services. *Transportation Research Part A: Policy and Practice* 149 (2021), 170–205.

[21] Jaap MJ Murre. 2014. S-shaped learning curves. *Psychonomic bulletin & review* 21 (2014), 344–356.

[22] Laurent Muzellec, Sébastien Ronteau, and Mary Lambkin. 2015. Two-sided Internet platforms: A business model lifecycle perspective. *Industrial Marketing Management* 45 (2015), 139–150.

[23] Ministry of Social Affairs and Employment. 2022. *Amount of the Minimum Wage - Minimum Wage - Government.Nl*. https://www.government.nl/topics/minimum-wage/amount-of-the-minimum-wage

[24] Harald Øverby, Jan A Audestad, and Gabriel Andy Szalkowski. 2023. Compartmental market models in the digital economy—extension of the Bass model to complex economic systems. *Telecommunications Policy* 47, 1 (2023), 102441.

[25] Arnold Overwater and Neil Yorke-Smith. 2022. Agent-based simulation of short-term peer-to-peer rentals: Evidence from the Amsterdam housing market. *Environment and Planning B: Urban Analytics and City Science* 49, 1 (2022), 223–240. https://doi.org/10.1177/23998083211000747

[26] Xinwu Qian and Satish V. Ukkusuri. 2017. Taxi Market Equilibrium with Third-Party Hailing Service. *Transportation Research Part B: Methodological* 100 (2017), 43–63.

[27] Jean-Charles Rochet and Jean Tirole. 2006. Two-sided markets: a progress report. *The RAND Journal of Economics* 37, 3 (2006), 645–667. https://doi.org/10.1111/j.1756-2171.2006.tb00036.x

[28] Hans Jochen Scholl. 2001. Agent-based and system dynamics modeling: a call for cross study and joint research. In *Proceedings of the 34th annual Hawaii international conference on system sciences*. IEEE, 8–pp.

[29] Shouheng Sun and Myriam Ertz. 2021. Dynamic evolution of ride-hailing platforms from a systemic perspective: Forecasting financial sustainability. *Transportation Research Part C: Emerging Technologies* 125 (2021), 103003.

[30] Uber. 2023. Choosing the right distance rate for your car. Retrieved Jul. 30, 2023 from https://help.ubercarshare.com/hc/en-gb/articles/360022882131-Choosing-your-car-s-distance-rate

[31] Uber. 2023. Uber Estimate, Get a Price Estimate in Your City. Retrieved Jul. 30, 2023 from https://www.uber.com/global/en/price-estimate/

[32] Evgueni Vinogradov, Birgit Leick, and Bjørnar Karlsen Kivedal. 2020. An agent-based modelling approach to housing market regulations and Airbnb-induced tourism. *Tourism Management* 77 (2020), 104004.

[33] Hai Wang and Hai Yang. 2019. Ridesourcing systems: A framework and review. *Transportation Research Part B: Methodological* 129 (2019), 122–155.

[34] Chiwei Yan, Helin Zhu, Nikita Korolko, and Dawn Woodard. 2020. Dynamic pricing and matching in ride-hailing platforms. *Naval Research Logistics (NRL)* 67, 8 (2020), 705–724.

[35] Menno Yap, Oded Cats, and Bart van Arem. 2020. Crowding valuation in urban tram and bus transportation based on smart card data. *Transportmetrica A Transport Science* 16, 1 (2020), 23–42.

[36] Junlin Zhang, Dong Mo, and Xiqun (Michael) Chen. 2022. Analyzing Ride-Sourcing Market Equilibrium and Its Transitions with Heterogeneous Users. *Journal of Advanced Transportation* 2022 (2022).