On the Joint Effects of Supply and Demand Multi-homing in the e-hailing Market

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1 Introduction

The e-hailing market operates as a two-sided platform matching passengers with drivers. This market experiences network effects, where a larger number of participants on one side increases the value for the other side. However, when multiple platforms exist, the market becomes fragmented, diluting these network effects and leading to inefficiencies such as increased cancellations and lower occupancy rates. Multi-homing behaviors—where passengers and drivers use multiple platforms—can mitigate these inefficiencies by extending access to the total demand and supply, but this aspect remains relatively underexplored in existing research.

Current studies on the e-hailing market typically employ either equilibrium models (Zha *et al.*, 2016), which view the market in aggregate and assume static conditions, or dynamic models (Alonso-Mora *et al.*, 2017), which focus on individual agents and matching algorithms. Few have delved into multi-homing behaviors, and those that have often consider extreme cases where either all passengers or all drivers multi-home or single-home. This leaves a gap in understanding the nuanced effects of varying levels of multi-homing among both passengers and drivers.

Addressing this gap, our study introduces both an aggregated equilibrium model and a disaggregated dynamic model that account for partial multi-homing by passengers and drivers in a market with two platforms. By treating the proportions of multi-homing agents as exogenous variables, we can analyze the effects of different combinations of multi-homing levels. Multi-homing passengers may check multiple platforms and potentially cancel trips due to impatience or dissatisfaction, while multi-homing drivers may choose between platforms to maximize earnings. Comparing results from both models allows us to quantify the isolated effects of multi-homing and offers insights into managing these behaviors to improve market efficiency.

2 Equilibrium Model of the E-Hailing Market with Multi-Homing

We develop an equilibrium model for a symmetric duopoly e-hailing market where both passengers and drivers can multi-home (use multiple platforms simultaneously). The total passenger demand rate D_p and driver supply V_t are exogenous, as are the passenger and driver multi-homing rates θ and ϕ.

Demand and Supply: Multi-homing passengers enter the market at rate θD_p, while single-homing passengers enter each platform at rate $\frac{(1-\theta)}{2}D_p$. Thus, the total passenger arrival rate into one platform is $\frac{(1+\theta)}{2}D_p$. Let p_w^u and p_w^s denote the number of waiting multi-homing and single-homing passengers on a platform, respectively. The proportion of waiting passengers who are multi-homing is $\theta^* = \frac{p_w^u}{2p_w^s+p_w^u}$.

Drivers can be single-homing or multi-homing. The total number of single-homing drivers on each platform is $v_i^s + v_m^s + v_o^s = \frac{(1-\phi)}{2}V_t$, and the total number of multi-homing drivers is $v_i^u + v_m^u + v_o^u = \phi V_t$, where v_i, v_m, v_o represent idle, matched, and occupied drivers, and superscripts s and u denote single-homing and multi-homing drivers. The idle driver multi-homing rate is $\phi^* = \frac{v_i^u}{2v_i^s+v_i^u}$.

Matching Process: The matching rate m between passengers and drivers is modeled using a Cobb-Douglas function:

$$m = A_0(p_w^s + p_w^u)^{\alpha_1}(v_i^s + v_i^u)^{\alpha_2},$$

where A_0 is a constant, and α_1 and α_2 are elasticities. The matching rates involving single-homing (m^s)

and multi-homing (m^u) drivers are:

$$m^s = m\left(\frac{1-\phi^*}{1+\phi^*}\right), \quad m^u = m\left(\frac{2\phi^*}{1+\phi^*}\right).$$

The probability that an idle driver is matched in a given interval Δ is $\xi_v = \frac{\Delta m}{v_i^s+v_i^u}$, and the effective accepted matching rate is $m^{\text{acc}} = m^s + m^u\left(1-\frac{\xi_v}{2}\right)$.

Passenger Cancellations: Passengers may cancel if not matched within their patience threshold τ, following a truncated normal distribution. For single-homing passengers, the Type I cancellation rate is:

$$c_1^s = \frac{(1-\theta)}{2}D_p - m^{\text{acc}}\left(\frac{1-\theta^*}{1+\theta^*}\right).$$

For multi-homing passengers, considering they might be matched by the other platform, the Type I cancellation rate is:

$$c_1^u = \theta D_p - (2-\xi_p)\, m^{\text{acc}}\left(\frac{2\theta^*}{1+\theta^*}\right),$$

where $\xi_p = \frac{\Delta m^{\text{acc}}}{p_w^s+p_w^u}$.

Pickup Times: The average passenger pickup time is estimated by:

$$w_p = \Gamma_0(p_w^s+p_w^u)^{\gamma_1}(v_i^s+v_i^u)^{\gamma_2},$$

with constants Γ_0, γ_1, γ_2. Due to multi-homing, the expected pickup times are adjusted: for multi-homing drivers, $w_p^u = w_p - \sigma_w\pi^{-1/2}$; for multi-homing passengers, $w_p^{uu} = w_p - \sigma_w\left(3\pi^{-3/2}\right)$.

Service Quality and Type II Cancellations: Passengers may also cancel after being matched if the service is unsatisfactory. The utility of a ride is:

$$u^{ij} = \beta_s - \beta_w w_p^{ij} - \beta_f f,$$

where $i, j \in \{s, u\}$ denote passenger and driver homing types, w_p^{ij} is the pickup time, f is the fare, and β_s, β_w, β_f are parameters. The acceptance probability is:

$$P_{\text{accept}}^{ij} = \frac{e^{u^{ij}}}{e^{u_o}+e^{u^{ij}}},$$

leading to the Type II cancellation rate:

$$c_2^{ij} = m^{ij}\left(1-P_{\text{accept}}^{ij}\right).$$

Driver States and Flow Conservation: After passengers accept matches, drivers transition between states. The number of matched single-homing drivers is:

$$v_m^s = w_p^{ss}(m^{ss}-c_2^{ss}) + w_p^{su}\left(1-\frac{\xi_p}{2}\right)(m^{su}-c_2^{su}),$$

and for multi-homing drivers:

$$v_m^u = 2\left[w_p^{us}(m^{us}-c_2^{us}) + w_p^{uu}\left(1-\frac{\xi_p}{2}\right)(m^{uu}-c_2^{uu})\right].$$

The number of occupied single-homing drivers is:

$$v_o^s = t\left(b^{ss}+b^{su}\right),$$

and for multi-homing drivers:

$$v_o^u = 2t\left(b^{us}+b^{uu}\right),$$

where t is the average trip duration, and boarding rates are:

$$b^{ss} = m^{ss}-c_2^{ss}, \quad b^{su} = \left(1-\frac{\xi_p}{2}\right)(m^{su}-c_2^{su}), \quad b^{us} = m^{us}-c_2^{us}, \quad b^{uu} = \left(1-\frac{\xi_p}{2}\right)(m^{uu}-c_2^{uu}).$$

Equilibrium Conditions: By solving these equations simultaneously, we determine the equilibrium state of the e-hailing market under given D_p, V_t, θ, and ϕ. The model captures the impact of multi-homing on matching rates, cancellations, pickup times, and driver states, providing insights into market efficiency under varying multi-homing levels.

3 Dynamic Model of the E-Hailing Market with Multi-Homing

We develop a dynamic model of the e-hailing market, focusing on interactions between passengers, drivers, and platforms from the perspective of one platform.

Passengers: Single-homing passengers join a platform, provide their origin and destination, and wait to be matched. When a potential match is found, the platform first asks the driver to accept; only after the driver's acceptance is the passenger notified. Passengers are impatient; if not notified within their matching patience $\Delta^{\mathrm{m}}_{i,1}$, they cancel their request. Upon notification, passengers evaluate the trip based on pickup time $w^{a,1}_{i,1}$ and fare $f_{i,1}$. The utility of accepting the trip is:

$$u^{\mathrm{r}}_{i,1} = \beta^{\mathrm{r}}_{i,1} - \beta^{\mathrm{t}}_{i,1} w^{a,1}_{i,1} + \epsilon^{\mathrm{r}}_{i,1},$$

while the utility of other modes is:

$$u^{\mathrm{o}}_{i,1} = \beta^{\mathrm{o}}_{i,1} + \epsilon^{\mathrm{o}}_{i,1}.$$

The probability of acceptance is:

$$\mathrm{Pr}^{\mathrm{r}}_{i,1} = \frac{e^{u^{\mathrm{r}}_{i,1}}}{e^{u^{\mathrm{r}}_{i,1}} + e^{u^{\mathrm{o}}_{i,1}}}.$$

Multi-homing passengers join both platforms simultaneously. If notified by one platform, they wait for a period $\Delta^{\mathrm{p}}_{\hat{k}}$ or until their overall matching patience $\Delta^{\mathrm{m}}_{\hat{k}}$ before deciding. If matched by both platforms, they select the trip with the shorter pickup time and decide to accept or reject it using the same utility model.

Drivers: Single-homing drivers always accept trips assigned by the platform and are paid a portion of the fare. They can be in one of four states: idle, pending passenger confirmation, matched (dispatched but unoccupied), and occupied. Multi-homing drivers are idle on both platforms. If notified of a match by one platform, they may wait for $\Delta^{\mathrm{v}}_{\hat{c}}$ for a potential match from the other platform. If matched by both, they compare per-unit-time earnings and choose the higher, $\frac{c^{a,1}_{i,1}}{w^{a,1}_{i,1} + |O_i D_i|}$, where $c^{a,1}_{i,1}$ is the driver's wage and $|O_i D_i|$ is the trip duration.

Platforms: Platforms have information on passengers' origins O_i, destinations D_i, and drivers' locations but cannot distinguish between single-homing and multi-homing agents. The fare structure includes a fixed base price λ^{c} and a variable price λ^{t} based on trip duration:

$$f_{i,1} = \lambda^{\mathrm{c}} + \lambda^{\mathrm{t}} |O_i D_i|.$$

Drivers receive a portion λ^{v} of the fare:

$$c^{a,1}_{i,1} = \lambda^{\mathrm{v}} f_{i,1}.$$

Platforms use a batch-matching algorithm every Δ seconds, matching idle vehicles $\bar{\mathcal{V}}_1$ and unmatched passengers $\bar{\mathcal{P}}_1$ to minimize total pickup times. The matching problem is formulated as:

$$\min_{x_{p,v}} \sum_{(p,v)\in\mathcal{E}} w_{p,v} x_{p,v},$$

subject to:

$$\sum_{v} x_{p,v} \leq 1, \quad \forall p \in \bar{\mathcal{P}}_1; \quad \sum_{p} x_{p,v} \leq 1, \quad \forall v \in \bar{\mathcal{V}}_1; \quad x_{p,v} \in \{0,1\}.$$

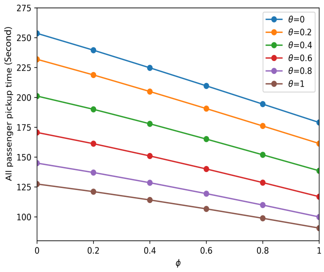
After matching, drivers are notified first; upon their acceptance, passengers are informed and decide whether to accept based on the utility model. If the pickup time exceeds a threshold Δ^{r}_1, the match is discarded to avoid excessively long pickups.

This dynamic model captures the behaviors and interactions of single-homing and multi-homing passengers and drivers in the e-hailing market, accounting for decision-making processes, matching algorithms, and platform operations.

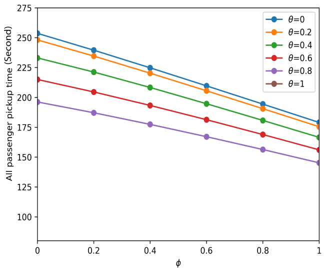
4 Numerical Experiments

We conducted numerical experiments using both the proposed equilibrium model and the dynamic simulation model to analyze the effects of joint passenger and driver multi-homing in an e-hailing market. For the equilibrium model, we specified exogenous variables and calibrated parameters. In the dynamic model, we simulated the Manhattan road network, where passengers with random origins and destinations entered the market at a given rate, and vehicles were incrementally added until reaching a fleet size of 4,000. Each experiment included a 60-minute warm-up period, after which performance indicators were measured and averaged over five runs to ensure reliability. Passenger and driver decision parameters were set to reflect heterogeneity among passengers, with some values drawn from bounded normal distributions. Pricing, wage structures, and matching method parameters were consistent across both platforms.

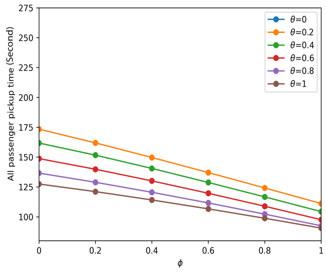
To assess the impact of multi-homing, we tested different combinations of passenger and driver multi-homing levels, defined as the proportion of passengers (θ) or drivers (ϕ) who use multiple platforms. Both θ and ϕ ranged from 0% to 100% in 20% increments, resulting in 36 distinct scenarios. In each experiment for both models, we maintained a total demand of four passenger requests per second. This systematic variation allowed us to examine the effects of multi-homing on key performance indicators across a spectrum of market conditions.



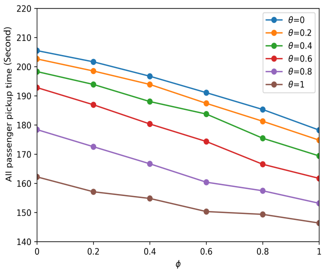
(a) *Passenger pickup time (Equilibrium model)*



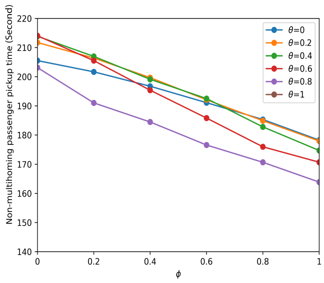
(b) *Single-homing passenger pickup time (Equilibrium model)*



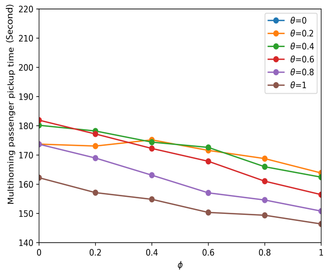
(c) *Multi-homing passenger pickup time (Equilibrium model)*



(d) *Passenger pickup time (Simulation model)*



(e) *Single-homing passenger pickup time (Simulation model)*



(f) *Multi-homing passenger pickup time (Simulation model)*

Figure 1 – *Average passenger pickup times for varying levels of passenger (θ) and driver (ϕ) multi-homing, including total, single-homing, and multi-homing passengers.*

Figure 1a shows the average pickup times for all passengers for varying combinations of passenger and driver multi-homing ratios using the equilibrium model. Whereas Figure 1d shows the same indicators using the simulation model. It can be observed that both sets of results exhibit similar trends. Both figures show that as multi-homing ratios increase for either passengers or drivers, the average passenger pickup time is reduced. In Figures 1e and 1f, the equilibrium model average pickup times for single-homing passengers and multi-homing passengers are shown respectively. Their counterparts in the simulation model are shown in Figures 1b and 1c respectively. It can still be observed that the average multi-homing passenger pickup time is reduced as either the passenger or driver multi-homing ratios increase. Interestingly, single-homing passengers' average pickup time is also reduced as there are more multi-homing passengers. Additionally, we observe that the multi-homing passengers' average pickup times are always lower than that of single-homing passengers. It suggests that all passengers benefit from additional passenger multi-homing, while multi-homing passengers benefit more than single-homing passengers by their own actions.

5 Summary

We develop equilibrium and dynamic models to evaluate passenger and driver multi-homing in e-hailing markets. Results show that multi-homing generally enhances market performance, benefiting multi-homing passengers while disadvantaging single-homing ones.

References

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